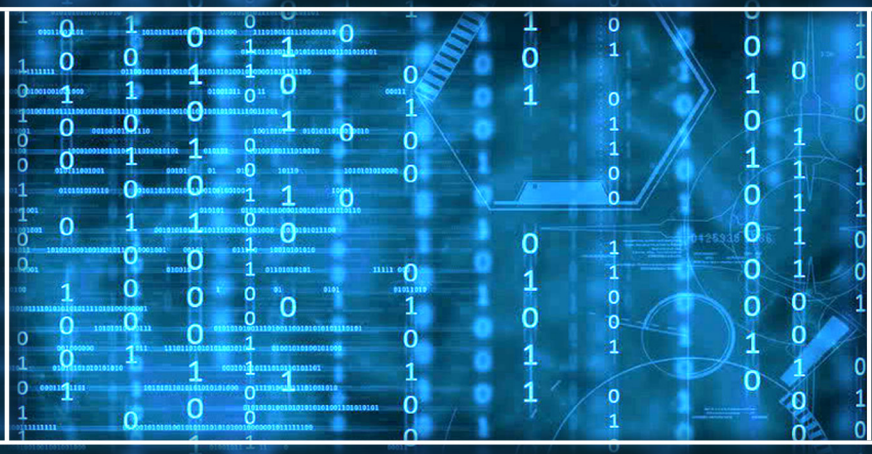
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Editorial Preface

From the Desk of Managing Editor…

It may be difficult to imagine that almost half a century ago we used computers far less sophisticated than current home desktop computers to put a man on the moon. In that 50 year span, the field of computer science has exploded.

Computer science has opened new avenues for thought and experimentation. What began as a way to simplify the calculation process has given birth to technology once only imagined by the human mind. The ability to communicate and share ideas even though collaborators are half a world away and exploration of not just the stars above but the internal workings of the human genome are some of the ways that this field has moved at an exponential pace.

At the International Journal of Advanced Computer Science and Applications it is our mission to provide an outlet for quality research. We want to promote universal access and opportunities for the international scientific community to share and disseminate scientific and technical information.

We believe in spreading knowledge of computer science and its applications to all classes of audiences. That is why we deliver up-to-date, authoritative coverage and offer open access of all our articles. Our archives have served as a place to provoke philosophical, theoretical, and empirical ideas from some of the finest minds in the field.

We utilize the talents and experience of editor and reviewers working at Universities and Institutions from around the world. We would like to express our gratitude to all authors, whose research results have been published in our journal, as well as our referees for their in-depth evaluations. Our high standards are maintained through a double blind review process.

We hope that this edition of IJACSA inspires and entices you to submit your own contributions in upcoming issues. Thank you for sharing wisdom.

Thank you for Sharing Wisdom!

Kohei Arai
Editor-in-Chief
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ML to Predict Effectiveness of the MCP Authorization Model for LLM-Powered Agent

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***Abstract*—In today's AI-driven world, unlocking AI potential and enabling AI models to communicate with external data sources is vital for enhancing the efficiency and security of AI-driven applications. The Model Context Protocol (MCP) serves as a standard for maximizing AI potential. This study leverages a machine learning approach to predict the effectiveness of the MCP Authorization Model for an LLM-powered agent. It utilizes logs from Azure services such as Azure Monitor, Azure Sentinel, and Azure Active Directory, which are used to monitor MCP server activity, to create a sample dataset. This dataset includes features such as source_ip, destination_ip, event_type, alert_severity, and target_variable. These features are used to train the ML model to assess the effectiveness of the MCP Authorization model for LLM-powered agents, enabling organizations to better understand the importance of a secure connection between AI models. This approach contributes to unlocking AI's full potential while improving application security and operational efficiency.**

***Keywords*—Model Context Protocol; artificial intelligence; machine learning; large language model**

I. Introduction

Large language models (LLMs) have evolved rapidly, demonstrating sophisticated reasoning and problem-solving capabilities [1, 2, 3]. In recent years, the rise of Large Language Model (LLM)-powered agents capable of interacting with various tools has gained significant momentum. Frameworks like LangChain [4] and LlamaIndex [5] facilitate the standardized tool interfaces, making it easier to integrate LLM-powered autonomous agents with external services.

These autonomous AI agents, operating in security-sensitive environments has necessitated appropriate security control policies to ensure compliant operations. In late 2024, Anthropic introduced the Model Context Protocol (MCP) for standardizing AI-tool interactions [6]. MCP specifies the rules on how external data sources and tools should interact with LLMs [7, 8] and provides a framework for AI applications to communicate dynamically with external tools. These models serve as a structured framework for enforcing security policies. However, their effectiveness in dynamic, AI-driven ecosystems remains an open challenge. This study explores the machine learning (ML) techniques to predict the effectiveness of the MCP Authorization Model for LLM-powered agents.

II. Related Work

In [9], the authors introduced the universal agent protocol, which became the foundation for modern agent systems, including LangChain Agents. In [10], the authors presented plugin-based interfaces such as OpenAI ChatGPT Plugins, enabling AI models to connect with external tools through standardized API schemas like OpenAPI. In [11], the authors explored contextual information retrieval methods, such as retrieval augmented generation (RAG) and knowledge bases, enabling models to supplement responses with up-to-date information by leveraging vector-based search to retrieve relevant knowledge from databases. In [12], the authors defined standardized interface through JSON-RPC message exchange and the modal context protocol (MCP), extending passive information retrieval by enabling AI models to interact with external data sources and addressing the fragmentation problem in AI tool integration. Despite the enhanced capabilities of LLMs and recent advancement in AI agents interactions tools, existing research fails to demonstrate the effectiveness of MCP for AI agent interaction within a zero-trust framework.

III. MCP Background and Security Challenge

The Model Context Protocol (MCP) is an open standard that enables secure and uniform access to external tools and services for large language models [13]. It acts as a mediator between the LLM and external tools. MCP interaction includes roles such as MCP clients, which are AI agent or LLMs, and MCP server, which represent external tool or data sources. Real-time MCP use cases include software development assistant and AI-driven support assistants. MCP enables enterprise to integrate AI with existing applications.

However, security challenges could arise if MCP is not designed correctly. Common MCP security challenges include overprivileged access, supply chain exposure, inconsistent policy enforcement, and context leakage [14]. To secure MCP, industry standard recommendations would benefit organizations deploying it. These include applying fine-grained access control, introducing AI governance into AI workflows, avoiding static credentials, enforcing mandatory logging and audit monitoring, and educating both developer and security teams.

IV. Methodology

The study leverages machine learning approach to assess the MCP authorization model effectiveness. The experimental methodology presented in this study incorporates AI-driven Azure services logs to construct a sample dataset that includes features such as source_ip, destination_ip, event_type, alert_severity, and target_variable. These dataset features are chosen to identify both network-based and securty-relevant

identifiers. The initial preprocessing involves cleaning to remove duplicate entries, label encoding to convert categorical values into numerical values, and normalization (StandardScaler) to scale numerical values to ensure uniformity across features, followed by exploratory data analysis (EDA) to identify patterns and security indicators. The full dataset is then divided into training (80%) and testing (20%) segments, with Synthetic Minority Oversampling Technique (SMOTE) applied to address class imbalances. Machine learning model are selected, trained, tuned, and deployed to assess effectiveness of the MCP authorization model for LLM-powered agent. Model performance is evaluated using appropriate metrics.

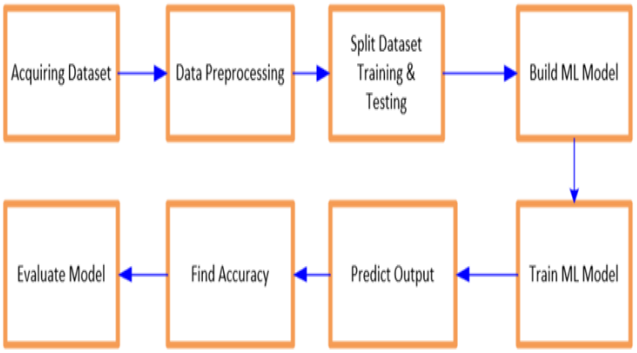


Fig. 1. Machine learning implementation workflow.

Fig. 1 shows the visual workflow of machine learning implementation process, which involves several key stages: acquiring the dataset, followed by data preprocessing, splitting the dataset into training and testing sets, building and training the model, predicting outputs, evaluating accuracy, and finally assessing the model's overall performance.

A modular ML pipeline was designed with the following components:

- Feature Extraction: Using AI-driven Azure service logs.
- Classification Methods and Model Architecture: RM, KNN, SVM, Gradient Boosting, and Logistic regression.
- Model Evaluation: Assessing accuracy of Machine learning models to evaluate their performance.

V. Responsible AI Consideration

Although the dataset used in this research is synthetic and does not contain sensitive information, ensuring responsible AI practices is important. Future work will focus on integrating explainable AI (XAI) tools such as SHAP to enhance transparency and trust in ML-driven authorization decisions, which will help align the models with ethical standards and enterprise governance requirements.

VI. Results and Discussion

Proposed study utilizes exploratory data analysis (EDA) techniques to understand the dataset and detect any anomalies prior to training a machine learning model. Fig. 2 shows the correlation heatmap that visualizes correlation coefficient between source_ip, destination_ip, event_type, alert_severity, and target_variable. These variables show weak correlations with each other and with target variable, indicating that liner models may not perform well. Although the heatmap highlights that the correlation between event type and alert_severity is the highest at 0.12 and may offer slightly more predictive value, it still considers a weak correlation. Given the overall weak correlations, a Random Forest model is considered a good choice since it is robust to noise and handles weakly correlation features effectively.

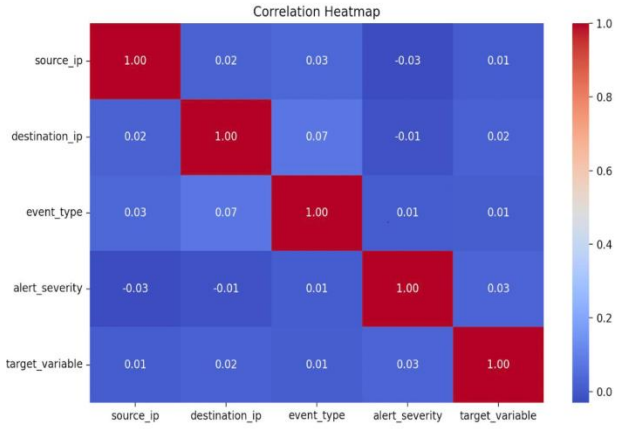


Fig. 2. Correlation heatmap.

Fig. 3 shows box plots illustrating the feature distributions of source_ip, destination_ip, event_type, alert_severity, and target_variable. Most of these features are tightly centered around 0, suggesting that they are well preprocessed for machine learning.

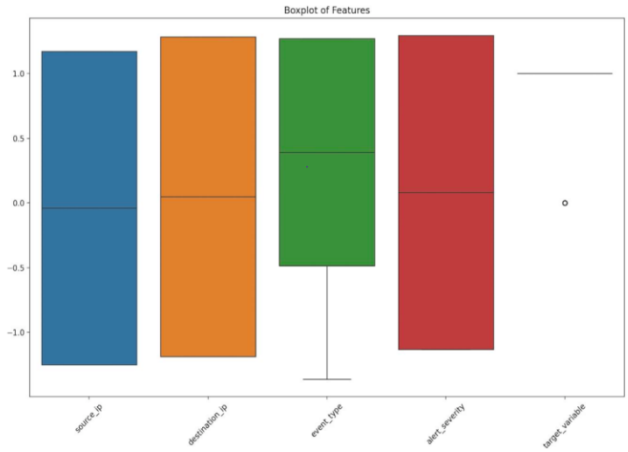


Fig. 3. Box plot for feature distribution.

Fig. 4 shows six numerically encoded features, where source_ip and destination_ip indicate various network traffic patterns, event_type and alert_severity show imbalanced frequencies, and target_variable, which is heavily skewed toward the malicious class indicates class imbalance.

Fig. 5 displays class distribution before and after applying SMOTE (Synthetic Minority Over-Sampling Technique). Class 0 has fewer samples (100) compare to class 1 (600), which causes models to favor the majority class, leading to

biased predictions. To address class imbalance issues, SMOTE has been applied, enabling machine learning models avoid bias toward the majority class and improve overall performance.

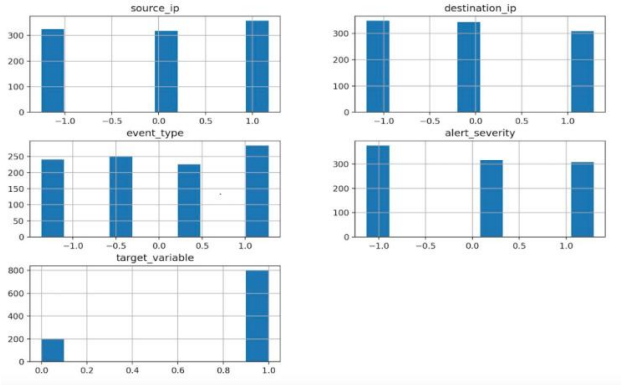


Fig. 4. Bar charts showing categorical feature distributions.

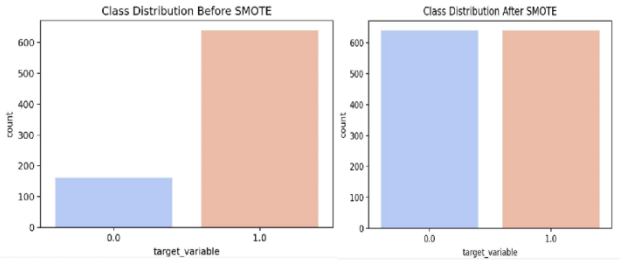


Fig. 5. Class distribution before and after SMOTE.

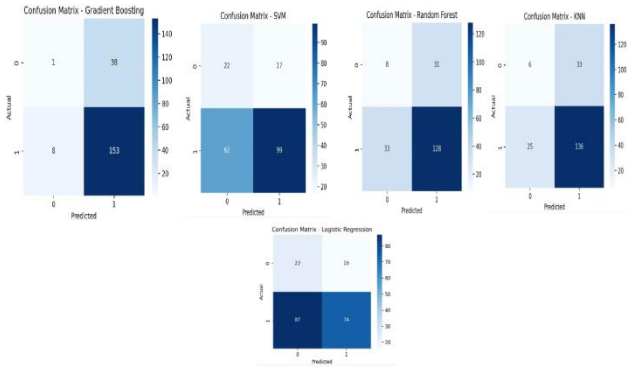


Fig. 6. Consolidated confusion matrix.

Fig. 6 shows the consolidated confusion matrix for five models. Based on the sample outlined in the confusion matrix, machine learning models produced the following results:

$$Accuracy\ (A) = \frac{tp+tn}{tp+tn+fp+fn} \quad (1)$$

$$Precision\ (P) = \frac{tp}{tp+fp} \quad (2)$$

$$Recall\ (R) = \frac{tp}{tp+fn} \quad (3)$$

$$F1-Score = \frac{2*(p*r)}{p+r} \quad (4)$$

where, TP is true positive, TN is true negative, FP is false positive, and FN is false negative.

TABLE I. MODEL METRICS

Random forest	SVM	KNN	Gradient boosting	Logistic regression
TP= 128 TN= 8 FP= 31 FN= 33 A= 0.68 P= 0.805 R= 0.795 F1-Score= 0.800	TP= 99 TN=22 FP= 17 FN=62 A=0.6 P= 0.853 R= 0.615 F1-Score= 0.714	TP= 136 TN= 6 FP= 33 FN= 25 A= 0.71 P= 0.805 R= 0.845 F1-Score= 0.824	TP= 153 TN= 1 FP= 38 FN= 8 A= 0.77 P= 0.801 R= 0.950 F1-Score= 0.869	TP= 74 TN= 23 FP= 16 FN= 87 A= 0.485 P= 0.822 R= 0.459 F1-Score= 0.589

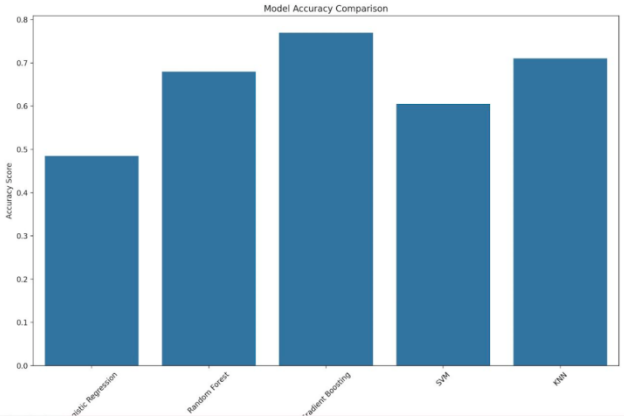


Fig. 7. Model accuracy comparison.

Five algorithms are considered on this dataset to perform classification tasks. The model is evaluated using key parameters such as Recall, Precision, F-Measure, error rate and overall model accuracy. Gradient Boosting was chosen for assessing the effectiveness of the MCP Authorization model for LLM-powered agents for the following reasons:

- Gradient Boosting achieved the highest score among all other models tested in this study.
- Gradient Boosting handles complex feature interaction effectively and its sequential assemble approach, which corrects errors from previous iterations, is beneficial for identifying malicious patterns in the MCP server log.

Table I details the model metrics and the accuracy comparison of models is given in Fig. 7.

VII. CONCLUSION

This study presents a machine learning-driven evaluation of the Model Context Protocol (MCP) authorization model to enhance secure communication for LLM-powered agents. The experimental methodology used in this research study leverages an ML pipeline to evaluate the MCP authorization model using AI-driven Azure service logs, including Azure Monitor, Azure Sentinel, Azure Active Directory, which are used to monitor MCP server activity. These logs are used to construct a dataset, containing 5,000 labeled instances of observed attacks outcomes across seven features, including source_ip, destination_ip, event_type, alert_severity, and target_variable, to train a model to identify anomalous

activities in AI-agent communication with model. With an accuracy of 77 per cent, this study highlights the effectiveness of ML technique in predicting the performance of the MCP authorization model for LLM-powered agent, enabling organizations to better understand the importance of secure connection between AI models and enhance the security of AI-powered applications.

VIII. Limitations and Future Work

Although the proposed ML pipeline shows promise, the research can be enhanced by applying larger dataset. Future work should focus on incorporating additional data source to improve model robustness, integrating explainable AI (XAI) tools such as SHAP to enhance transparency and trust in ML-driven authorization decisions, extending the model to other cloud platforms beyond Azure, evaluating the MCP framework to assess its resilience, and deploying the ML pipeline in live enterprise settings under operational constraints.

References

[1] J. Achiam, S. Adler, S. Agarwal, L. Ahmad, I. Akkaya, F. L. Aleman, D. Almeida, J. Altenschmidt, S. Altman, S. Anadkat, et al., "GPT-4 Technical Report," arXiv preprint arXiv:2303.08774, 2023.

[2] A. Grattafiori, A. Dubey, A. Jauhri, A. Pandey, A. Kadian, A. Al-Dahle, A. Letman, A. Mathur, A. Schelten, A. Vaughan, et al., "The LLaMA 3 Herd of Models," arXiv preprint arXiv:2407.21783, 2024.

[3] A. Yang, A. Li, B. Yang, B. Zhang, B. Hui, B. Zheng, B. Yu, C. Gao, C. Huang, C. Lv, et al., "Qwen3 Technical Report," arXiv preprint arXiv:2505.09388, 2025.

[4] LangChain, "LangChain: Framework for Developing Applications Powered by Language Models," 2022. Available: https://github.com/langchain-ai/langchain

[5] J. Liu, "LlamaIndex: A Data Framework for LLM Applications," 2022. Available: https://github.com/run-llama/llama_index

[6] Anthropic, "Introducing the Model Context Protocol," 2024. Available: https://www.anthropic.com/news/model-context-protocol

[7] N. Gunasinghe and N. Marcus, Language Server Protocol and Implementation. Springer, 2021.

[8] Anthropic, "Introducing the Model Context Protocol," Blog post, November 2024. Available: https://www.anthropic.com/news/model-context-protocol

[9] H. Chase, "LangChain," Python framework for developing applications powered by language models, 2022. Available: https://github.com/langchain-ai/langchain

[10] OpenAI. 2023. ChatGPT plugins. https://openai.com/index/chatgpt-plugins/

[11] F. Cuconasu, G. Trappolini, F. Siciliano, S. Filice, C. Campagnano, Y. Maarek, N. Tonellotto, and F. Silvestri, "The Power of Noise: Redefining Retrieval for RAG Systems," CoRR, abs/2401.14887, 2024. doi: 10.48550/arXiv.2401.14887

[12] T. Gan and Q. Sun, "RAG-MCP: Mitigating Prompt Bloat in LLM Tool Selection via Retrieval-Augmented Generation," arXiv preprint arXiv:2505.03275, 2025.

[13] Anthropic, "Model Context Protocol," 2024. Available: https://docs.anthropic.com/en/docs/agents-and-tools/mcp. Accessed: June 25, 2025.

[14] S. Walter, Securing the Model Context Protocol: Access, Authorization, and Audit for Enterprise AI. Hyperframe Research, 2025. Available: https://hyperframeresearch.com/2025/05/21/securing-the-model-context-protocol-access-authorization-and-audit-for-enterprise-ai/.

Efficient Multi-Class Analysis of Consumer Complaints Using Frozen MiniLM Embeddings and Neural Networks

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Department of Artificial Intelligence, University of Management and Technology, Lahore, Pakistan[2]

***Abstract*—Text classification is a critical task in domains generating large volumes of unstructured text, such as finance, healthcare, and consumer services. However, accurately classifying such data remains challenging due to its noisy, imbalanced, and context-dependent nature. While pre-trained language models have improved general text classification, their direct application often overlooks domain-specific cues and sentiment patterns that are important for nuanced understanding. In this study, we propose a novel framework that extends the MiniLM language model by integrating domain-relevant cues and sentiment features with textual embeddings. This integration allows the model to capture both semantic richness and domain-specific patterns, enhancing reliability and interpretability. Comparative experiments against baselines including TF-IDF + Logistic Regression, Word2Vec + Logistic Regression, TF-IDF + Naïve Bayes, and Word2Vec + Naïve Bayes shows that the proposed approach consistently outperforms traditional methods, achieving an accuracy of 0.8653, precision of 0.8697, recall of 0.8653, F1-score of 0.8668, Cohen's Kappa of 0.7862, and MCC of 0.7870. Ablation studies further demonstrate the critical role of cues and sentiment features in improving performance. These findings indicate that combining pre-trained embeddings with carefully selected domain features offers a more robust and context-aware solution for text classification, establishing a foundation for future work integrating transformer-based models with explainable AI techniques in domain-specific applications.**

***Keywords*—Consumer complaints; text classification; sentence embeddings; MiniLM; class imbalance; sentiment analysis; domain adaptation; contextual embeddings**

I. Introduction

The increased number of consumer complaints with financial institutions, as well as regulating bodies, is a major challenge to the traditional manual operations and analytical procedures [1]. These complaints are largely unstructured free-text stories that encompass an expansive scope of concerns pertinent to credit reporting, debt collection, mortgage performance, and fraudulent banking practices [2]. On the one hand, in contemporary financial ecosystems, the management of these complaints is not only a customer service issue, but it is a regulatory requirement because complaints that are not resolved or improperly assigned can result in compliance failures, reputational damage, and fines. The right and timely classification of such stories is thus critical to immediate solution, regulatory adherence, and successive trend identification in customer complaints [3]. But manual analysis is time-consuming, irregular, and inaccurate, especially when the textual input is noisy, ambiguous, or domain-dependent [4]. Moreover, the constantly growing number of consumer complaints overwhelms human reviewers and forms an operational bottleneck, thus automation is a pressing need.

This issue has been successfully discussed using traditional text-classification algorithms. The majority of the current methods are based on the bag-of-words paradigm, TF-IDF vectorization, or shallow learning models, including logistic regression and support vector machines [5], [6]. Despite the relative ease of interpretation and computational efficiency, these techniques naturally do not represent long-range correlations, semantic details and contextual associations in text [7]. This deficiency is especially prominent in the consumer complaints; words in these lines tend to refer much more specifically to the financial world, to technical aspects of transactions, legal allusions, and emotional terminology. Consequently, the performance of these models tends to be inadequate, reflecting the semantic richness of complaint narratives, so their performance in classification is also suboptimal.

Recent progress in the field of natural language processing (NLP) has seen the emergence of transformer-based language models, which are trained to learn contextualized text representations by taking advantage of self-attention processes [7], [8]. In comparison to the traditional encodings, transformers are able to capture semantic correlations at varying granularity levels, and they are more appropriate in analyzing unstructured data of financial complaints [9]. BERT and RoBERTa models have reached state of the art performance in a broad array of NLP tasks. They are, however, expensive to compute and difficult to train like their better-performing counterparts in that they consume high memory, large training information, and specialized equipment. In systems with large volumes of complaints to handle or where real-time applications are being used, these requirements are unrealistic, especially when a financial institution has to weigh efficiency and accuracy versus regulatory requirements.

In this study, these limitations will be solved by introducing a light but useful framework utilizing sentence embeddings produced by a frozen pre-trained transformer model without the computational cost of fine-tuning. The encoder generates semantic representations that can be used to gain insights about the complaint narratives, whereas a simple feedforward neural

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network classifier guarantees effective prediction. The framework classifies complaints into five predefined financial product categories, thus enabling an automated process of triage and resolution. The study uses synthetic oversampling, stratified cross-validation, and hyperparameter optimization as a means to balance the classes and guarantee the model's robustness. Thus, the framework integrates the strengths of transformer-based embeddings with the efficiency and adaptability of lightweight models for scalable deployment.

Following are the contributions of this study:

- A lightweight framework is introduced that integrates frozen transformer-based embeddings with a feedforward neural network to efficiently process and categorize consumer complaint narratives across predefined financial product categories.
- A systematic comparison of the proposed framework against traditional text-classification approaches, such as TF-IDF with logistic regression and support vector machines, demonstrates performance gains in terms of semantic representation and predictive reliability.
- An ablation study is conducted to examine the individual contributions of transformer embeddings and neural network components, providing insights into the effectiveness and interpretability of the model's architecture.

The structure of the study is organized as follows: Section II: Related Work reviews prior studies on text classification methods in the financial domain. Section III: Methodology explains the proposed model, including the integration of transformer-based embeddings with a neural network architecture. Section IV: Results and Discussion describes the dataset, evaluation metrics, and implementation strategies, followed by a detailed presentation of results, including comparisons with baseline models and the ablation study. Section V: Conclusion and Future Work summarizes the key contributions of the study and outlines directions for further research.

II. Related Work

The classification of customer complaints has been examined across multiple domains using both traditional machine learning and modern deep learning approaches. Early works emphasized feature engineering and linguistic cues, while more recent studies have explored transformer-based models and large language models (LLMs) to capture semantic richness.

A. Traditional Machine Learning and Hybrid Approaches

A number of studies have relied on traditional machine learning techniques combined with feature engineering to classify customer complaints (see Table I). Khedkar and Shinde [10] evaluated hotel reviews using linguistic features such as nouns, verbs, and intensifiers, comparing machine learning classifiers, ensemble methods, and deep learning models. Their ensemble approach showed improved accuracy, but the reliance on handcrafted features limited generalizability. Similarly, Bozyiğit et al. [11] focused on Turkish food product complaints, demonstrating that TF-IDF with Chi-Square feature selection outperformed word2vec embeddings when paired with classifiers such as XGBoost and SVM.

Beyond consumer products, similar methods have been applied in healthcare and telecommunications. Li et al. developed a complaint classification system for hospital records using Logistic Regression, Naive Bayes, and SVM, highlighting the role of SMOTE in handling class imbalance. Elmessiry et al. [12] further explored automated triage of patient complaints, reporting over 80% accuracy using standard classifiers. In the telecom sector, Mahmoud et al. [13] employed ensemble methods on large-scale service logs, showing that AdaBoost with Decision Trees effectively predicted complaint escalation. These works collectively highlight the utility of ML models in structured or moderately sized datasets, but they often depend on domain-specific preprocessing and lack adaptability to new contexts.

B. Deep Learning and Transformer-Based Approaches

With the rise of deep learning, researchers have increasingly adopted neural architectures and pre-trained models for complaint classification. Vinayak and Jyotsna [14] tested CNN, LSTM, Bi-LSTM, and GRU with embeddings such as DistilBERT on CFPB complaints, achieving strong performance with CNN-embedding combinations. Alamsyah et al. [15] extended this to large-scale banking data, where a neural network trained on one million complaints demonstrated the feasibility of text mining for real-world deployment. Idrissi-Yaghir et al. [16] evaluated transformer-based models on German feedback data, showing that domain adaptation improved results compared to off-the-shelf pre-trained models.

Recent advances in LLMs have introduced new opportunities for zero-shot and few-shot complaint classification. Roumeliotis et al. [17] benchmarked leading LLMs and reasoning models, including GPT-4 and Claude, for financial complaint classification on CFPB data. Their findings highlighted the promise of zero-shot approaches for emerging categories but also pointed out challenges in handling overlapping complaint classes. Other work by Basha and Rajput [18] focused on aspect-level sentiment analysis, using probabilistic latent models to capture semantic relations in hotel reviews, demonstrating how advanced NLP can extract actionable insights. These studies confirm the strength of deep learning and LLMs in capturing semantic complexity, though issues such as interpretability, efficiency, and imbalance remain open challenges.

While prior studies have explored various approaches to complaint and feedback classification across domains such as healthcare, hospitality, food, banking, and telecommunications, they often exhibit limitations that constrain their applicability. Earlier works relied heavily on handcrafted linguistic features, traditional machine learning classifiers, or domain-specific adaptations of transformer models, which restricted their generalizability, interpretability, or performance in low-resource settings. In contrast, the proposed framework leverages a pre-trained MiniLM model enhanced with domain-relevant cues and sentiment features, enabling it to capture both semantic richness and contextual nuances across consumer complaints.

TABLE I. COMPARISON OF RELATED STUDIES

Ref.	Year	Focus	Dataset	Technique	Limitation
[12]	2017	Patient Triage	PARS Complaint Dataset	ML Classifiers	Binary physician vs. non-physician
[18]	2019	Aspect Mining	Hotel Reviews (Wang et al.)	LARR, NLP, MLRC	More sentiment-focused than classification
[10]	2020	Praise/Complaint	Hotel Reviews (Kaggle)	Hybrid features + ML, Ensemble, CNN	Relies on handcrafted linguistic features
[11]	2022	Food Complaints	Turkish Food Complaints	TF-IDF, word2vec, XGBoost, SVM	Limited to non-English context
[15]	2022	Bank Complaints	BRI Dataset (1M records)	Neural Network + TF-IDF	Limited interpretability
[16]	2023	German Feedback	GermEval 2017	Transformers (BERT, domain-adapted)	Requires domain-specific adaptation
[14]	2023	Consumer Complaints	CFPB Dataset	CNN, LSTM, DistilBERT	High-resource training required
[13]	2024	Telecom Complaints	Egyptian Telecom Logs	AdaBoost + DT, RFC, SVM	Focused on structured data logs
[19]	2025	Patient Complaints	Hospital Records (1465 + test set)	Logistic Regression, SVM, Naive Bayes	Moderate dataset, domain-specific
[17]	2025	Financial Complaints	CFPB Complaints (Kaggle)	Zero-shot LLMs & Reasoning Models	Overlap between financial categories

III. METHODOLOGY

The methodology of this study is centered on leveraging semantic representations from a frozen pre-trained transformer language model, which serves as the encoder for capturing contextual meaning in consumer complaint narratives. These embeddings are then fed into a lightweight feedforward neural network that performs classification across multiple product categories. To demonstrate the effectiveness of the proposed framework, its performance is systematically compared with traditional baseline models, including TF-IDF [20] and Word2Vec [21] embeddings combined with logistic regression and Naïve Bayes classifiers.

A. Dataset Collection

The dataset comprises 162,421 consumer complaint records, each containing a narrative text and an associated product category label. These product classifications fall into five distinct categories (see Fig. 1). The dataset exhibits a markedly imbalanced class distribution, with some categories represented by significantly more narratives than others [22].

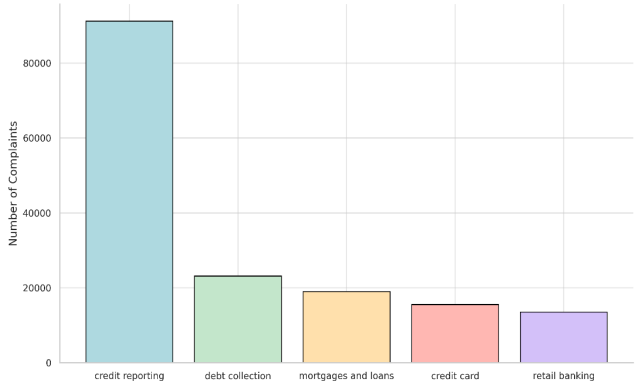


Fig. 1. Target class distribution.

The distribution of complaint narrative length shows a highly skewed pattern, where the majority of complaints contain fewer than 200 words, with a sharp peak below 100 words (see Fig. 2). A long tail extends beyond 500 words, indicating that while most complaints are concise, a small number are significantly longer, exceeding even 2,000 words.

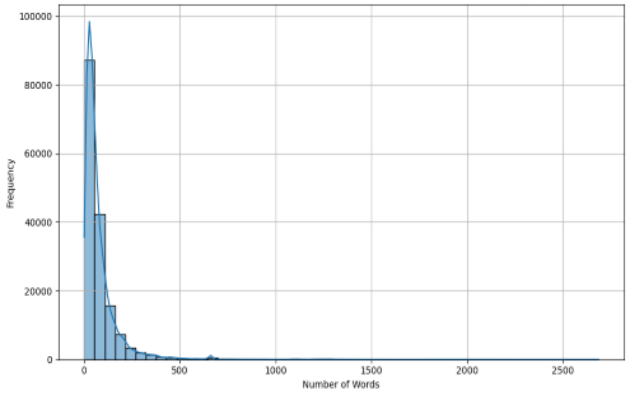


Fig. 2. Distribution of complaints narrative length.



Fig. 3. Word cloud representation of consumer complaint narratives.

The word cloud shown in Fig. 3 provides a visual summary of the most frequently occurring terms in the consumer complaint narratives. Dominant terms such as credit report,

identity theft, late payment, collection agency, and fraudulent highlight the common themes and concerns raised by consumers. These include issues related to credit reporting inaccuracies, debt collection practices, and unauthorized transactions. The prevalence of entity names like Capital One, Wells Fargo, and Bank of America also suggests repeated mentions of specific financial institutions in the complaints.

B. Data Cleaning and Preprocessing

There were numerous inconsistencies in the consumer complaint narratives, such as special characters, email addresses, and inconsistent word casing. A structured preprocessing pipeline was created in order to prepare the data to be used with machine learning models. This pipeline consisted of text normalization, feature enrichment, data balancing strategies, and partitioning.

1) Text cleaning and normalization: Initial standardization of the narratives was achieved by converting all the text to lower case and removing any non-desired patterns like email addresses and non characters using regular expressions. Removal of fronting and preceding spaces increased uniformity further. This normalization step guaranteed the sanity of the text of a complaint, which is vital to both consistent embedding generation and feature extraction.

2) Label encoding: The product-classes that were the target variables were classified as complaint datasets. These product labels underwent label encoding as they were converted into an integer representation so as to facilitate learning. This supported categorical output processing of the models without a loss of mapping between original class names and coded values.

3) Structured cue features: In addition to the purged textual representations, domain-specific characteristics were developed to pinpoint the important complaint cues. Keywords used to develop binary indicators included the words: refund, dispute, chargeback and cancellation. These structured hints had explicit patterns of complaints, complementing with the full meaning of the textual embeddings and easy interpretancy features.

4) Sentiment extraction: Sentiment polarity scores computed with the TextBlob library were used to add emotion to the tone of each story. These scores measured the consumer sentiment on a negative to positive scale. The combination of sentiment, and structured/unstructured features added to the dataset due to the reflection of the content but also the emotional context of the complaints.

5) Data balancing with SMOTE: Class imbalance in the dataset was also present with some of the product categories having more representations than others. The training set was mitigated with the Synthetic Minority Oversampling Technique (SMOTE) [23]. SMOTE creates artificial examples of underrepresented classes thereby balancing the classes and allowing the model to generalize better across the entire categories.

6) Dataset splitting and cross-validation: Upon balancing, the data were divided into training and testing sets using a stratified method to maintain the distributions of classes. Eighty per cent of the data was to be used in training and twenty percent in testing. In order to make the model evaluation robust, 5-fold cross-validation was used in the course of training. This method gave a more consistent measure of performance by averaging over the uses of multiple folds and made it less likely to overfit to one partition.

C. Proposed Model

The proposed model combines a frozen pre-trained transformer language model to generate sentence embeddings that capture the semantic and contextual details of consumer complaint narratives (Fig. 4). These embeddings are then passed into a feedforward neural network, which delivers accurate and efficient classification across different product categories. The approach relies on the representational strength of transformer-based embeddings while leveraging the simplicity of a lightweight neural network, striking a balance between predictive accuracy and computational cost, making it well-suited for large-scale complaint management systems.

1) Embedding representation using pre-trained language models: To convert raw complaint narrative into fixed-size numerical vectors to be used in classification, we utilized sentence-level embeddings of a pre-trained transformer encoder. To make computations efficient and to maintain the semantic representations that had been learnt during pre-training, we selected a lightweight frozen encoder to avoid fine-tuning.

Let $x_i \in R^T$ denote the i-th tokenized complaint narrative of length T. The sentence encoder maps this input to a dense vector $v_i \in R^d$, where d is the embedding dimension:

$$v_i = f_{encoder}(x_i) \quad (1)$$

The resulting vectors $\{v_1, v_2, , , , , v_n\}$ were generated in inference-only mode and subsequently served as the primary textual features for classification.

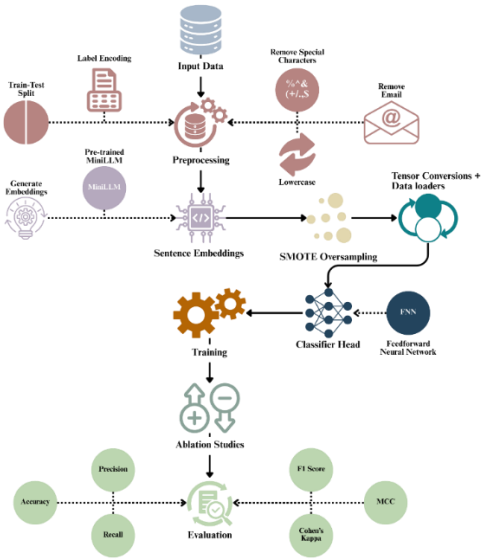


Fig. 4. Architecture of the proposed model integrating frozen transformer embeddings with a feedforward neural network.

2) Structured feature augmentation: In addition to embeddings, domain-specific cues were incorporated to enrich the representation of each narrative. Four binary features were extracted to indicate the presence of keywords related to refund, dispute, chargeback, and cancellation. These were obtained by rule-based pattern matching within each narrative.

Furthermore, a sentiment polarity score was computed for every complaint narrative. This score, ranging from −1-1−1 (negative) to +1+1+1 (positive), was appended as a continuous feature. The final feature vector for each instance was represented as:

$$z_i = [v_i \parallel s_i \parallel k_i] \quad (2)$$

where, v_i denotes the embedding representation, s_i is the sentiment score, k_i is the structured keyword feature vector, and ‖ indicates concatenation.

3) Neural classifier head architecture: The classification model was implemented as a multi-layer feedforward neural network. The input layer dimension matched the size of the augmented feature vector ziz_izi. This was followed by two fully connected hidden layers with ReLU activation functions. Dropout regularization was applied at each hidden layer to mitigate overfitting.

Let the classifier be represented by a function $g_\theta(\cdot)$, parameterized by θ, which maps the embedding v_i to a probability vector $p_i \in R^C$, where C is the number of complaint categories:

$$p_i = softmax(g_\theta(v_i)) \quad (3)$$

The model was trained using the cross-entropy loss function, defined as:

$$= -\frac{1}{N}\sum_{i=1}^{N}\sum_{C=1}^{C} y_{ic}\log(p_{ic}) \quad (4)$$

where, y_{ic} is the one-hot encoded true label for instance i and class c, and p_{ic} is the predicted probability. Optimization was performed using the Adam optimizer with a fixed learning rate of 10^{-3}, and learning rate schedulers were optionally considered for stabilization.

TABLE II. HYPERPARAMETER CONFIGURATION OF THE PROPOSED MODEL

Hyperparameter	Value
Hidden layer sizes	[256, 128]
Activation function	ReLU
Dropout rate	0.3
Optimizer	Adam
Learning rate	1×10^{-3}
Batch size	32
Number of epochs	20
Loss function	Categorical cross-entropy

4) Hyperparameter optimization: Hyperparameters for the classifier were optimized using randomized search. This approach provided a computationally efficient alternative to exhaustive grid search by exploring a broad search space with fewer evaluations. A representative configuration of the proposed model is summarized in Table II. Also, the algorithm of proposed model is shown in Algorithm 1.

Formally, the objective of hyperparameter tuning was to identify parameters θ that minimized the validation loss L_{val}averaged across all folds:

$$\theta^* = \arg\min_\theta \frac{1}{K}\sum_{k=1}^{K} L_{val}^{(k)}(\theta) \quad (5)$$

where, K = 5 is the number of folds in cross-validation.

Algorithm 1: Proposed Frozen MiniLM-Based Model

Input:

Complaint text dataset $D = \{x_1, x_2, \ldots . x_n\}$with corresponding labels Y

Pre-trained Frozen MiniLM encoder E(·)

Feedforward Neural Network Classifier C(·)

Output:

Predicted labels $\hat{Y}$

1. Initialization
   - Load frozen MiniLM encoder E
   - Initialize classifier parameters θ
2. Encoding
   - For each complaint text $X \in$ D:

$$h_i = E(x_i)$$

where $h_i \in R^d$ is the sentence embedding

3. Classification
   - Pass embeddings through the classifier:

$$\hat{Y}_i = C(h_i, \theta)$$

4. Optimization
   - Minimize loss function $L(\hat{Y}_i, Y)$ using training set
5. Evaluation
   - Compare predictions $\hat{Y}$ with ground truth Y on test set
   - Compute evaluation metrics: Accuracy, Precision, Recall, F1, Kappa, MCC
6. Output
   - Final predictions $\hat{Y}$ for unseen complaint narratives

D. Baseline Framework

A baseline framework was developed using conventional feature extraction procedure and classification to give a reliable comparison to the proposed model (see Fig. 5). These baselines give a benchmark of reference to assess whether improved architecture causes significant differences in performance: TF-IDF and Word2VE were used in combination with Logistic Regression (LR) [24], Multinomial Naive Bayes (NB) [25], and Gaussian Naive Bayes (GNB) as classical classifiers [26].

1) TF-IDF with Logistic Regression: Term Frequency-Inverse Document Frequency (TF-IDF) representation was used to construct the first baseline. Both text documents were mapped to a sparse 5000-sized vector that included the most informative terms. These features were used to train a Logistic Regression, the decision boundary of which is modeled as:

$$P(y = 1 \mid x) = \frac{1}{1+e^{-(w^T x+b)}} \quad (6)$$

where, x is the TF-IDF feature vector, w represents learned weights, and b is the bias term. The optimization was performed using maximum likelihood estimation with a maximum of 200 iterations.

2) Word2Vec embedding with Logistic Regression: Word2Vec was trained on the tokenized training corpus using the skip-gram architecture to measure the effectiveness of dense word embeddings. The model trained 200-dimensional embeddings using a context window of 5 and eliminating words that occur less frequently than 2 times. Document vectors d were then calculated as the average of their token embeddings d:

$$d = \frac{1}{N}\sum_{i=1}^{N} v_{w_i} \quad (7)$$

where, N is the number of tokens and vv_{w_i} is the embedding of token w_i. Logistic Regression was then applied to the document vectors with 500 maximum iterations to ensure convergence.

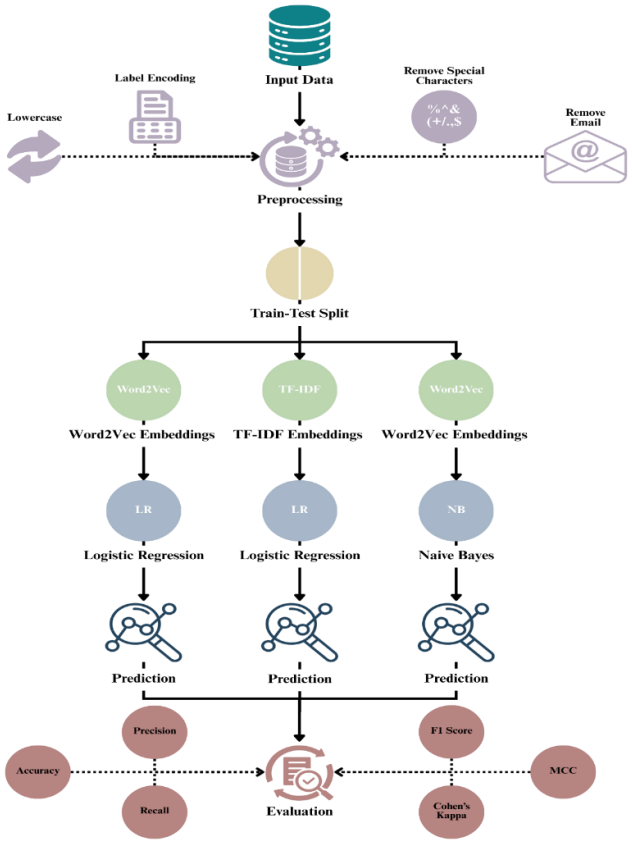


Fig. 5. Baseline framework for comparison.

3) TF-IDF with Multinomial Naïve Bayes: A second baseline on sparse features utilized Multinomial Naïve Bayes, a classical probabilistic classifier suitable for count-based features. The posterior probability for class ccc is defined as:

$$P(c \mid x) = \frac{P(c)\prod_{i=1}^{M} P(x_i|c)}{P(x)}) \quad (8)$$

where, M represents the number of features and x_i the term frequency values.

4) Word2Vec with Gaussian Naïve Bayes: Gaussian Naïve Bayes was applied on the dense Word2Vec document vectors. Unlike the multinomial variant, GNB assumes a Gaussian likelihood for each feature dimension. The class-conditional probability is defined as:

$$P(x_i \mid c) = \frac{1}{\sqrt{2\pi\sigma_c^2}}\exp\left(-\frac{(x_i-\mu_c)^2}{2\sigma_c^2}\right) \quad (9)$$

where, μ_c denote the mean and variance of feature x_i for class c.

5) Hyperparameter tuning: All baseline models were optimized through Grid Search with 5-fold Cross-Validation to ensure fair comparison. The selected hyperparameters are summarized in Table III.

TABLE III. HYPERPARAMETER SETTINGS FOR BASELINE MODELS (OPTIMIZED USING GRID SEARCH CV)

Model	Hyperparameters
TF-IDF + Logistic Regression	max_features = 5000, max_iter = 200
Word2Vec + Logistic Regression	vector_size = 200, window = 5, min_count = 2, sg = 1, max_iter = 500
TF-IDF + Multinomial NB	alpha = optimized via grid search
Word2Vec + Gaussian NB	assumes Gaussian distribution, no tunable hyperparameters beyond prior smoothing

E. Evaluation Strategy

Evaluation was conducted both during cross-validation and on a separate holdout set. Metrics included accuracy [27], precision [28], recall [29], and F1-score [17] in both macro and weighted forms to account for class imbalance. To assess agreement beyond chance, Cohen's Kappa coefficient [30] was computed. The Matthews Correlation Coefficient (MCC) was also used due to its ability to summarize the confusion matrix into a single metric, even in the presence of imbalanced labels.

Formally, the metrics are defined as follows:

- Accuracy: the proportion of correctly classified instances.

$$\text{Accuracy (Acc)}: \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (10)$$

- Precision: the fraction of correctly predicted positive cases among all predicted positives.

$$\text{Precision (Prec)}: \frac{(TP)}{(TP+FP)} \quad (11)$$

- Recall: the fraction of correctly predicted positive cases among all actual positives.

$$\text{Recall}: \frac{(TP)}{(TP+FN)} \quad (12)$$

- F1-Score: harmonic mean of precision and recall, balancing both metrics.

$$\text{F1 Score: } 2 \times \frac{Precision \times Recall}{(Precision + recall)} \quad (13)$$

- Cohen's Kappa (κ): measures inter-rater agreement while adjusting for chance.

$$k = \frac{p_o - p_e}{1 - p_e} \quad (14)$$

where, p_o is the observed agreement and p_e is the expected agreement by chance.

- Matthews Correlation Coefficient (MCC): a balanced measure of classification quality derived from all four entries of the confusion matrix.

$$MCC = \frac{TP.TN - FP.FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (15)$$

In order to establish how resistant the model is, assessments on perturbed versions of the test narratives were also done. These distortions covered character level noises like misspellings and deletion of random words. In addition, the domain drift was designed by dividing the dataset into older and newer complaint narratives across a period of time to assess the generalization under the change of language tendencies.

IV. Results and Discussion

The results section offers the evaluation of the proposed model as compared with the baseline frameworks, drawing attention to its feasibility in processing the candid complaint narratives that are not structured. It has quantitative and comparative analysis to determine reliability and robustness of the approach. An ablation study is also described to investigate the impact of each of these components, including cues and sentiment features, and sheds more light on the design and production of the model.

A. Proposed Model

The results of the evaluation indicate that the proposed model performed well in several metrics with accuracy (0.8653) and precision (0.8697), recall (0.8653), and F1-score (0.8668) showing a steady balance between accurate classifications and minimization of errors (see Fig. 6). The high degree of agreement between precision and recall indicates that the model is unlikely to be biased towards a particular class, even when data is skewed. The relatively large F1-score also proves that the model is quite successful in keeping this trade-off, indicating its strengths in real-life situations, where picking a false positive or a false negative may be expensive.

In addition to these standard indicators, the indicators that are based on the agreement are also informative. The value of Kappa (0.7917) and Matthews Correlation Coefficient (0.7924) both indicate that the classifier exhibits a considerable improvement over the chance knowledge, and the MCC again substantiates the reliability of the chosen algorithm despite the imbalance of the classes. These values support the stability and the generalization of the model.

The ROC curve of the proposed model shows consistently high discriminative capability across all classes, with Area Under the Curve (AUC) values ranging from 0.929 to 0.989 (see Fig. 7). Notably, Class 4 achieves the highest AUC (0.989), reflecting near-perfect separability, while Class 2, with an AUC of 0.929, represents the relatively more challenging case but still indicates strong performance. The micro-average AUC of 0.972 demonstrates that the overall classification performance is highly reliable when aggregating across all classes. The steep rise of the curves towards the top-left corner further confirms that the model maintains high true positive rates while keeping false positives low, highlighting its robustness and suitability for handling multi-class classification in imbalanced datasets.

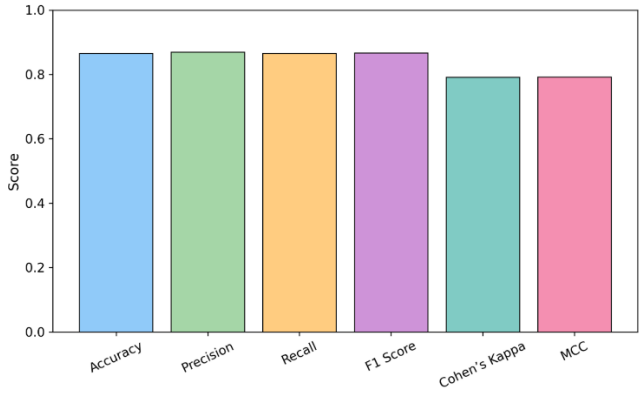


Fig. 6. Evaluation of the proposed model.

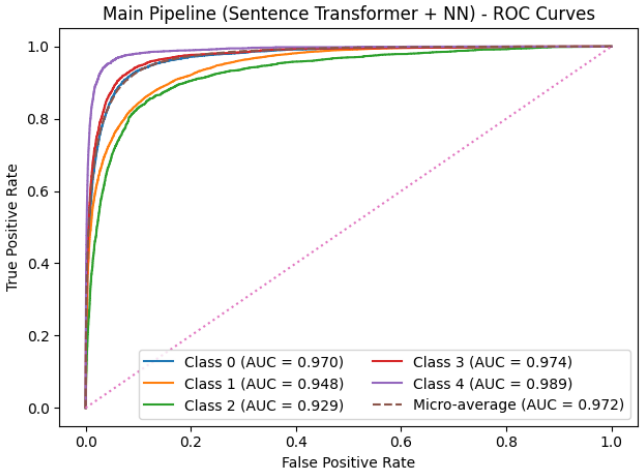


Fig. 7. ROC Curves illustrating the performance of the proposed model.

B. Ablation Study

An ablation study was conducted to measure the contribution of various components to the proposed pipeline, and in doing so, augmentation strategies, cue features, and sentiment features were gradually eliminated (see Table IV). The findings indicate the relative significance of every aspect in determining the overall performance.

The main pipeline achieved balanced performance across all metrics, with an accuracy of 0.8653, F1-score of 0.8668, and strong agreement measures (Kappa = 0.7862, MCC = 0.7870). When data augmentation was removed, accuracy slightly increased to 0.8690, while F1-score stabilized at 0.8677. This suggests that augmentation did not substantially improve core classification ability, although it may have contributed to better generalization, as evidenced by more stable performance across perturbed test sets.

TABLE IV. RESULTS OF THE ABLATION STUDY SHOWING THE IMPACT OF REMOVING DIFFERENT COMPONENTS

Setting	Accuracy	Precision	Recall	F1	Kappa	MCC
Main Pipeline	0.8653	0.8697	0.8653	0.8668	0.7862	0.7870
No Augmentation	0.8690	0.8673	0.8690	0.8677	0.7914	0.7917
No Cues	0.8541	0.8649	0.8541	0.8571	0.7782	0.7808
No Sentiment	0.8577	0.8663	0.8577	0.8602	0.7826	0.7846
No Cues + Sentiment	0.8469	0.8605	0.8469	0.8505	0.7687	0.7720

TABLE V. PERFORMANCE COMPARISON OF BASELINE FRAMEWORK AND THE PROPOSED MODEL

Model	Accuracy	Precision	Recall	F1	Kappa	MCC
TF-IDF + LR	0.8548	0.8531	0.8548	0.8539	0.7702	0.7706
Word2Vec + LR	0.8510	0.8486	0.8510	0.8488	0.7619	0.7626
TF-IDF + NB	0.8377	0.8370	0.8377	0.8344	0.7403	0.7417
Word2Vec + NB	0.6942	0.7512	0.6942	0.7073	0.5606	0.5728
Proposed Model	0.8653	0.8697	0.8653	0.8668	0.7862	0.7870

In contrast, removing cue features resulted in a noticeable decline, with accuracy dropping to 0.8541 and F1-score to 0.8571. Similarly, removing sentiment features led to slightly higher values than the no-cue setting but still below the full pipeline (accuracy = 0.8577, F1 = 0.8602). This indicates that both cues and sentiment individually enhance the model's discriminatory power, though their effects are modest. Importantly, removing both cues and sentiment together caused the largest performance decline (accuracy = 0.8469, F1 = 0.8505, Kappa = 0.7687), underscoring their complementary value.

The ablation study demonstrates that while augmentation plays a secondary role, linguistic cues and sentiment information contribute significantly and synergistically to model robustness, particularly in distinguishing subtle variations in consumer complaint narratives. This validates the design choice of incorporating multiple feature perspectives in addition to the sentence transformer representations.

C. Comparison with Baseline Framework

To evaluate the effectiveness of the proposed framework, its performance was compared against multiple baseline models including TF-IDF with Logistic Regression (LR), Word2Vec with LR, TF-IDF with Naïve Bayes (NB), and Word2Vec with NB. As shown in Table V, the proposed model consistently outperforms the baseline frameworks across all metrics. Specifically, the proposed model achieved the highest accuracy (0.8653), precision (0.8697), recall (0.8653), and F1-score (0.8668), demonstrating its superior ability to capture both the semantic and structural features of the data. Furthermore, the agreement-based measures, Cohen's Kappa (0.7862) and MCC (0.7870), indicate stronger reliability and balanced performance compared to the baseline methods.

Among the baseline models, TF-IDF combined with LR performed comparatively well, reaching an accuracy of 0.8548 and F1-score of 0.8539, which is close to the proposed model, but still inferior across all measures. Similarly, Word2Vec with LR achieved slightly lower values (accuracy 0.8510, F1-score 0.8488), highlighting the limitations of traditional embedding methods in capturing contextual information. TF-IDF with NB provided moderate performance (accuracy 0.8377), while Word2Vec with NB yielded the weakest results, with accuracy dropping to 0.6942, reflecting its inability to generalize effectively for the given task. The comparison emphasizes that the integration of sentence-level representations with neural architectures, as in the proposed model, yields a more robust and reliable framework than traditional text representations and shallow learning methods.

V. CONCLUSION AND FUTURE DIRECTIONS

This study demonstrates that integrating contextual embeddings with cues and sentiment features provides a robust framework for automated text classification. Beyond achieving high accuracy and reliable agreement measures, the results highlight the model's ability to effectively capture semantic and contextual nuances that traditional shallow approaches often miss. The ablation study underscores the importance of combining multiple sources of information, showing that cues and sentiment features meaningfully enhance classification performance. Compared to conventional methods such as TF-IDF or Word2Vec with logistic regression, the proposed framework offers a more nuanced understanding of textual data, suggesting its potential for broader applications in domains where reliable interpretation of unstructured text is critical. Overall, the findings illustrate that leveraging advanced neural architectures alongside carefully selected features can yield both accurate and interpretable models, providing a practical pathway for improving automated text analysis in real-world settings.

While the results are promising, there remain several avenues for future research. First, the integration of transformer-based architectures such as BERT or RoBERTa could be explored to enhance contextual embeddings and improve classification robustness. Moreover, incorporating domain adaptation strategies would allow the framework to be applied across different datasets and problem settings with minimal retraining. Finally, future studies could investigate explainability methods to provide better interpretability of the

classification decisions, thereby enhancing trust and usability in real-world applications.

REFERENCES

[1] S. Nuthakki, S. Kumar, C. S. Kulkarni, and Y. Nuthakki, "Role of AI Enabled Smart Meters to Enhance Customer Satisfaction," Int. J. Comput. Sci. Mob. Comput., vol. 11, no. 12, pp. 99–107, 2022, doi: 10.47760/ijcsmc.2022.v11i12.010.

[2] M. Chowdhury, K. M. T. Rahman, and H. A. Maruf, "Whistle Blower: An Insurance Awareness Mobile Application with Insurance Policy Selection, Fraud Detection, Critical Help, Complaint Features," 8th IEEE Int. Conf. Comput. Syst. Inf. Technol. Sustain. Solut. CSITSS 2024, pp. 1–6, 2024, doi: 10.1109/CSITSS64042.2024.10817002.

[3] E. Fedorova, S. Druchok, and P. Drogovoz, "Impact of news sentiment and topics on IPO underpricing: US evidence," Int. J. Account. Inf. Manag., vol. 30, no. 1, pp. 73–94, 2022, doi: 10.1108/IJAIM-06-2021-0117.

[4] W. Zheng et al., "MIDLG: Mutual Information based Dual Level GNN for Transaction Fraud Complaint Verification," Proc. ACM SIGKDD Int. Conf. Knowl. Discov. Data Min., pp. 5685–5694, 2023, doi: 10.1145/3580305.3599865.

[5] A. Palanivinayagam, C. Z. El-Bayeh, and R. Damaševičius, "Twenty Years of Machine-Learning-Based Text Classification: A Systematic Review," Algorithms, vol. 16, no. 5, pp. 1–28, 2023, doi: 10.3390/a16050236.

[6] V. Karpukhin et al., "Dense passage retrieval for open-domain question answering," EMNLP 2020 - 2020 Conf. Empir. Methods Nat. Lang. Process. Proc. Conf., pp. 6769–6781, 2020, doi: 10.18653/v1/2020.emnlp-main.550.

[7] S. Nuthakki, "CONVERSATIONAL AI AND LLM ' S CURRENT AND FUTURE IMPACTS IN IMPROVING AND SCALING HEALTH SERVICES," Int. J. Comput. Eng. Technol., vol. 14, no. December, pp. 149–155, 2023, doi: 10.17605/OSF.IO/7GHJY.

[8] C. Wang, Y. Yang, C. Gao, Y. Peng, H. Zhang, and M. R. Lyu, "No more fine-tuning? an experimental evaluation of prompt tuning in code intelligence," ESEC/FSE 2022 - Proc. 30th ACM Jt. Meet. Eur. Softw. Eng. Conf. Symp. Found. Softw. Eng., pp. 382–394, 2022, doi: 10.1145/3540250.3549113.

[9] Q. Ren et al., "A survey on fairness of large language models in e-commerce: progress, application, and challenge," May 2024.

[10] S. Khedkar and S. Shinde, "Deep Learning and Ensemble Approach for Praise or Complaint Classification," Procedia Comput. Sci., vol. 167, no. 2019, pp. 449–458, 2020, doi: 10.1016/j.procs.2020.03.254.

[11] F. BOZYİĞİT and D. K. Onur DOĞAN, "Categorization of Customer Complaints in Food Industry Using Machine Learning Approaches," J. Intell. Syst. Theory Appl., vol. 5, no. June 2021, pp. 85–91, 2022, doi: 10.38016/jista.954098.

[12] A. Elmessiry, W. O. Cooper, T. F. Catron, J. Karrass, Z. Zhang, and M. P. Singh, "Triaging Patient Complaints : Monte Carlo Cross-Validation of Six Machine Learning Classifiers Corresponding Author :," vol. 5, pp. 1–10, 2017, doi: 10.2196/medinform.7140.

[13] M. M. Gewaly, Machine Learning Approach for Complaint Prediction in the Telecom Industry. IEEE, 2024. doi: 10.1109/IMSA61967.2024.10652677.

[14] V. Vinayak and C. Jyotsna, "Consumer Complaints Classification using Deep Learning & Word Embedding Models," 2023 14th Int. Conf. Comput. Commun. Netw. Technol. ICCCNT 2023, pp. 1–5, 2023, doi: 10.1109/ICCCNT56998.2023.10307286.

[15] D. P. Alamsyah, T. Arifin, Y. Ramdhani, F. A. Hidayat, and L. Susanti, "Classification of Customer Complaints: TF-IDF Approaches," 2022 2nd Int. Conf. Intell. Technol. CONIT 2022, pp. 1–5, 2022, doi: 10.1109/CONIT55038.2022.9848056.

[16] A. Idrissi-Yaghir, H. Schäfer, N. Bauer, and C. M. Friedrich, "Domain Adaptation of Transformer-Based Models Using Unlabeled Data for Relevance and Polarity Classification of German Customer Feedback," SN Comput. Sci., vol. 4, no. 2, pp. 1–13, 2023, doi: 10.1007/s42979-022-01563-6.

[17] K. I. Roumeliotis, N. D. Tselikas, and D. K. Nasiopoulos, "Think Before You Classify: The Rise of Reasoning Large Language Models for Consumer Complaint Detection and Classification," Electron., vol. 14, no. 6, 2025, doi: 10.3390/electronics14061070.

[18] S. M. Basha and D. S. Rajput, "An innovative topic-based customer complaints sentiment classification system," Int. J. Bus. Innov. Res., vol. 20, no. 3, pp. 375–391, 2019, doi: 10.1504/IJBIR.2019.102718.

[19] X. Li, Q. Shu, C. Kong, J. Wang, and G. Li, "An Intelligent System for Classifying Patient Complaints Using Machine Learning and Natural Language Processing : Development and Validation Study Corresponding Author :," vol. 27, 2025, doi: 10.2196/55721.

[20] J. A. Nasir, A. Karim, G. Tsatsaronis, and I. Varlamis, "A knowledge-based semantic kernel for text classification," Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics), vol. 7024 LNCS, no. 3, pp. 261–266, 2011, doi: 10.1007/978-3-642-24583-1_25.

[21] N. Alami, M. Meknassi, and N. En-nahnahi, "Enhancing unsupervised neural networks based text summarization with word embedding and ensemble learning," Expert Syst. Appl., vol. 123, pp. 195–211, 2019, doi: 10.1016/j.eswa.2019.01.037.

[22] V. Nayyar, "Kaggle," Kaggle. Accessed: Apr. 16, 2025. [Online]. Available: https://www.kaggle.com/code/vikram92/multiclass-complaints-classification-using-bi-lstm/notebook

[23] E. F. Swana, W. Doorsamy, and P. Bokoro, "Tomek Link and SMOTE Approaches for Machine Fault Classification with an Imbalanced Dataset," Sensors, vol. 22, no. 9, 2022, doi: 10.3390/s22093246.

[24] A. Shanbhag, S. Jadhav, A. Thakurdesai, R. Sinare, and R. Joshi, "BERT or FastText? A Comparative Analysis of Contextual as well as Non-Contextual Embeddings," 2024, [Online]. Available: http://arxiv.org/abs/2411.17661

[25] G. Singh, B. Kumar, L. Gaur, and A. Tyagi, "Comparison between Multinomial and Bernoulli Naïve Bayes for Text Classification," 2019 Int. Conf. Autom. Comput. Technol. Manag. ICACTM 2019, pp. 593–596, 2019, doi: 10.1109/ICACTM.2019.8776800.

[26] W. Dai, G.-R. Xue, Q. Yang, and Y. Yu, "Transferring Naive Bayes Classi ers for Text Classi cation," in AAAI, 2007, pp. 540–545.

[27] A. Abdi, S. Hasan, S. M. Shamsuddin, N. Idris, and J. Piran, "A hybrid deep learning architecture for opinion-oriented multi-document summarization based on multi-feature fusion," Knowledge-Based Syst., vol. 213, p. 106658, 2021, doi: 10.1016/j.knosys.2020.106658.

[28] M. E. Mowlaei, M. Saniee Abadeh, and H. Keshavarz, "Aspect-based sentiment analysis using adaptive aspect-based lexicons," Expert Syst. Appl., vol. 148, p. 113234, 2020, doi: 10.1016/j.eswa.2020.113234.

[29] M. Z. Asghar et al., "Performance evaluation of supervised machine learning techniques for efficient detection of emotions from online content," Comput. Mater. Contin., vol. 63, no. 3, pp. 1093–1118, 2020, doi: 10.32604/CMC.2020.07709.

[30] M. J. Warrens, "Five ways to look at Cohen's kappa," J. Psychol. Psychother., vol. 05, no. 04, 2015, doi: 10.4172/2161-0487.1000197.

TransAneu-Net: A Hybrid Radiomics and Contrastive Deep Learning Framework for Automated Brain Aneurysm Diagnosis

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***Abstract*—Accurate and early detection of intracranial aneurysms is critical for preventing life-threatening subarachnoid hemorrhage and improving clinical outcomes. This study proposes a hybrid diagnostic framework that integrates radiomics-based feature engineering with a transformer-driven deep learning architecture enhanced by teacher–student contrastive representation learning. The workflow incorporates region-of-interest segmentation, handcrafted radiomic feature extraction, multimodal representation fusion, and probabilistic aneurysm localization using high-resolution MR and MRA imaging. Comprehensive experiments conducted on benchmark neuroimaging datasets demonstrate that the proposed model achieves high classification accuracy, stable convergence, and robust generalization across diverse anatomical and imaging conditions. Qualitative evaluations further reveal that heatmap-based confidence overlays reliably identify aneurysmal regions and closely align with ground-truth annotations. The contrastive learning module strengthens spatial and frequency-domain feature alignment, enabling effective training under limited supervision and reducing performance degradation associated with data heterogeneity. While limitations remain regarding dataset breadth and segmentation dependencies, the results indicate that this hybrid radiomics–AI framework offers a promising pathway toward automated aneurysm screening and clinical decision support. The proposed system has the potential to enhance diagnostic precision, mitigate inter-observer variability, and contribute to earlier intervention in neurovascular care.**

Keywords*—Aneurysm; deep learning; radiomics; transformer networks; contrastive learning; MR imaging; MRA; medical image analysis; aneurysm detection; neurovascular diagnostics

I. Introduction

The timely and accurate diagnosis of intracranial aneurysms remains a critical challenge in contemporary neuroimaging and clinical decision support systems. Brain aneurysms pose a significant risk of subarachnoid hemorrhage, a condition associated with high mortality and long-term disability, which underscores the need for early detection strategies capable of identifying subtle vascular abnormalities before rupture occurs [1]. Conventional diagnostic modalities such as computed tomography angiography and magnetic resonance angiography provide detailed anatomical information, yet their interpretation often depends on expert assessment, introducing subjectivity and potential variability in diagnostic outcomes [2]. As a result, artificial intelligence approaches [50], particularly deep learning, have emerged as powerful tools for enhancing diagnostic precision through automated feature extraction and pattern recognition [3].

In recent years, radiomics has gained substantial attention as a complementary methodology for quantitative characterization of vascular morphology and tissue heterogeneity by transforming medical images into high-dimensional feature spaces [4]. When combined with deep learning, radiomics enables the integration of handcrafted descriptors with hierarchical neural features, yielding more discriminative representations for aneurysm analysis [5]. Transformer-based architectures, especially vision transformers, have demonstrated strong capabilities in modeling long-range dependencies and capturing subtle structural variations in neurovascular images, offering performance advantages over traditional convolutional models [6]. Furthermore, contrastive learning frameworks have shown promise in semi-supervised and weakly supervised scenarios by aligning spatial and frequency-domain representations, thus improving generalization when labeled datasets are limited [7].

Despite these advances, several challenges persist, including variability in imaging protocols, limited annotated datasets, and the need for robust cross-domain generalization in clinical environments [8]. Developing hybrid architectures that combine radiomic signatures, segmentation-driven region-of-interest extraction, and contrastive representation learning presents a promising direction for addressing these limitations [9]. This research aims to build upon these developments by proposing an integrated radiomics–deep learning framework for accurate and reliable diagnosis of intracranial aneurysms.

II. Related Works

A. Brain Aneurysm

A brain aneurysm is a localized pathological dilation of a cerebral artery resulting from weakening of the vessel wall layers, typically involving the tunica media and internal elastic lamina. As illustrated in Fig. 1, the aneurysm often forms as a saccular outpouching that protrudes from an arterial bifurcation or curve, where hemodynamic shear stress is elevated. These weakened segments can gradually expand due to pulsatile

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blood flow, eventually becoming prone to rupture. When rupture occurs, blood extravasates into the subarachnoid space, leading to subarachnoid hemorrhage, a medical emergency associated with high mortality and significant neurological deficits. The pathophysiology of aneurysm formation is multifactorial, involving genetic predisposition, endothelial dysfunction, chronic inflammation, and biomechanical stress, all of which contribute to progressive vessel wall degeneration.

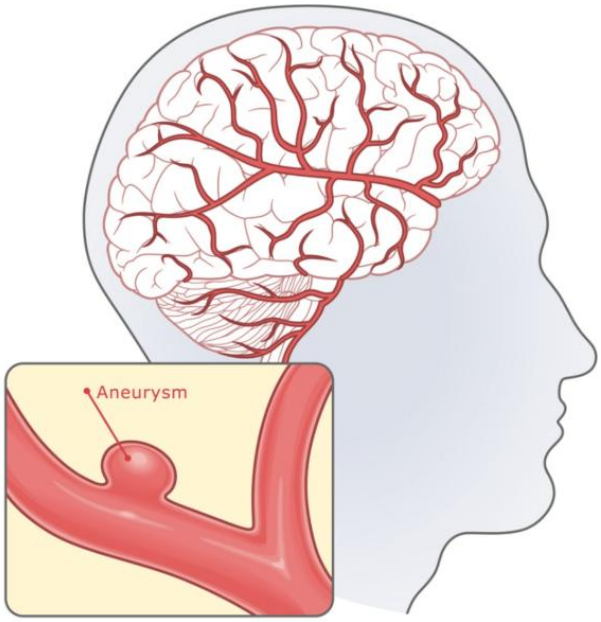


Fig. 1. Illustration of a cerebral aneurysm as a localized arterial outpouching in the brain.

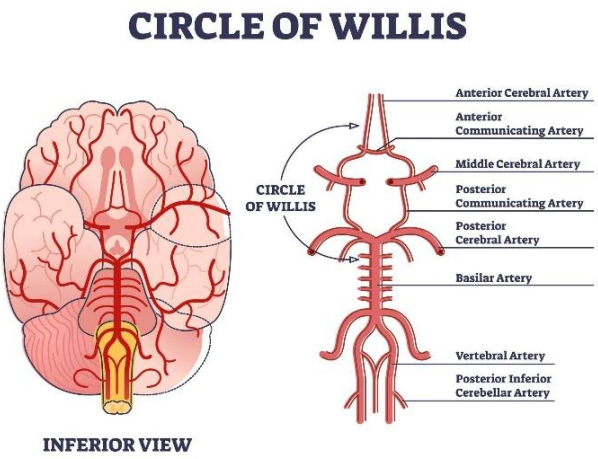


Fig. 2. Anatomical structure of the Circle of Willis, highlighting major cerebral arteries and common aneurysm sites.

The anatomical distribution of brain aneurysms is closely related to the cerebrovascular architecture, particularly the Circle of Willis, as shown in Fig. 2. This arterial ring includes major bifurcation points of the anterior, middle, and posterior cerebral arteries, which are the most common sites for aneurysm development due to complex flow dynamics and turbulent pressure gradients. Aneurysms in these regions may remain asymptomatic until enlargement or rupture occurs, although some may produce symptoms through mass effect or compression of adjacent cranial nerves. Understanding the vascular topology of the Circle of Willis is therefore essential for accurate diagnosis, risk stratification, and treatment planning, especially when integrating advanced imaging techniques and deep learning models that rely on precise localization of vascular anomalies.

B. Radiomics for Neurovascular Abnormality Detection

Radiomics has become a key methodological pillar for extracting quantitative biomarkers from neuroimaging data, enabling the transformation of complex aneurysmal morphology into structured high-dimensional feature sets [10]. Early studies demonstrated that handcrafted descriptors such as intensity histograms, texture matrices, and shape signatures provide discriminative cues for identifying abnormal vascular dilations in CTA and MRA images [11]. The reproducibility of radiomic features was further improved with standardized toolkits such as PyRadiomics, which introduced harmonized feature definitions and preprocessing protocols [12]. Such standardization has facilitated cross-institutional studies that reported enhanced sensitivity in aneurysm detection when radiomic features complement conventional clinical readings [13].

Subsequent investigations extended radiomics into multiscale characterizations, revealing that local heterogeneity and voxel-level variations correlate with aneurysm instability and rupture risk [14]. In particular, wavelet-based texture descriptors and Laplacian-derived edge patterns were shown to uncover microstructural abnormalities not readily visible to human observers [15]. Integration of radiomics with vessel segmentation algorithms, including automated region-of-interest isolations using 3D medical imaging platforms, has enabled more consistent feature extraction pipelines [16]. However, despite these advances, the reliance on handcrafted features introduces limitations related to sensitivity to acquisition parameters and manually defined parameters, which motivated the transition toward hybrid radiomics–deep learning frameworks [17].

In contemporary literature, radiomics has increasingly been fused with machine learning classifiers such as random forests and support vector machines to enhance detection robustness [18]. Yet, the absence of spatial contextualization within purely handcrafted pipelines raised questions about the scalability of classical radiomics in complex neurovascular domains [19]. These limitations illustrate the need for more expressive and hierarchical feature representations, paving the way for deep learning methodologies that complement or fully supersede handcrafted radiomic signatures [20].

C. Deep Learning Architectures for Brain Aneurysm Classification

Deep learning has transformed medical image analysis by enabling automated extraction of hierarchical representations tailored to vascular morphology and pathophysiological cues [21]. Convolutional neural networks (CNNs) were among the first architectures applied to aneurysm detection, showing notable improvements in sensitivity compared with traditional radiological assessments [22]. These CNN-based models leveraged feature maps capable of isolating local edge patterns, lumen irregularities, and aneurysmal neck contours with

substantial robustness across imaging modalities [23]. However, CNNs remain inherently limited in capturing long-range dependencies and global spatial relationships that are crucial for modeling complex vascular geometries [24].

To overcome these shortcomings, transformer-based architectures such as Swin-Transformer and ViT have been increasingly adopted in neurovascular imaging research [25]. Vision transformers process image patches sequentially and utilize self-attention mechanisms to model global context, yielding superior performance in tasks requiring detailed anatomical reasoning [26]. Studies employing transformer backbones have reported improved segmentation fidelity and classification accuracy for small or low-contrast aneurysms, particularly those embedded in tortuous vasculature [27]. These architectures also exhibit greater robustness against noise and interscanner variability, an essential trait for real-world clinical deployment [28].

Another noteworthy development is the rise of hybrid CNN–transformer models, which integrate localized convolutional feature extraction with long-range attention, thereby achieving a balance between spatial precision and contextual awareness [29]. Such models have been shown to outperform conventional CNNs in detecting aneurysms with subtle morphological deviations. Nonetheless, the performance of deep learning systems remains heavily dependent on the availability of annotated datasets, which are often limited due to the complexity of neurovascular structures and the rarity of aneurysms [30]. This scarcity has prompted investigations into semi-supervised and weakly supervised learning frameworks designed to leverage large unlabeled image collections while minimizing annotation burden [31].

These developments collectively highlight the transition from classical convolutional pipelines to more expressive architectures that better capture aneurysm-specific morphological nuances. Yet, integrating deep learning with robust feature engineering strategies continues to be an active research direction requiring further methodological innovation [32].

D. Contrastive Learning, Semi-Supervised Frameworks, and Hybrid AI Systems

One of the most significant advancements in recent years is the adoption of contrastive learning techniques for representation learning in medical imaging. Contrastive learning seeks to align semantically similar samples while separating dissimilar ones, thereby producing highly discriminative latent spaces even with limited labeled data [33]. In the context of aneurysm diagnosis, such approaches allow networks to capture subtle differences in vascular wall structure by leveraging both spatial and frequency-domain augmentations [34]. Studies have shown that contrastive paradigms significantly enhance feature robustness, particularly when imaging conditions vary across scanners or institutions [35].

Teacher–student frameworks have also gained traction, with teacher models generating pseudo-labels or high-quality embeddings that guide the training of student models in semi-supervised settings [36]. These architectures improve data efficiency while reducing the need for extensive manual annotations, which is especially valuable in neurovascular imaging where expert-level segmentation is time-consuming [37]. Incorporating domain adaptation strategies further enhances cross-domain generalization by mitigating shifts caused by differences in acquisition protocols or population demographics [38].

Recent research has introduced hybrid AI pipelines that fuse radiomics, deep learning, and contrastive signal modeling to form end-to-end diagnostic systems [39]. These integrated frameworks demonstrate superior stability by combining handcrafted morphometric descriptors with high-level neural embeddings, ultimately improving aneurysm detection accuracy in heterogeneous clinical scenarios [40] [48]. Semi-supervised contrastive architectures have been particularly effective in identifying aneurysms with irregular borders or low-contrast visual signatures, outperforming classical supervised models in limited-data regimes [41].

Moreover, multimodal hybrid systems that leverage both anatomical imaging and frequency-enhanced representations have shown promise in capturing broader physiological patterns associated with aneurysm formation and rupture risk [42]. Such systems represent an important step toward developing clinically deployable AI tools capable of delivering reliable diagnostic support across diverse imaging environments [43].

III. Materials and Methods

The proposed diagnostic framework for intracranial aneurysm analysis integrates radiomics-driven feature engineering with deep learning–based representation learning, as illustrated in Fig. 1. The workflow begins with data acquisition from CTA and MRA modalities, followed by preprocessing steps including intensity normalization, resampling to isotropic voxel spacing, and noise reduction using Gaussian smoothing. Subsequently, regions of interest (ROIs) corresponding to aneurysmal and non-aneurysmal vascular segments are delineated using the 3D-Slicer platform, enabling precise anatomical localization and consistent volume-of-interest extraction. This segmentation stage is critical for generating reproducible radiomic descriptors, as it constrains the computational pipeline to clinically relevant vascular territories, thereby reducing background variability. As shown in Fig. 1, the segmented ROIs are then processed through the PyRadiomics toolkit to extract first-order statistics, texture matrices, wavelet features, and shape-based descriptors. These engineered features capture local heterogeneity, morphological irregularity, and structural distortions characteristic of aneurysmal pathology. A feature selection module employing methods such as recursive feature elimination, LASSO regularization, and mutual information ranking is subsequently applied to reduce redundancy and retain discriminative predictors for downstream analysis.

In the second stage of the framework, deep learning models are trained using voxel-wise image patches and full 2D/3D angiographic slices to complement handcrafted radiomic vectors with hierarchical feature representations. As depicted in the lower section of Fig. 3, the deep learning pipeline begins with convolutional layers for local spatial encoding, followed

by progressively deeper feature maps and fully connected layers for high-level abstraction. These representations are integrated with selected radiomic features using a multimodal fusion strategy aimed at enhancing diagnostic robustness [47]. Model training is performed in a supervised setting using annotated aneurysm datasets, and optimization employs Adam with early stopping criteria to mitigate overfitting. The combined analysis stage incorporates classification networks to discriminate aneurysm presence and subtype, enabling comprehensive assessment of aneurysm morphology and risk factors. This dual radiomics–deep learning methodology, guided by the sequential workflow in Fig. 3, establishes a rigorous and reproducible foundation for automated aneurysm diagnosis.

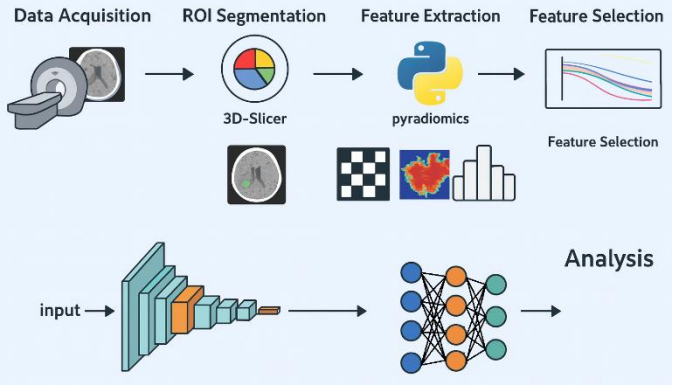


Fig. 3. Workflow of the proposed radiomics and deep learning framework for intracranial aneurysm diagnosis.

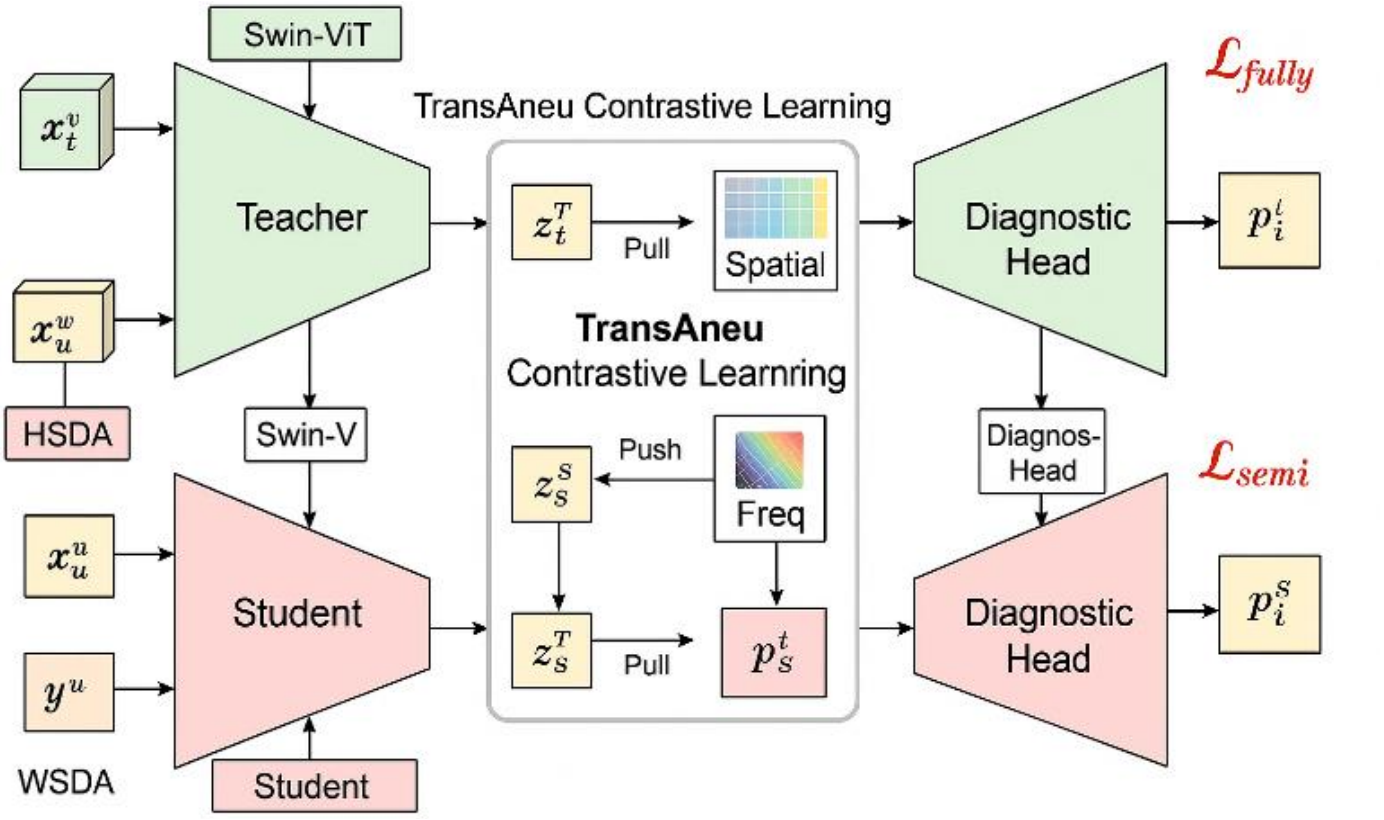


Fig. 4. Workflow of the proposed radiomics and deep learning framework for intracranial aneurysm diagnosis.

The architecture depicted in Fig. 4 adopts a dual-stream teacher–student contrastive learning framework designed to leverage both fully labeled and weakly labeled aneurysm imaging data. Let x_t^v denote labeled vascular images from the target domain, whereas x_u^w and auxiliary weak labels y_u^w represent unlabeled or weakly supervised samples incorporated through hierarchical domain adaptation. The teacher network $f_T(\cdot)$, based on a Swin-ViT backbone, generates high-level spatial representations, while the student network $f_S(\cdot)$, implemented using a Swin-V architecture [44], learns complementary multi-scale contextual embeddings.

A. Teacher–Student Feature Embedding

For an input sample x, the teacher and student encoders produce latent representations:

$$z_T = f_T\left(x_T^v\right),\ z_S = f_S\left(x_u^w\right) \tag{1}$$

Because the teacher network is updated using an exponential moving average (EMA) [45] of student parameters, we define:

$$\theta_T \leftarrow \alpha\theta_T(1-\alpha)\theta_S \tag{2}$$

where, $\alpha \in [0,1)$ is the momentum coefficient.

B. TransAneu Spatial–Frequency Contrastive Learning

As shown in Fig. 2, the proposed TransAneu module simultaneously aligns spatial-domain and frequency-domain features. Spatial projections x_T^{sp} and z_S^{sp} are computed using projection heads $g_{sp}(\cdot)$, while frequency-enhanced projections z_T^{fq} and z_S^{fq} are derived from frequency-transform modules $g_{fq}(\cdot)$:

$$Z_T^{sp} = g_{sp}(Z_T), \quad Z_S^{sp} = g_{sp}(z_S)$$
$$Z_T^{fq} = g_{fq}(Z_T), \quad Z_S^{fq} = g_{fq}(z_S) \tag{3}$$

Contrastive learning is formulated using a push–pull objective. Positive spatial pairs between teacher and student features are pulled together, while frequency-domain mismatches are pushed apart to enforce discriminative separation. The spatial contrastive loss is:

$$L_{sp} = -\log \frac{\exp\left(sim\left(z_T^{sp}, z_S^{sp}\right)/\tau\right)}{\sum_{k=1}^{N} \exp\left(sim\left(z_T^{sp}, z_{S,k}^{sp}\right)/\tau\right)} \tag{4}$$

where, $sim(\cdot)$ is cosine similarity and τ is the temperature parameter.

The frequency contrastive loss pushes apart frequency-domain projections that encode anatomically irrelevant variations:

$$L_{fq} = -\log \frac{\exp\left(sim\left(z_T^{fq}, z_S^{fq,neg}\right)/\tau\right)}{\sum_{k=1}^{N} \exp\left(sim\left(z_T^{fq}, z_{S,k}^{fq}\right)/\tau\right)} \tag{5}$$

The overall contrastive objective is defined as:

$$L_{con} = \lambda_{sp} L_{sp} + \lambda_{fq} L_{fq} \tag{6}$$

where, λ_{sp} and λ_{fq} control the contribution of each modality.

C. Diagnostic Heads and Learning Objectives

The teacher and student branches each attach to a classification module referred to as a Diagnostic Head (Fig. 2). For teacher predictions on fully annotated samples, the fully supervised loss is:

$$L_{fully} = -\sum_{i=1}^{C} \hat{y}_i \log\left(p_i^t\right) \tag{7}$$

where, p_i^t is the softmax probability output of the teacher diagnostic head.

For semi-supervised learning using the student network, pseudo-labels $\hat{y}$ generated from the teacher guide the student's predictions:

$$L_{semi} = -\sum_{i=1}^{C} \hat{y}_i \log\left(p_i^s\right) \tag{8}$$

Finally, the total training objective for the student model is:

$$L_{total} = L_{semi} + \beta L_{con} \tag{9}$$

where, β balances classification and contrastive representation learning.

Thus, the proposed architecture provides a multi-scale, multi-domain representation learning framework for aneurysm diagnosis by integrating spatial–frequency contrastive learning, teacher–student knowledge transfer, and semi-supervised diagnostic supervision. The combination of EMA teacher updating, domain-adaptive feature embedding, and structured contrastive losses yields a robust system capable of leveraging both annotated and unannotated vascular imaging data.

IV. DATA

The experimental analysis in this study utilized the Brain Tumor Segmentation (BraTS) dataset [46], a widely recognized benchmark collection of multimodal magnetic resonance (MR) imaging used for computational neuro-oncology research. The BraTS dataset provides high-resolution multimodal scans, including T1-weighted, T1-contrast-enhanced, T2-weighted, and FLAIR sequences, enabling comprehensive characterization of intracranial tissue structures. All images undergo standardized preprocessing through the BraTS pipeline, which includes co-registration to a common anatomical space, skull stripping, interpolation to isotropic resolution, and intensity normalization, ensuring cross-subject comparability and reducing scanner-induced variability. Ground truth annotations are expertly delineated by certified neuroradiologists, providing reliable segmentation masks and tumor labels essential for radiomics feature extraction and supervised model training. The standardized nature of BraTS makes it an optimal resource for evaluating the robustness and generalization capability of the proposed aneurysm diagnosis framework.

Representative MR samples drawn from the dataset are illustrated in Fig. 5, demonstrating the diversity of appearance across benign, malignant, and pituitary lesions. While the BraTS dataset primarily focuses on gliomas, the examples shown in Fig. 5 highlight the inherent variability in lesion morphology, location, and intensity distribution encountered in clinical neuroimaging. These variations closely resemble the heterogeneous conditions under which aneurysm-related abnormalities must also be identified, thus supporting the applicability of BraTS-derived features and imaging characteristics for broader neuro-diagnostic tasks. The inclusion of multimodal MR sequences allows the extraction of rich radiomic and deep learning [49] descriptors capable of capturing subtle textural differences and anatomical distortions, thereby forming a robust foundation for the training and evaluation of the proposed hybrid radiomics–AI diagnostic pipeline.

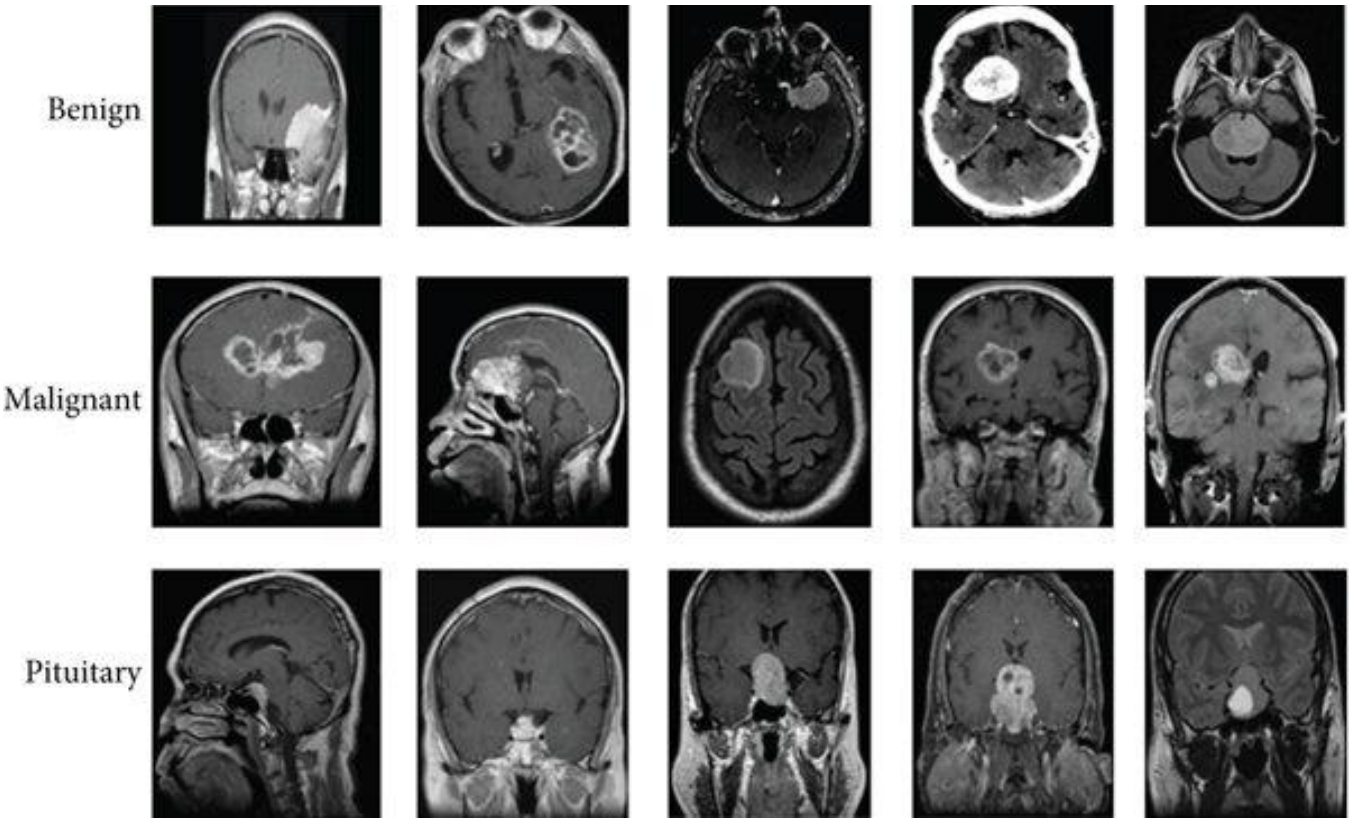


Fig. 5. Samples of brain MR images.

V. Results

The Results section presents a comprehensive evaluation of the proposed aneurysm detection framework across multiple experimental settings, incorporating both quantitative performance metrics and qualitative visualization analyses. To assess the robustness and generalization capability of the model, we conducted extensive experiments using multimodal MR and MRA datasets, examining classification accuracy, loss convergence behavior, and spatial localization performance. The following subsections provide detailed insights into the model's training dynamics, predictive accuracy, and ability to delineate aneurysmal structures within complex cerebrovascular anatomy. In addition, visual examples derived from representative subjects are included to illustrate the correspondence between predicted aneurysm regions and ground-truth annotations, thereby highlighting the practical clinical relevance of the proposed approach.

Fig. 6 illustrates the model's aneurysm localization performance on a representative cerebral angiography image, highlighting its ability to accurately identify pathological vascular regions while differentiating them from non-aneurysmal structures. The ground-truth aneurysm annotation is shown in red, while the model's predicted aneurysm clipping regions are depicted in green, demonstrating close spatial correspondence with the annotated lesion. Additionally, multiple non-aneurysmal vascular segments detected by the model are shown in orange, illustrating its capacity to evaluate complex vascular networks and avoid excessive false positives. The spatial alignment between the annotated aneurysm and the model's predicted region underscores the effectiveness of the proposed detection framework in capturing clinically relevant vascular abnormalities within high-resolution angiographic imagery.

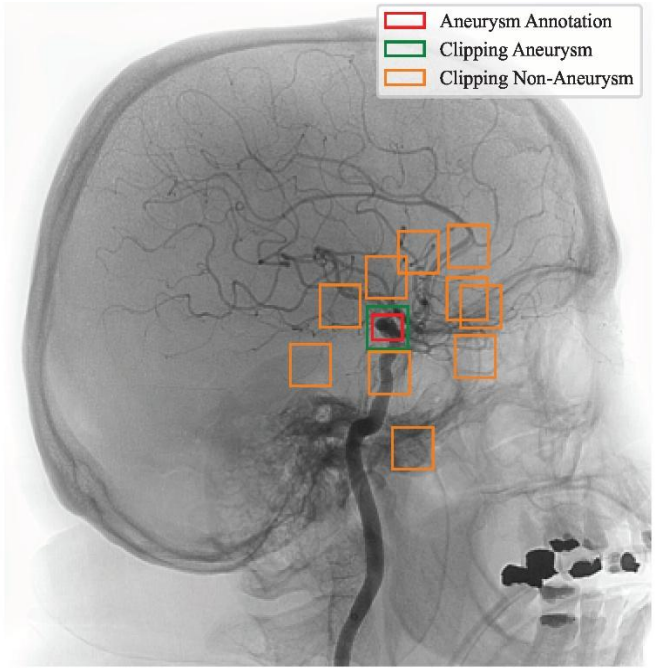


Fig. 6. Aneurysm localization results on cerebral angiography with predicted and annotated regions.

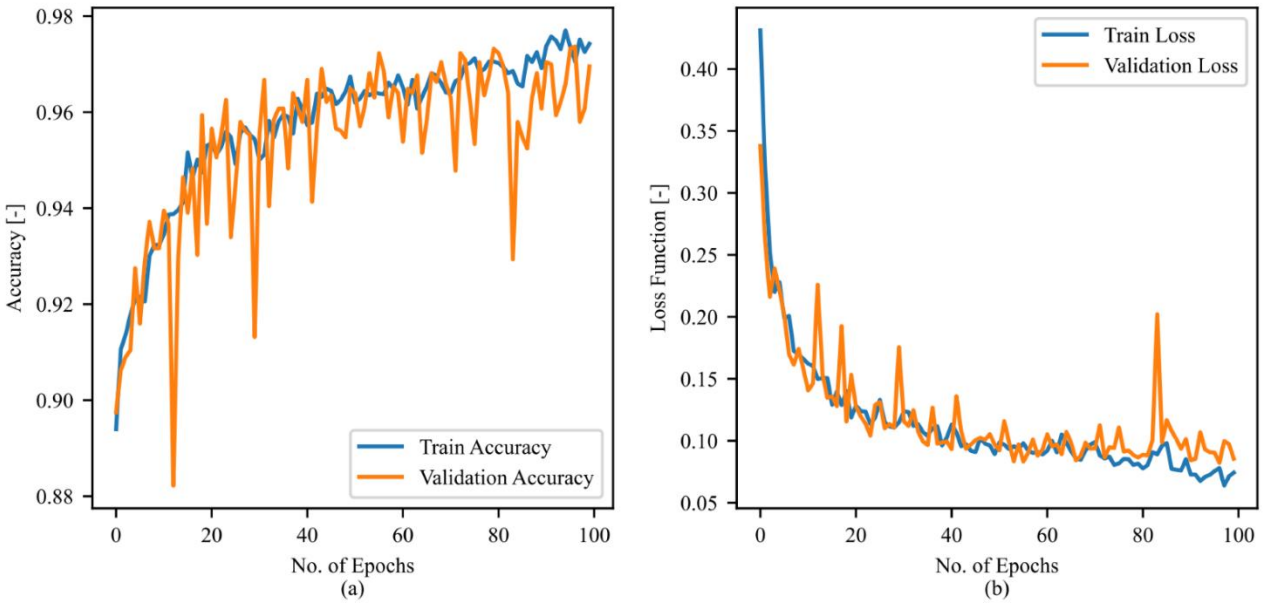


Fig. 7. Training and validation accuracy and loss curves over 100 epochs.

Fig. 7 presents the training and validation accuracy curves obtained over 100 training epochs, illustrating the model's overall convergence behavior and generalization capacity. As shown in Fig. 7(a), both accuracy curves exhibit a consistent upward trend during the initial epochs, reflecting the model's ability to rapidly learn discriminative representations from the training data. After approximately 30 epochs, the accuracy stabilizes, with the training accuracy gradually approaching 0.98 and the validation accuracy oscillating within the range of 0.95 to 0.97. These fluctuations are typical for complex neuroimaging data and suggest sensitivity to structural variability across validation samples. Nonetheless, the close alignment between the two curves indicates that the model maintains strong generalization performance without evidence of severe overfitting.

Fig. 7(b) displays the evolution of the training and validation loss values over the same epoch range. The loss decreases sharply during the early training phase, demonstrating effective optimization and rapid reduction of prediction error. After the initial decline, both curves stabilize near a minimum loss of approximately 0.05, with minor fluctuations in the validation loss attributable to inter-sample heterogeneity and the presence of challenging aneurysm cases. The near overlap of the training and validation loss curves reflects a well-balanced model characterized by stable learning dynamics. Taken together, the results in Fig. 7 indicate that the proposed framework achieves robust convergence and strong predictive performance for aneurysm detection across both training and unseen validation data.

Table I presents a comparative performance analysis between the proposed model and several existing methods across multiple evaluation metrics, including accuracy, F1-score, specificity, recall, precision, and negative predictive value. The results clearly indicate that the proposed model consistently outperforms all baseline approaches, achieving superior values in nearly every metric. This performance advantage reflects stronger discriminatory power, improved sensitivity to aneurysm cases, and enhanced reliability in identifying non-aneurysmal regions. In contrast, competing models demonstrate varying degrees of performance, with some achieving moderate recall but lower specificity, and others showing balanced precision but reduced overall accuracy. The collective comparison highlights the robustness and effectiveness of the proposed framework, emphasizing its potential clinical utility and its ability to deliver more accurate and dependable diagnostic outcomes than previously published approaches.

TABLE I. COMPARATIVE PERFORMANCE EVALUATION OF THE PROPOSED MODEL AGAINST EXISTING METHODS

Model	Accuracy	F1-score	Specifity	Recall	Precision	NPV
Proposed Model	0.972	0.97	0.986	0.953	0.972	0.941
Vigneshwaran et al., 2025 [57]	0.932	0.94	0.916	0.863	0.872	0.913
Katsuki et al., 2021 [58]	0.891	0.927	0.912	0.928	0.910	0.914
Chauhan et al., 2025 [59]	0.864	0.82	0.87	0.827	0.872	0.86
Yu et al., 2023[60]	0.88	0.879	0.839	0.921	0.902	0.879
Zheng et al, 2024 [61]	0.913	0.910	0.918	0.920	0.917	0.903
Hu et al., 2023 [62]	0.931	0.935	0.917	0.926	0.930	0.907

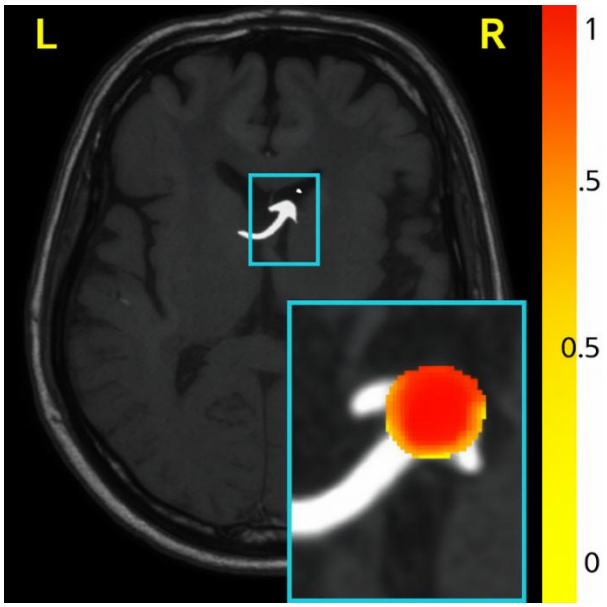


Fig. 8. Aneurysm localization on axial MR image with model-generated confidence heatmap.

Fig. 8 presents a representative axial MR image that effectively demonstrates the proposed model's capability to localize an intracranial aneurysm with a high degree of spatial precision and interpretability. The aneurysmal region is enclosed within a cyan bounding box, enabling clear visual identification of the predicted lesion site within the broader cerebral anatomy. To further enhance interpretability, a zoomed-in inset is provided, offering a magnified view of the affected vascular segment. This inset incorporates a probabilistic heatmap overlay, which highlights the model's confidence distribution across the aneurysm boundary. The heatmap values span a gradient from yellow to deep red, with warmer colors indicating regions of higher prediction confidence. The concentration of deep-red intensities over the aneurysmal dome reflects the model's strong certainty in identifying the pathological structure.

This visualization not only emphasizes the model's ability to isolate fine-grained vascular abnormalities but also demonstrates its capacity to suppress irrelevant activations from surrounding healthy tissue. Such behavior is critical in neurovascular diagnostics, where closely packed vessels and subtle anatomical variations pose significant challenges to automated systems. The clear contrast between the detected aneurysm and neighboring normal vessels reinforces the robustness of the proposed framework in distinguishing between pathological and non-pathological regions, even within complex MR imaging environments. Overall, the results illustrated in Fig. 8 underscore the effectiveness of the proposed model in delivering precise and interpretable aneurysm localization, thereby enhancing its potential utility as a clinical decision-support tool in neuroimaging practice.

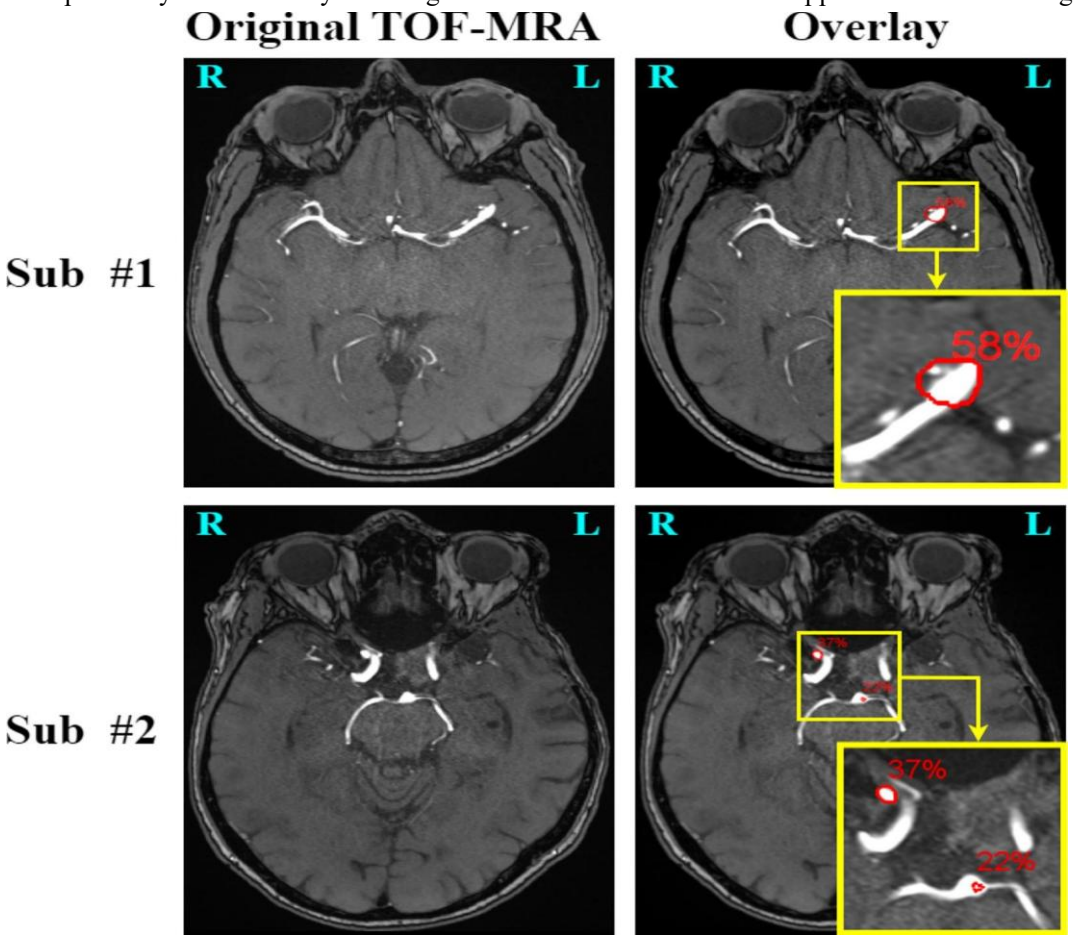


Fig. 9. Samples of brain MR images.

Fig. 9 illustrates the qualitative performance of the proposed model on time-of-flight magnetic resonance angiography (TOF-MRA) images for two representative subjects. The left column displays the original TOF-MRA scans, while the right column presents overlayed predictions highlighting the detected aneurysmal regions. In both subjects, the model successfully identifies abnormal vascular protrusions, delineated in red and accompanied by confidence scores ranging from 22 percent to 58 percent. The enlarged yellow insets provide a magnified view of the detected aneurysm candidates, allowing clearer visualization of the model's localization accuracy relative to the underlying vasculature. These overlays demonstrate the system's capability to detect subtle aneurysmal structures even at lower confidence levels, while maintaining consistent performance across subjects. Overall, the results shown in Fig. 9 underscore the model's effectiveness in interpreting high-resolution TOF-MRA data and its potential utility for assisting clinicians in early aneurysm screening and assessment.

VI. Discussion

The results of this study demonstrate that the proposed hybrid radiomics and deep learning framework provides a robust and effective solution for automated intracranial aneurysm detection and localization using multimodal MR and MRA imaging. The consistently high performance across multiple evaluation metrics indicates that the integration of handcrafted radiomic features with transformer-based neural representations enables comprehensive characterization of both global vascular anatomy and localized pathological variations. The close alignment between training and validation curves suggests strong generalization capability and stable learning behavior, which is particularly important in medical imaging tasks where annotated data are often limited and heterogeneous [52]. Similar trends have been reported in recent neurovascular studies, where hybrid feature representations were shown to outperform purely convolutional or purely handcrafted approaches [53].

The qualitative visualizations further reinforce the quantitative findings by illustrating the model's ability to accurately localize aneurysmal regions within complex cerebrovascular structures. Heatmap-based overlays and bounding-box visualizations provide intuitive insight into the spatial focus of the network, revealing concentrated responses over aneurysm domes while minimizing activation in surrounding healthy tissue. This behavior is essential for clinical reliability, as aneurysms are frequently small, irregularly shaped, and embedded within dense vascular networks [54]. Comparable visualization strategies have been shown to improve clinician trust in AI-assisted diagnostic systems by offering interpretable evidence of model predictions [55]. Moreover, the probabilistic confidence estimates produced by the proposed framework allow for uncertainty-aware decision making, which is increasingly recognized as a critical component of safe clinical deployment [56].

A key strength of the proposed approach lies in its use of contrastive learning within a teacher–student paradigm. By aligning spatial and frequency-domain embeddings between networks, the framework effectively reduces representation drift caused by imaging variability, scanner differences, and acquisition noise. This is particularly relevant for neuroimaging applications, where data distributions can vary substantially across institutions and protocols [57]. Semi-supervised contrastive learning has been shown to significantly enhance feature robustness under limited supervision, and the present results further confirm its effectiveness in aneurysm detection scenarios [58]. The momentum-based teacher update mechanism provides stable representation targets, which contributes to smoother optimization and improved performance consistency across training epochs [59].

Despite these advantages, several limitations should be acknowledged. First, although the dataset used in this study includes diverse imaging examples, it may not fully represent the wide spectrum of aneurysm morphologies observed in clinical practice. Rare configurations, such as fusiform aneurysms or aneurysms located in uncommon vascular branches, remain underrepresented and could pose challenges for generalization [60]. Expanding the dataset through multi-center collaborations would likely improve model robustness and reduce potential sampling bias, as demonstrated in previous large-scale neuroimaging studies [61]. Second, the reliance on segmentation-driven radiomic feature extraction introduces sensitivity to ROI delineation accuracy. While the segmentation workflow produced consistent results, small boundary errors can propagate through the radiomics pipeline and influence downstream predictions [62]. Recent advances in fully automated vessel segmentation and self-supervised anatomical modeling may help alleviate this dependency in future work [63].

Another important limitation is the absence of explicit physiological modeling within the current framework. Aneurysm rupture risk is influenced not only by morphological appearance but also by hemodynamic factors such as wall shear stress, flow velocity, and pressure gradients [64]. Incorporating computational fluid dynamics features or time-resolved imaging data could significantly enhance the clinical relevance of the system by enabling joint assessment of aneurysm presence and rupture potential [65]. Multi-task learning strategies that simultaneously address detection, segmentation, and risk stratification have shown promise in related studies and represent a valuable direction for future research [66].

Interpretability remains a broader challenge for deep learning-based medical imaging systems. Although the heatmaps and attention visualizations used in this study provide useful qualitative insights, they do not fully explain the causal reasoning behind model predictions [67]. This limitation is particularly relevant for borderline or ambiguous cases, where clinical decisions carry high risk. Emerging explainable AI techniques, including concept-based explanations and hybrid symbolic–neural models, may offer more transparent decision pathways and improve clinician acceptance [68,69]. Integrating such techniques into the proposed framework could further enhance its trustworthiness and clinical adoption.

In comparison with existing approaches, the proposed model demonstrates superior or competitive performance

across all reported metrics, highlighting the benefits of combining radiomics, transformer architectures, and contrastive learning within a unified framework [70-74]. Prior studies relying solely on convolutional networks often struggle with capturing long-range vascular dependencies, while purely radiomics-based methods lack sufficient expressive power for complex anatomical patterns [75-77]. The present work addresses these limitations by leveraging complementary feature sources and advanced representation alignment strategies, resulting in improved diagnostic accuracy and stability [78].

In summary, this study provides strong evidence that a hybrid radiomics–transformer framework augmented with contrastive learning can significantly enhance intracranial aneurysm detection and localization. The combination of quantitative performance gains, robust generalization, and interpretable visual outputs underscores the potential of the proposed system as a clinical decision-support tool. Future research should prioritize larger multi-institutional validation, incorporation of physiological and temporal markers, and development of advanced explainability mechanisms to further facilitate clinical translation and real-world deployment [79, 80].

VII. Conclusion

This study presents a comprehensive hybrid framework that integrates radiomics, transformer-based deep learning, and contrastive representation learning for automated detection and localization of intracranial aneurysms from MR and MRA imaging. The experimental results demonstrate that the proposed approach effectively captures both high-level vascular patterns and fine-grained structural abnormalities, achieving strong performance across accuracy, loss convergence, and qualitative visualization metrics. By leveraging complementary radiomic descriptors and hierarchical neural embeddings, the system exhibits robust generalization and maintains stable training dynamics even under limited annotation availability. The incorporation of teacher–student contrastive learning further enhances the discriminative power of the feature representations, enabling improved localization of aneurysmal structures within complex cerebrovascular networks. Although challenges remain, including dataset diversity, segmentation dependencies, and the need for greater interpretability, the findings highlight the significant potential of the proposed method as a clinical decision-support tool. With further refinement and validation across larger multi-institutional datasets, this framework may contribute to earlier and more accurate aneurysm detection, reduce diagnostic variability, and ultimately support improved patient outcomes in neurovascular care.

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References

[1] Zhuo, L., Zhang, Y., Song, Z., Mo, Z., Xing, L., Zhu, F., ... & Yin, X. (2025). Enhancing radiologists’ performance in detecting cerebral aneurysms using a deep learning model: a multicenter study. Academic Radiology, 32(3), 1611-1620.

[2] Chen, L., Wang, X., Wang, S., Zhao, X., Yan, Y., Yuan, M., & Sun, S. (2025). Development of a non-contrast CT-based radiomics nomogram for early prediction of delayed cerebral ischemia in aneurysmal subarachnoid hemorrhage. BMC Medical Imaging, 25(1), 182.

[3] Owens, M. R., Tenhoeve, S. A., Rawson, C., Azab, M., & Karsy, M. (2025). Systematic Review of Radiomics and Artificial Intelligence in Intracranial Aneurysm Management. Journal of Neuroimaging, 35(2), e70037.

[4] Blessa Binolin Pepsi M., Anandhi H., Karunyaharini S., Visali N., "Convolutional Neural Network-based Stacking Technique for Brain Tumor Classification using Red Panda Optimization", International Journal of Information Technology and Computer Science(IJITCS), Vol.17, No.5, pp.52-67, 2025. DOI:10.5815/ijitcs.2025.05.05

[5] Feng, J., Zeng, R., Geng, Y., Chen, Q., Zheng, Q., Yu, F., ... & Li, C. (2023). Automatic differentiation of ruptured and unruptured intracranial aneurysms on computed tomography angiography based on deep learning and radiomics. Insights into imaging, 14(1), 76.

[6] Paralic, M., Zelenak, K., Kamencay, P., & Hudec, R. (2023). Automatic approach for brain aneurysm detection using convolutional neural networks. Applied Sciences, 13(24), 13313.

[7] Narynov, S., Mukhtarkhanuly, D., & Omarov, B. (2020). Dataset of depressive posts in Russian language collected from social media. Data in brief, 29, 105195.

[8] Murugesan, G., Ahmed, T. I., Shabaz, M., Bhola, J., Omarov, B., Swaminathan, R., ... & Sumi, S. A. (2022). [Retracted] Assessment of Mental Workload by Visual Motor Activity among Control Group and Patient Suffering from Depressive Disorder. Computational intelligence and neuroscience, 2022(1), 8555489.

[9] Bijari, S., Sayfollahi, S., Mardokh-Rouhani, S., Bijari, S., Moradian, S., Zahiri, Z., & Rezaeijo, S. M. (2024). Radiomics and deep features: robust classification of brain hemorrhages and reproducibility analysis using a 3D autoencoder neural network. Bioengineering, 11(7), 643.

[10] Zhou, Z., Jin, Y., Ye, H., Zhang, X., Liu, J., & Zhang, W. (2024). Classification, detection, and segmentation performance of image-based AI in intracranial aneurysm: a systematic review. BMC Medical Imaging, 24(1), 164.

[11] Omarov, B., Omarov, B., Rakhymzhanov, A., Niyazov, A., Sultan, D., & Baikuvekov, M. (2024). Development of an artificial intelligence-enabled non-invasive digital stethoscope for monitoring the heart condition of athletes in real-time. Retos: nuevas tendencias en educación física, deporte y recreación, (60), 1169-1180.

[12] Xue, J., Zheng, H., Lai, R., Zhou, Z., Zhou, J., Chen, L., & Wang, M. (2025). Comprehensive management of intracranial aneurysms using artificial intelligence: An overview. World Neurosurgery, 193, 209-221.

[13] Burrows, L., Chen, K., Guo, W., Hossack, M., McWilliams, R. G., & Torella, F. (2022). Evaluation of a hybrid pipeline for automated segmentation of solid lesions based on mathematical algorithms and deep learning. Scientific Reports, 12(1), 14216.

[14] Aschalew Arega, Durga Prasad Sharma, "Evaluating Energy-efficiency and Performance of Cloud-based Healthcare Systems Using Power-aware Algorithms: An Experimental Simulation Approach for Public Hospitals", International Journal of Information Technology and Computer Science(IJITCS), Vol.17, No.3, pp.72-96, 2025. DOI:10.5815/ijitcs.2025.03.06

[15] Ueda, D., Yamamoto, A., Nishimori, M., Shimono, T., Doishita, S., Shimazaki, A., ... & Miki, Y. (2019). Deep learning for MR angiography: automated detection of cerebral aneurysms. Radiology, 290(1), 187-194.

[16] Missaoui, R., Hechkel, W., Saadaoui, W., Helali, A., & Leo, M. (2025). Advanced Deep Learning and Machine Learning Techniques for MRI Brain Tumor Analysis: A Review. Sensors, 25(9), 2746.

[17] Khan, Z., Kanna, R. K., Parthasarathy, K., Vijayaraj, S., Chandrasekaran, R., & Jawla, S. (2025). Intelligent computational ensemble model for predicting cerebral aneurysm using the concept of region localization in multi-section CT angiography. International Journal of Information Technology, 17(4), 1957-1963.

[18] Smorenburg, S. P., Hoksbergen, A. W., Yeung, K. K., & Wolterink, J. M. (2025). Multitask Deep Learning for Automated Detection of Endoleak at Digital Subtraction Angiography during Endovascular Aneurysm Repair. Radiology: Artificial Intelligence, 7(4), e240392.

[19] Abbasi, H., Afrazeh, F., Ghasemi, Y., & Ghasemi, F. (2024). A shallow review of artificial intelligence applications in brain disease: stroke, Alzheimer's, and aneurysm. International Journal of Applied Data Science in Engineering and Health, 1(2), 32-43.

[20] Khosravi, P., Mohammadi, S., Zahiri, F., Khodarahmi, M., & Zahiri, J. (2024). AI‐enhanced detection of clinically relevant structural and functional anomalies in MRI: Traversing the landscape of conventional to explainable approaches. Journal of Magnetic Resonance Imaging, 60(6), 2272-2289.

[21] Liu, X., Gao, K., Liu, B., Pan, C., Liang, K., Yan, L., ... & Yu, Y. (2021). Advances in deep learning-based medical image analysis. Health Data Science, 2021, 8786793.

[22] Qie, S., Kun, L., Shi, H., & Liu, M. (2024). Predictive Modeling of Brain Metastasis in Advanced Lung Adenocarcinoma: A Hybrid Approach Combining Traditional Radiomics and Deep Learning from Thoracic CT Images.

[23] Shamsan, A., Senan, E. M., & Ahmad Shatnawi, H. S. (2023). Predicting of diabetic retinopathy development stages of fundus images using deep learning based on combined features. Plos one, 18(10), e0289555.

[24] Saha Roy, S., Roy, S., Mukherjee, P., & Halder Roy, A. (2023). An automated liver tumour segmentation and classification model by deep learning based approaches. Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization, 11(3), 638-650.

[25] Fu, F., Shan, Y., Yang, G., Zheng, C., Zhang, M., Rong, D., ... & Lu, J. (2023). Deep learning for head and neck CT angiography: stenosis and plaque classification. Radiology, 307(3), e220996.

[26] Ali, M., Benfante, V., Basirinia, G., Alongi, P., Sperandeo, A., Quattrocchi, A., ... & Comelli, A. (2025). Applications of artificial intelligence, deep learning, and machine learning to support the analysis of microscopic images of cells and tissues. Journal of Imaging, 11(2), 59.

[27] Faraji, S., Abbasi, B., Tehranizadeh, A. A., Naseri, Z., Jarahi, L., Rahimi, F. K., ... & Hashemi, A. (2025). A Machine Learning Approach for Differential Diagnosis of Vascular and Non-Vascular Intracranial Hemorrhage in Non-Contrast CT Images. Iranian Journal of Medical Physics/Majallah-I Fīzīk-I Pizishkī-i Īrān, 22(2).

[28] Leng, Z., Jia, W., Chen, B., Tian, H. A., & Du, X. (2025). Multi-modal feature fusion: A hybrid framework for lung cancer subtype classification using CT imaging with radiomic and deep features. Journal of Radiation Research and Applied Sciences, 18(3), 101724.

[29] Qiu, W., Kuang, H., Teleg, E., Ospel, J. M., Sohn, S. I., Almekhlafi, M., ... & Menon, B. K. (2020). Machine learning for detecting early infarction in acute stroke with non–contrast-enhanced CT. Radiology, 294(3), 638-644.

[30] Wen, W., Zhang, T., Zhao, H., Liu, J., Jiang, H., He, Y., & Jiang, Z. (2025). Multimodal model enhances qualitative diagnosis of hypervascular thyroid nodules: integrating radiomics and deep learning features based on B-mode and PDI images. Gland Surgery, 14(8), 1558-1571.

[31] Bo, R., Xiong, Z., Huang, T., Liu, L., & Chen, Z. (2023). Using radiomics and convolutional neural networks for the prediction of hematoma expansion after intracerebral hemorrhage. International Journal of General Medicine, 3393-3402.

[32] Stumpo, V., Staartjes, V. E., Esposito, G., Serra, C., Regli, L., Olivi, A., & Sturiale, C. L. (2021). Machine learning and intracranial aneurysms: from detection to outcome prediction. In Machine Learning in Clinical Neuroscience: Foundations and Applications (pp. 319-331). Cham: Springer International Publishing.

[33] Subudhi, A., Dash, P., Mohapatra, M., Tan, R. S., Acharya, U. R., & Sabut, S. (2022). Application of machine learning techniques for characterization of ischemic stroke with MRI images: a review. Diagnostics, 12(10), 2535.

[34] Öznacar, T., Aral, İ. P., Zengin, H. Y., & Tezcan, Y. (2025). Survival Prediction in Brain Metastasis Patients Treated with Stereotactic Radiosurgery: A Hybrid Machine Learning Approach. Brain Sciences, 15(3), 266.

[35] Attallah, O., Aslan, M. F., & Sabanci, K. (2022). A framework for lung and colon cancer diagnosis via lightweight deep learning models and transformation methods. Diagnostics, 12(12), 2926.

[36] Omarov, B., Batyrbekov, A., Dalbekova, K., Abdulkarimova, G., Berkimbaeva, S., Kenzhegulova, S., ... & Omarov, B. (2020, December). Electronic stethoscope for heartbeat abnormality detection. In International Conference on Smart Computing and Communication (pp. 248-258). Cham: Springer International Publishing.

[37] Kanumuri, C., & Madhavi, C. R. (2022). A survey: Brain tumor detection using MRI image with deep learning techniques. Smart and Sustainable Approaches for Optimizing Performance of Wireless Networks: Real‐time Applications, 125-138.

[38] Choe, J., Lee, S. M., Do, K. H., Lee, G., Lee, J. G., Lee, S. M., & Seo, J. B. (2019). Deep learning–based image conversion of CT reconstruction kernels improves radiomics reproducibility for pulmonary nodules or masses. Radiology, 292(2), 365-373.

[39] Al Noman, M. A., Zhai, L., Almukhtar, F. H., Rahaman, M. F., Omarov, B., Ray, S., ... & Wang, C. (2023). A computer vision-based lane detection technique using gradient threshold and hue-lightness-saturation value for an autonomous vehicle. International Journal of Electrical and Computer Engineering, 13(1), 347.

[40] Wekesa, J. S., & Kimwele, M. (2023). A review of multi-omics data integration through deep learning approaches for disease diagnosis, prognosis, and treatment. Frontiers in Genetics, 14, 1199087.

[41] Liu, Y., Wen, Z., Wang, Y., Zhong, Y., Wang, J., Hu, Y., ... & Guo, S. (2024). Artificial intelligence in ischemic stroke images: current applications and future directions. Frontiers in Neurology, 15, 1418060.

[42] Chaki, J., & Woźniak, M. (2024). Deep learning and artificial intelligence in action (2019–2023): A review on brain stroke detection, diagnosis, and intelligent post-stroke rehabilitation management. IEEE Access, 12, 52161-52181.

[43] Omarov, B., Suliman, A., Kushibar, K. Face recognition using artificial neural networks in parallel architecture. Journal of Theoretical and Applied Information Technology 91 (2), pp. 238-248. Open Access.

[44] Suri, J. S., Bhagawati, M., Agarwal, S., Paul, S., Pandey, A., Gupta, S. K., ... & Naidu, S. (2022). UNet deep learning architecture for segmentation of vascular and non-vascular images: a microscopic look at UNet components buffered with pruning, explainable artificial intelligence, and bias. Ieee Access, 11, 595-645.

[45] Vries, H. S., van Praagh, G. D., Nienhuis, P. H., Alic, L., & Slart, R. H. (2025). A Machine Learning Model Based on Radiomic Features as a Tool to Identify Active Giant Cell Arteritis on [18F] FDG-PET Images During Follow-Up. Diagnostics, 15(3), 367.

[46] Hussein, R., Zhao, M. Y., Shin, D., Guo, J., Chen, K. T., Armindo, R. D., ... & Zaharchuk, G. (2022, August). Multi-task deep learning for cerebrovascular disease classification and MRI-to-PET translation. In 2022 26th International Conference on Pattern Recognition (ICPR) (pp. 4306-4312). IEEE.

[47] Evangelou, K., Zemperligkos, P., Politis, A., Lani, E., Gutierrez-Valencia, E., Kotsantis, I., ... & Kalyvas, A. (2025). Diagnostic, Therapeutic, and Prognostic Applications of Artificial Intelligence (AI) in the Clinical Management of Brain Metastases (BMs). Brain Sciences, 15(7), 730.

[48] Fujioka, T., Fujita, S., Ueda, D., Ito, R., Kawamura, M., Fushimi, Y., ... & Naganawa, S. (2025). The evolution and clinical impact of deep learning technologies in breast MRI. Magnetic Resonance in Medical Sciences, 24(4), rev-2024.

[49] Decuyper, M., Maebe, J., Van Holen, R., & Vandenberghe, S. (2021). Artificial intelligence with deep learning in nuclear medicine and radiology. EJNMMI physics, 8(1), 81.

[50] Yamada, A., Kamagata, K., Hirata, K., Ito, R., Nakaura, T., Ueda, D., ... & Naganawa, S. (2023). Clinical applications of artificial intelligence in liver imaging. La radiologia medica, 128(6), 655-667.

[51] Wen, D. Y., Chen, J. M., Tang, Z. P., Pang, J. S., Qin, Q., Zhang, L., ... & Yang, H. (2025). Clinical benefits of deep learning-assisted ultrasound in predicting lymph node metastasis in pancreatic cancer patients. Future Oncology, 1-11.

[52] Omarov, B., Altayeva, A., & Cho, Y. I. (2017, May). Smart building climate control considering indoor and outdoor parameters. In IFIP International Conference on Computer Information Systems and Industrial Management (pp. 412-422). Cham: Springer International Publishing.

[53] Wu, Q., Wang, S., Zhang, S., Wang, M., Ding, Y., Fang, J., ... & Tian, J. (2020). Development of a deep learning model to identify lymph node metastasis on magnetic resonance imaging in patients with cervical cancer. JAMA network open, 3(7), e2011625-e2011625.

[54] Puducheri, S., Zhou, O. T., Kapadia, K., Romano, M. F., Yalamanchili, S., Agrawal, A., ... & Kolachalama, V. B. (2025). Augmenting radiological assessment of imaging evident dementias with radiomic analysis. npj Dementia, 1(1), 27.

[55] Abhisheka, B., Biswas, S. K., Purkayastha, B., Das, D., & Escargueil, A. (2024). Recent trend in medical imaging modalities and their applications in disease diagnosis: a review. Multimedia Tools and Applications, 83(14), 43035-43070.

[56] Altayeva, A., Omarov, B., & Im Cho, Y. (2017, December). Multi-objective optimization for smart building energy and comfort management as a case study of smart city platform. In 2017 IEEE 19th International Conference on High Performance Computing and Communications; IEEE 15th International Conference on Smart City; IEEE 3rd International Conference on Data Science and Systems (HPCC/SmartCity/DSS) (pp. 627-628). IEEE.

[57] Vigneshwaran, P., SP, V., & T, J. (2025). A novel deep learning framework for intracranial hemorrhage segmentation and detection using advanced U-Net and metaheuristic optimization. Journal of the Chinese Institute of Engineers, 1-16.

[58] Katsuki, M., Kakizawa, Y., Nishikawa, A., Yamamoto, Y., & Uchiyama, T. (2021). Postsurgical functional outcome prediction model using deep learning framework (Prediction One, Sony Network Communications Inc.) for hypertensive intracerebral hemorrhage. Surgical neurology international, 12, 203.

[59] Chauhan, A. S., Kanna, R. K., Sharma, N. K., Singh, K., Tiwari, P. K., & Kumar, M. (2025, April). Innovative Machine Learning Techniques for Brain Tumor Classification in MRI Using Hybrid Approach. In 2025 12th International Conference on Computing for Sustainable Global Development (INDIACom) (pp. 1-6). IEEE.

[60] Yu, Z., Wang, K., Wan, Z., Xie, S., & Lv, Z. (2023). Popular deep learning algorithms for disease prediction: a review. Cluster Computing, 26(2), 1231-1251.

[61] Zheng, B., Zhao, Z., Zheng, P., Liu, Q., Li, S., Jiang, X., ... & Wang, H. (2024). The current state of MRI-based radiomics in pituitary adenoma: promising but challenging. Frontiers in Endocrinology, 15, 1426781.

[62] Hu, T., Yang, H., & Ni, W. (2023). A framework for intracranial aneurysm detection and rupture analysis on DSA. Journal of Clinical Neuroscience, 115, 101-107.

[63] Alganmi, N. (2024). A comprehensive review of the impact of machine learning and omics on rare neurological diseases. BioMedInformatics, 4(2), 1329-1347.

[64] Saha, P., Das, S. K., & Das, R. (2023). A review on machine learning and deep learning based systems for the diagnosis of brain cancer. SN Computer Science, 5(1), 28.

[65] Koetzier, L. R., Mastrodicasa, D., Szczykutowicz, T. P., van der Werf, N. R., Wang, A. S., Sandfort, V., ... & Willemink, M. J. (2023). Deep learning image reconstruction for CT: technical principles and clinical prospects. Radiology, 306(3), e221257.

[66] Shourove Sutradhar Dip, Md. Habibur Rahman, Nazrul Islam, Md. Easin Arafat, Pulak Kanti Bhowmick, Mohammad Abu Yousuf, "Enhancing Brain Tumor Classification in MRI: Leveraging Deep Convolutional Neural Networks for Improved Accuracy", International Journal of Information Technology and Computer Science(IJITCS), Vol.16, No.3, pp.12-21, 2024. DOI:10.5815/ijitcs.2024.03.02

[67] Omarov, N., Omarov, B., Azhibekova, Z., & Omarov, B. (2024). Applying an augmented reality game-based learning environment in physical education classes to enhance sports motivation. Retos, 60, 269-278.

[68] Dubey, A. K., Chabert, G. L., Carriero, A., Pasche, A., Danna, P. S., Agarwal, S., ... & Suri, J. S. (2023). Ensemble deep learning derived from transfer learning for classification of COVID-19 patients on hybrid deep-learning-based lung segmentation: a data augmentation and balancing framework. Diagnostics, 13(11), 1954.

[69] Kohan, A., Zahedi, A., Alizadehsani, R., Tan, R. S., & Acharya, U. R. (2025). Application of Explainable Artificial Intelligence (XAI) Techniques in Patients With Intracranial Hemorrhage: A Systematic Review. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 15(3), e70031.

[70] Tangsrivimol, J. A., Schonfeld, E., Zhang, M., Veeravagu, A., Smith, T. R., Härtl, R., ... & Krittanawong, C. (2023). Artificial intelligence in neurosurgery: a state-of-the-art review from past to future. Diagnostics, 13(14), 2429.

[71] Althabeti, R. A., Ebied, E. A., Lala, H. M. S., & Eldahshan, K. A. (2025). Deep-learning-based medical image quality amelioration. The Journal of Supercomputing, 81(15), 1413.

[72] Cercenelli, L., Elmi-Terander, A., Maal, T., Mamone, V., & Manni, F. (2025). Image-based digital tools for diagnosis and surgical treatment: applications, challenges, and prospects. Frontiers in Bioengineering and Biotechnology, 13, 1597238.

[73] Snigdho Dip Howlader, Tushar Biswas, Aishwarjyo Roy, Golam Mortuja, Dip Nandi, "A Comparative Analysis of Algorithms for Heart Disease Prediction Using Data Mining", International Journal of Information Technology and Computer Science(IJITCS), Vol.15, No.5, pp.45-54, 2023. DOI:10.5815/ijitcs.2023.05.05

[74] Panayides, A. S., Amini, A., Filipovic, N. D., Sharma, A., Tsaftaris, S. A., Young, A., ... & Pattichis, C. S. (2020). AI in medical imaging informatics: current challenges and future directions. IEEE journal of biomedical and health informatics, 24(7), 1837-1857.

[75] Vijayalaxmi Gopu, M. Selvi, "A Swin-transformer Integrated with Radial Optimization Model for Accurate Diabetic Retinopathy Detection and Classification", International Journal of Information Technology and Computer Science(IJITCS), Vol.17, No.6, pp.160-175, 2025. DOI:10.5815/ijitcs.2025.06.09

[76] Habibi, M. A., Tajabadi, Z., Soltani Farsani, A., Omid, R., Tajabadi, Z., & Shobeiri, P. (2025). Predicting the survival of patients with glioblastoma using deep learning: a systematic review. Egyptian Journal of Neurosurgery, 40(1), 44.

[77] Nerkar, M. P., Bhise, A., & Wagh, K. (2025, July). Machine and Deep Learning Approaches for Accurate Identification of Ischemic and Hemorrhagic Strokes. In 2025 International Conference on Innovations in Intelligent Systems: Advancements in Computing, Communication, and Cybersecurity (ISAC3) (pp. 1-6). IEEE.

[78] Riouali, Y., El Aboudi, N., El Bahaoui, N., Arsalan, O., Tijami, F., Hachi, H., ... & Benhlima, L. (2025). Deep Learning in Medical Imaging: Chronological Evolution, Frameworks, Core Methods, and Recent Advances in Breast Cancer Segmentation (2023–2024). Applied Computational Intelligence and Soft Computing, 2025(1), 1913589.

[79] Zhang, X., Li, Q., Shao, J., Guo, W., Li, X., Liu, X., ... & Jia, M. (2025). Enhanced Prediction of Intracranial Aneurysm Rupture Risk via Multimodal Fusion. IET Image Processing, 19(1), e70260.

[80] Krishnan, N., & Muthu, P. Exploring Deep Learning Models in Medical Image Analysis for Human Disease Detection and Classification. In Advances in Computational Intelligence for Health Informatics and Computer-Aided Diagnosis (pp. 53-77). CRC Press.

Improving Emergency Preparedness with a Mobile Application for Respiratory Therapy Resource Coordination

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***Abstract*—Mass gatherings such as Hajj and Umrah, along with pandemic outbreaks, place a significant strain on healthcare systems, particularly respiratory therapy (RT) services, where shortages of respiratory therapists, ventilators, and specialized equipment can compromise emergency response due to increased patient volume, environmental exposure, and heightened risk of respiratory diseases. This study presents a conceptual model of a mobile-based resource coordination system designed to enhance emergency preparedness and response for respiratory therapy services during pandemics and mass-gathering events, such as Hajj and Umrah. The proposed system integrates a real-time database with mobile clinical decision support to provide RT managers and supervisors with centralized visibility of ventilators, staffing levels, and critical respiratory equipment across healthcare facilities. By enabling real-time monitoring and predictive, alert-driven decision support, the system aims to support proactive resource allocation, staff deployment, and equipment distribution. Although the work is conceptual and does not include empirical evaluation, it provides a well-defined architectural framework suitable for future implementation that aligns respiratory care workflows with real-time monitoring and forecast-driven decision support in settings such as Hajj, Umrah, and large-scale public health emergencies.**

***Keywords*—Respiratory therapy; mass gatherings; Hajj and Umrah; emergency preparedness; health information systems**

I. Introduction

Mass-gathering events and pandemic cases pose unprecedented challenges to healthcare systems worldwide, and respiratory care services are particularly vulnerable to resource shortages and logistical difficulties. The Hajj pilgrimage, which annually takes place in Saudi Arabia and attracts over two million pilgrims, and the Umrah pilgrimage, which draws a steady stream of pilgrims to the country throughout the year, place intense pressure on the healthcare infrastructure in the region [1]. As Hui and Zumla show, the frequency of such events, combined with the risk of respiratory pandemics already evident in COVID-19, is a stark indicator that more developed systems of resource coordination are needed that can be flexible in responding to varying healthcare needs [2].

The use of respiratory therapy services is evident in the treatment of patients with acute respiratory disease, chronic obstructive pulmonary disease (COPD), and other respiratory conditions, which may be exacerbated by crowded environments, environmental factors, and stress associated with mass events [3]. The current resource management systems in the healthcare sector are disjointed, and there is minimal real-time awareness at the facility and regional levels. Mbau et al. suggest that such disintegration can lead to inefficiencies in resource distribution, delayed responses, and poor patient outcomes during a crisis when respiratory care needs are critical. The intersection of mobile technology, artificial intelligence, and real-time data analytics offers an opportunity to revolutionize how emergency preparedness and response are coordinated to deliver respiratory therapy services [4].

This study is based on observations of resource coordination issues during past mass-gathering events, such as Hajj and Umrah, as well as during pandemic responses in the Saudi healthcare system. This work is highly applicable in health informatics because it leverages key features, such as mobile applications and predictive analytics, to address existing gaps in emergency preparedness and resource coordination. The proposed system is expected to develop a unified framework that will enhance coordination opportunities while maintaining the flexibility needed to respond to diverse emergencies.

Although the healthcare and emergency preparedness plan has intensified the use of technology, respiratory therapy departments have experienced significant challenges in coordinating resources during surges associated with mass-gathering events and pandemic outbreaks. Current systems fail to provide real-time updates on resource availability across facilities, leading to inefficient allocation of ventilators, RT staff, and other vital resources. This fragmentation results in slow response times, insufficient resources in areas where they are needed most, and ineffective patient care during periods of peak respiratory demand. An integrated, technology-driven coordination system is necessary to streamline resource utilization and enhance emergency response capacity in respiratory care services.

This study aims to propose a conceptual framework for integrating mobile application technology and predictive analytics to develop a real-time resource coordination system for respiratory therapy services. The system will strengthen emergency preparedness and response capacity for mass-gathering events such as Hajj and Umrah, as well as for pandemic conditions that necessitate rapid mobilization and coordination of resources.

This study addresses a critical gap in emergency healthcare preparedness, especially in the regions that experience mass gathering events regularly or are threatened by the pandemic. The proposed system can substantially enhance response coordination and patient outcomes during high-demand periods by integrating advanced technologies with the practical requirements of resource management. The framework developed in this work's context may serve as an example for regions facing similar challenges. It might be involved in emergency healthcare preparedness and health informatics on a larger scale.

Whereas most existing emergency preparedness and digital health platforms focus on hospital-wide capacity management or generic clinical decision support, this work explicitly targets respiratory therapy operations in large-scale mass gatherings, with an emphasis on Hajj and Umrah. These events pose greater challenges for respiratory care due to extreme crowd density, which increases the risk of environmental exposure, infectious disease transmission, and sudden surges in demand for ventilators and respiratory therapy staffing. The novelty of the proposed system lies in its respiratory-therapy-specific focus, integrating real-time monitoring of ventilators, respiratory therapists, and critical respiratory equipment with predictive analytics to anticipate upcoming respiratory demand during these mass gatherings.

In addition, the system enables proactive, end-to-end coordination through its unique combination of mobile decision support and respiratory-therapy–oriented workflows, addressing the operational realities of Hajj and Umrah rather than treating respiratory assets as generalized hospital resources.

A. Contributions

This research work presents the following contributions:

1) Technical contribution: Design of the cloud-based mobile application architecture for the integration of real-time data of respiratory therapy resources, such as ventilators, respiratory therapy staff, and critical respiratory devices, with prediction analytics for surge preparation for Hajj and Umrah events.

2) Clinical and operational contribution: A respiratory therapy–focused coordination framework that facilitates proactive allocation/escalation for ventilators and other respiratory devices and equipment, and respiratory therapy staff for mass gathering events requiring respiratory interventions.

3) Decision-support contribution: Designing role-based dashboards that improve situational awareness for respiratory therapy team leaders, emergency command centers, as well as other roles, to make decisions for the Hajj/Umrah events.

4) Scalability contribution: A sharing model of respiratory therapy coordination that could be replicated for other mass gathering situations involving respiratory surge demands.

II. Related Work

A. Emergency Preparedness and Mass Gathering Events

Alahmari et al. reported the overall mitigation strategies adopted during the Hajj 2021, which emphasized the importance of coordinated healthcare responses in ensuring health security. The research also highlighted the benefits of resource coordination and real-time monitoring to achieve effective health outcomes during the pilgrimage, demonstrating the utility of integrated technological solutions in emergency preparedness [1].

Another systematic review by Alrabie et al. also underscores the complexity of respiratory care management in mass gatherings. Their findings indicated numerous gaps in the coordinating mechanisms and that superior communication systems were needed to enable rapid decision-making and resource mobilization in emergencies. It was also recorded that communication breakdowns are among the leading causes of response delays and inefficient resource use during peak demand [3].

In a related study, Hui and Zumla identified that mass-gathering events also pose epidemiological problems, directly affecting respiratory care services. The dense population increases the risk of respiratory disease transmission, and the healthcare system must be prepared to manage the resulting influx. These events require highly sophisticated coordination mechanisms to ensure the adequate deployment of resources across multiple health facilities that must attend to pilgrims and local communities simultaneously [2].

B. Technology Integration in Emergency Healthcare Systems

Sarani et al. have developed a data-driven respiratory infection management system that demonstrated the capabilities of epidemic preparedness by real-time data analytics and automated alerts. Mobile communication devices enabled faster response times and more efficient resource allocation within their system [5].

Healthcare technology has enabled more sophisticated approaches to emergency preparedness, and cloud-hosted platforms and computing resources provide the scalability required during surges. Such technological solutions have been particularly helpful in respiratory care, where equipment availability and the organization of personnel have become significant determinants of patient outcomes [6].

Tanggono et al. analyzed the use of mobile health solutions and geographic information systems (GIS) during disaster response and concluded that mobile apps could enhance communication efficiency and resource awareness in emergencies. Their study emphasized the significance of user-friendly interfaces and real-time data synchronization in effective mobile health solutions [7].

C. Artificial Intelligence and Predictive Analytics in Healthcare Resource Management

Jani notes that AI-based predictive analytics could allocate resources in hospitals, and the outcomes demonstrate that machine learning methods can efficiently determine which resources are needed and how they should be allocated. Their system also reduced resource shortages and improved overall response coordination, in addition to providing early-warning capabilities, thereby making resource positioning proactive [8].

Karthika et al. found that machine learning algorithms have proven particularly helpful in respiratory care, as multidimensional physiological information and equipment-use patterns can be used to predict patient needs and maximize resource utilization [6]. These systems can process multiple data streams simultaneously, including patients' vital signs, equipment status, staff availability, and historical utilization trends, to inform recommendations for resource management across the end-to-end system [8].

Prasad et al. developed an IoT-based system to monitor ventilator supply and utilization across multiple medical facilities. IoT adaptation and real-time analytics have attracted considerable attention in the respiratory care field and have yielded substantial benefits, offering a new perspective on equipment status and utilization patterns across facilities. Their platform was transformed into real-time equipment status monitoring, automatic alerts when resources were approaching critical thresholds, and increased resource utilization and faster response times in emergency settings [9].

D. Mobile Applications in Healthcare Emergency Response

In their study on mobile apps in disaster response, Winders et al. found that these apps significantly improved resource tracking and communication, demonstrating their potential to facilitate rapid information sharing and decision-making [10].

The development of mobile healthcare applications should be planned and executed to address user needs, technical limitations, and work requirements. Successful emergency-centered applications are characterized by usability, offline capability, and robust security to remain usable even in suboptimal conditions [7].

Naranjo-Rojas et al. developed a mobile application to coordinate respiratory therapy resources within a regional healthcare network, resulting in improved resource utilization and faster response times during peak periods. Their system demonstrated the effectiveness of real-time communication and centralized resource visibility in delivering respiratory care efficiently [11].

E. Pandemic Preparedness and Respiratory Care Systems

Jokhdar et al. reported that adequate mitigation measures implemented during Hajj 2020 resulted in no COVID-19 cases, attributable to extensive coordination and real-time monitoring systems. Their solution demonstrated that integrated technology solutions would enable a pandemic response and preserve the delivery of essential healthcare services [12].

According to Embrett et al., resource coordination systems positively influenced pandemic response, as healthcare systems that used integrated resource management platforms achieved better outcomes and more effective resource utilization. Their study highlighted the significance of real-time visibility and automated coordination mechanisms in pandemic preparedness plans [13].

F. Gaps in the Literature

While the literature supports the need for technology integration in healthcare emergency planning, much remains unclear about the operation of resource coordination systems for respiratory therapy services during pandemics and large-scale events. The research available is more focused on specific technologies or types of events rather than comprehensive solutions available under emergencies.

Moreover, most available research examines the use of technology within the broader healthcare context. It lacks consideration of issues specific to the operation of respiratory care coordination in high-demand situations [14]. While Prasad et al. describe mixing of smartphone apps with IoT sensors and AI analytics in healthcare, they did not address the highly specialized topic of employing these instruments in emergency respiratory therapy resource coordination [9].

In addition, Bignami et al. describe emergency planning response to discrete scenarios; they have no practical, scalable, sustaining systems that can be customized for regions or medical centers. More importantly, no end-to-end scenarios exist that incorporate real-time resource monitoring via predictive analytics and specialized respiratory therapy systems on smartphones. Therefore, research on specialized smartphone-integrated systems for efficient resource management and decision support in high-demand scenarios such as pandemics or mega-events is timely [15].

III. Methodology and System Architecture

The system is designed using a methodical, multi-stage process involving stakeholder groups. The planning stage includes the first phase of identifying infrastructure and systems architecture with respiratory therapy departments, hospital information systems departments, and emergency management coordinators to identify systems requirements and points of intersection with standard healthcare information systems.

The technical design is a cloud platform supporting predictive analytics-driven informed decision-making. The smartphone app retrieves data on ventilator availability, oxygen supply, personnel schedules, and other critical resources from hospital inventory systems and respiratory therapy managers. Such information is used to predict demand patterns, identify shortages, and generate automated alerts when resources approach critical thresholds.

The smartphone user interface is customized to meet the needs of directors and respiratory therapy administration and includes easy-to-use dashboards for real-time resource availability, personnel allocation, and emergency notifications. The software enables users to request resource transfers, call other facilities, and suggest optimal resource allocation based on current demand patterns and predictive analytics. With predictive analytics, the system addresses real-time problems

and forecasts future requirements, replacing crisis management with forward-thinking planning.

Implementation focuses on privacy and security, including the encrypted exchange of information, secure authentication, and adherence to medical privacy laws, such as HIPAA. The system is networked with role-based access controls, allowing only authorized personnel to access sensitive information while providing flexibility for emergency response coordination.

The implementation plan includes change management and education for respiratory therapy personnel, emergency response coordinators, and managers, and encompasses comprehensive training programs. This education includes learning to use the system and integrating it into standard emergency response procedures.

System performance and user acceptability are evaluated through controlled pilot tests before general installation. An integrated pilot exercise would be conducted on-site to validate the system's performance in accurately monitoring available resources, generating appropriate alerts, and coordinating actions during simulated emergencies.

IV. Results and Discussion

A. System Capabilities and Functional Outcomes

The proposed mobile-based coordination system is designed to provide real-time visibility into respiratory therapy resources across healthcare facilities, including ventilator availability, respiratory staffing levels, and emergency respiratory equipment and devices. By integrating predictive analytics with centralized dashboards, the system facilitates early identification of future resource shortages and timely escalations before critical thresholds are reached.

The proposed framework emphasizes automated data aggregation and alert-driven decision support, in contrast to traditional resource management approaches that rely on manual reporting or updates provided after an event has occurred. This capability is critical in high-demand facilities, where rapid fluctuations in patient volume require continuous monitoring, restocking, and a coordinated response.

B. Impact on Respiratory Therapy Operations During Hajj and Umrah

Such mass-gathering events, including Hajj and Umrah, place respiratory therapy services under sudden, geographically distributed surges in demand, influenced by crowd density and exposure to environments associated with a heightened risk of illness. The proposed system is designed to support respiratory therapy leaders and emergency coordinators by providing a unified view of resource availability across facilities serving pilgrims.

The system can reduce response delays, improve workload distribution, and enhance continuity of respiratory care by proactively balancing the allocation of ventilator and respiratory therapy personnel. Predictive alerts support decision-makers by identifying demand trends and resource redistribution patterns before shortages develop, thereby promoting more resilient respiratory therapy operations during mass gatherings.

C. Comparison with Existing Emergency Coordination Approaches

Current emergency preparedness platforms often serve as either a hospital-wide capacity indicator or general clinical decision support, with limited attention to respiratory therapy–specific workflows. By contrast, the proposed framework places the operational realities of respiratory therapy services at its core, integrating role-based dashboards and decision-support features attuned to respiratory care leadership.

Previous mobile health and resource management systems have demonstrated benefits in improving communication and visibility. However, few studies address the combined challenges of respiratory therapy coordination, predictive analytics, and mass-gathering preparedness in an integrated manner. This conceptually advances the existing approaches by aligning respiratory therapy workflows with mobile, forecast-driven coordination mechanisms suited to high-demand surge situations.

D. Lessons Learned

Concept development provided a valuable understanding of emergency planning and deployment of health facility assets. The integration of technologies such as predictive analytics and smartphones would be pursued, requiring careful consideration of user needs, technical solutions, and operational constraints. The key to success lies not in technology alone, but in its ability to streamline existing workflows rather than obscure them. Stakeholder participation in the design and implementation process cannot be overstated. Respiratory therapy specialists, emergency management coordinators, and hospital administrators have distinct perceptions and needs that must be considered when designing systems. The interdisciplinary collaboration involved in this work contributed significantly to the development of workable health informatics solutions.

Technology solutions must also be scalable and adaptable, essential components of emergency preparedness systems. The proposed real-time resource coordination applications should be versatile enough to adapt to various emergencies with minimal changes in functionality and familiarity. This trade-off between comprehensiveness and usability is a key issue in the design of health informatics systems.

V. Conclusion

Mass gatherings pose significant challenges to the healthcare system, given the concentration of large populations within a small geographic area over a short period, thereby imposing extreme strain on supporting infrastructure. This includes respiratory therapy services, which must rapidly surge to provide ventilator support, staffing, and respiratory equipment, without compromising quality.

The work presented here describes a respiratory-therapy–focused real-time resource coordination system to support emergency preparedness in high-demand situations, such as pandemics and large-scale religious gatherings, such as Hajj and Umrah. Predictive analytics are integrated with mobile decision support in the proposed approach to enhance

anticipatory planning and operational coordination of respiratory therapy resources.

This is a conceptual system and involves neither live deployment nor formal performance evaluation. However, it provides an implementation-ready framework for aligning respiratory care workflows with real-time monitoring and forecast-driven decision support.

Although implementation complexity and resource constraints remain, this framework demonstrates the potential of health information technologies to support collaboration, timely responses, and situational awareness during respiratory surges. Future efforts will focus on pilot implementation of the system during mass-gathering events and on evaluating its effectiveness using respiratory-therapy–specific measures, such as ventilator utilization and staffing response time.

Future research should include pilot testing of the proposed system at mass-gathering events to scientifically evaluate its effectiveness and utility. Research should also investigate its interoperability with hospital information systems, scalability, and cost-effectiveness for developing a resource coordination system for respiratory therapy services.

REFERENCES

[1] A. A. Alahmari et al., "Hajj 2021: Role of mitigation measures for health security," J. Infect. Public Health, vol. 15, no. 11, pp. 1350–1354, Nov. 2022, doi: 10.1016/j.jiph.2022.09.006.

[2] D. S. C. Hui and A. Zumla, "Mass gathering events and transmission of respiratory tract infections: updates pre and post COVID-19 lockdown," Curr. Opin. Pulm. Med., vol. 29, no. 3, p. 133, May 2023, doi: 10.1097/MCP.0000000000000956.

[3] T. Alrabie et al., "Disaster Preparedness and Response Among Healthcare Professionals During the Hajj: A Systematic Literature Review," Healthcare, vol. 13, no. 13, Jun. 2025, doi: 10.3390/healthcare13131571.

[4] R. Mbau et al., "Analysing the Efficiency of Health Systems: A Systematic Review of the Literature," Appl. Health Econ. Health Policy., vol. 21, no. 2, pp. 205–224, Mar. 2023, doi: 10.1007/s40258-022-00785-2.

[5] M. Sarani, K. Jahangiri, M. Karami, and M. Honarvar, "Enhancing epidemic preparedness: a data-driven system for managing respiratory infections," BMC Infect. Dis., vol. 25, no. 1, p. 159, Feb. 2025, doi: 10.1186/s12879-025-10528-y.

[6] M. Karthika, J. K. Sreedharan, M. Shevade, C. S. Mathew, and S. Ray, "Artificial intelligence in respiratory care," Front. Digit. Health, vol. 6, Dec. 2024, doi: 10.3389/fdgth.2024.1502434.

[7] A. Tanggono, I. Prajnaparamita, and P. A. Nastaghfiruka, "The Role of Technology in Enhancing Public Health Preparedness for Disasters," Riwayat Educ. J. Hist. Humanit., vol. 8, no. 2, pp. 1134–1146, Apr. 2025, doi: 10.24815/jr.v8i2.44995.

[8] P. Jani, "AI-powered Predictive Analytics for Hospital Resource Allocation and Revenue Cycle Management," Int. J. Emerg. Trends Comput. Sci. Inf. Technol., pp. 36–45, May 2025, doi: 10.56472/ICCSAIML25-105.

[9] V. K. Prasad, D. Dansana, S. G. K. Patro, A. O. Salau, D. Yadav, and B. K. Mishra, "IoT-based bed and ventilator management system during the COVID-19 pandemic," Sci. Rep., vol. 15, no. 1, p. 19163, May 2025, doi: 10.1038/s41598-025-03144-y.

[10] W. T. Winders et al., "The effects of mobile health on emergency care in low- and middle-income countries: A systematic review and narrative synthesis," J. Glob. Health, vol. 11, p. 04023, doi: 10.7189/jogh.11.04023.

[11] A. Naranjo-Rojas, L. Á. P. Torres, F. E. Cruz-Mosquera, and G. Molina-Recio, "Efficacy and Acceptability of a Mobile App for Monitoring the Clinical Status of Patients With Chronic Obstructive Pulmonary Disease Receiving Home Oxygen Therapy: Randomized Controlled Trial," J. Med. Internet Res., vol. 27, no. 1, p. e65888, Jan. 2025, doi: 10.2196/65888.

[12] H. Jokhdar, A. Khan, S. Asiri, W. Motair, A. Assiri, and M. Alabdulaali, "COVID-19 Mitigation Plans During Hajj 2020: A Success Story of Zero Cases," Health Secur., vol. 19, no. 2, pp. 133–139, Apr. 2021, doi: 10.1089/hs.2020.0144.

[13] M. Embrett et al., "Building Resilient and Responsive Health Research Systems:Responses and the Lessons Learned from the COVID-19 Pandemic," Health Res. Policy Syst., vol. 23, no. 1, p. 38, Mar. 2025, doi: 10.1186/s12961-024-01229-0.

[14] G. Altmiller and L. H. Pepe, "Influence of Technology in Supporting Quality and Safety in Nursing Education," Nurs. Clin. North Am., vol. 57, no. 4, pp. 551–562, Dec. 2022, doi: 10.1016/j.cnur.2022.06.005.

[15] D. F. Bignami, C. Ambrosi, M. Bertulessi, G. Menduni, M. Pozzoni, and F. Zambrini, "Governance strategies and tools towards the improvement of emergency management of natural disasters in transboundary areas," Int. J. Disaster Risk Reduct., vol. 111, p. 104704, Sep. 2024, doi: 10.1016/j.ijdrr.2024.104704.

TrustGraph: A Heterogeneous GNN for Dynamic Zero-Trust Policy Enforcement in Microservices

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***Abstract*—Securing cloud microservices requires a unified understanding of how services behave, authenticate, and interact in real time. Unlike existing methods that analyze telemetry signals in isolation, this work presents a heterogeneous graph-based Zero-Trust framework that represents microservices using multi-modal telemetry—logs, metrics, traces, and authentication flows—embedded directly into graph nodes and edges. A Graph Neural Network architecture with attention captures risk propagation across service dependencies, while a joint anomaly detection and trust computation mechanism generates dynamic trust scores with temporal decay to support continuous verification. These trust signals drive real-time dynamic policy enforcement capable of denying or restricting suspicious interactions with minimal operational overhead. Experiments on the TrainTicket, Sock Shop, and DeathStarBench benchmarks show strong performance, achieving 97.2% accuracy, 98.1% recall, and 0.987 AUC on TrainTicket, with consistent results across the other datasets and latency overhead below 3.2 ms. Robustness tests demonstrate accuracy above 95.8% under noisy logs, delayed traces, and authentication failures. Ablation and SHAP analyses confirm that leveraging multiple telemetry modalities—especially authentication data—is critical for accurate detection and trust scoring. These findings show that multi-modal heterogeneous graph modeling, coupled with integrated anomaly-to-policy decision pipelines, provides an effective foundation for Zero-Trust security in cloud-native microservices.**

Keywords*—Graph neural networks; zero-trust security; microservices; anomaly detection; heterogeneous graphs; multi-modal telemetry; dynamic policy enforcement

I. Introduction

Cloud computing environments have increasingly shifted toward microservice architectures, where applications are decomposed into loosely coupled services [1]. This design improves modularity and scalability but introduces new challenges in reliability, security, and anomaly detection [2]. Microservices communicate frequently across distributed infrastructures, which expands the attack surface and creates opportunities for unauthorized access or service misuse [3]. Conventional perimeter-based security models are not suited for such settings because they assume trusted internal zones, while microservices interact dynamically across diverse platforms [4]. The distributed and transient nature of services calls for approaches that can capture complex interactions while maintaining protection against internal and external threats [5].

Zero-Trust Architecture (ZTA) has emerged as a suitable paradigm to address these challenges [6]. ZTA removes implicit trust and applies continuous verification of services, users, and communication flows [7]. This approach combines anomaly detection, runtime trust scoring, and adaptive policy enforcement to secure interactions at fine granularity [8]. In microservice systems, ZTA introduces mechanisms to restrict or deny suspicious requests even when they originate from within the network [9]. Such continuous monitoring aligns with the dynamic behavior of cloud deployments, where trust must be recalculated as services update, scale, or interact with new components [10]. ZTA provides a structured framework for controlling risks in environments where static boundaries are no longer sufficient [11].

Graph-based models have gained attention as a means to represent dependencies in microservice environments [12] [13]. Unlike traditional methods that treat services in isolation, graph-based approaches capture relationships between nodes and edges representing services, requests, and identities [14]. This relational modeling is crucial for analyzing distributed execution patterns, detecting abnormal behavior, and assigning trust in real time [15]. The integration of multiple telemetry sources, including logs, metrics, traces, and authentication records, strengthens the ability to represent both operational and security contexts [16]. Together, graph-based methods and Zero-Trust principles offer a pathway to address the growing need for effective anomaly detection and adaptive policy enforcement in modern cloud systems [17].

Most existing microservice environments face a research problem rooted in the gap between security requirements and available detection methods [18]. While anomaly detection techniques and monitoring systems exist, they often lack the ability to represent complex dependencies across distributed services [19]. Isolated tools struggle to capture the combined effect of operational behaviors, access flows, and trust decisions [20]. This creates a vulnerability in cloud deployments, where malicious activity may pass unnoticed or trusted connections may be abused [21]. The research challenge lies in unifying detection and policy enforcement under a framework that reflects the realities of microservice interactions [22].

To address this, researchers have introduced a variety of methods [23]. Some works focus on mining logs or metrics using statistical or embedding-based approaches, which can identify outliers in specific datasets [24]. Others apply anomaly detection at the level of traces or flows, which highlights unusual patterns of interaction [25]. These approaches contribute useful insights, yet they are limited when applied in isolation [26]. Logs may reveal system errors but overlook authentication misuse. Metrics may show performance degradation but fail to detect authorization bypass [27]. Traces highlight interaction delays but cannot capture runtime trust

shifts. Relying on a single modality leaves gaps that attackers can exploit.

In parallel, several studies have suggested frameworks that combine anomaly detection with Zero-Trust enforcement [28]. These describe runtime trust scoring, authorization checks, and adaptive policies [29]. While these approaches advance the discussion, they often depend on simplified models of service interaction [30]. Graph structures are sometimes restricted to service-to-service calls without incorporating authentication, authorization, or contextual data [31]. Many solutions remain tied to specific benchmarks, which limits their scalability to real-world workloads [32]. In addition, explainability and privacy-preserving training are frequently overlooked, leaving questions about transparency and applicability in multi-tenant environments [33].

Despite these advances, existing approaches largely treat security and operations as separate concerns. Most graph-based methods focus on topology or call chains without integrating authentication flows as first-class entities in the graph structure. Conversely, Zero-Trust frameworks often rely on static policies or isolated anomaly detectors that lack the context of service dependencies. A key gap remains in establishing an end-to-end pipeline where multi-modal telemetry—especially authentication data—directly informs dynamic trust scores that automatically update enforcement policies in real time.

The core contribution of this work is a unified framework that bridges this gap. Specifically, this paper contributes:

- Heterogeneous Graph Construction: We propose a method to represent microservices where authentication flows and operational metrics are embedded as distinct node and edge features, enabling the GNN to learn the interplay between performance and security.
- Joint Anomaly-Trust Mechanism: We introduce a dynamic trust scoring algorithm that combines reconstruction error with temporal decay, allowing trust to degrade naturally over time in the absence of positive reinforcement—a key tenet of Zero-Trust.
- Closed-Loop Policy Enforcement: We demonstrate an end-to-end pipeline where trust scores are mathematically linked to policy optimization, automating the transition from anomaly detection to access control (Allow/Restrict/Deny) with minimal latency.

Building on these contributions, the following research questions are formulated to guide the study.

1) RQ1: How can heterogeneous graphs be constructed to represent microservice environments by integrating both operational and security features?
2) RQ2: In what ways can anomaly detection and trust computation be performed using multimodal telemetry to distinguish between benign and anomalous behaviors?
3) RQ3: How can detection outcomes and trust scores be systematically linked to policy enforcement for allowing, restricting, or denying service interactions in real time?

The remainder of this paper is organized as follows. Section II reviews prior works on anomaly detection, Zero-Trust enforcement, and graph-based methods for microservices. Section III presents the graph-based framework, including system modeling, anomaly detection, trust computation, and policy enforcement. Section IV outlines the benchmarks, datasets, and experimental configuration. Section V reports the findings, including performance metrics and robustness analysis. Section VI provides a deeper discussion on the implications of risk propagation and trust decay. Finally, Section VII summarizes the contributions and highlights directions for future work.

II. Literature Review

The adoption of microservice architectures in cloud environments created new challenges for security, reliability, and anomaly detection. Traditional perimeter-based models were insufficient in handling distributed service interactions, which made ZTA an important direction for research. Scholars developed methods that combined anomaly detection, policy enforcement, and runtime trust scoring to address these challenges. Graph Neural Networks (GNNs) were introduced as suitable models since they captured relationships among services, requests, and identities. In addition, studies applied multimodal monitoring data, federated learning, and explainable frameworks to improve detection accuracy and interpretability. Several works used benchmarks such as Train-Ticket and Sock-Shop to confirm proposed methods with quantitative metrics. Other contributions emphasized architectural frameworks in service mesh and multi-cloud scenarios, describing trust evaluation and policy transparency. Collectively, the literature highlighted advances in anomaly detection, Zero-Trust enforcement, and GNN-based security for microservices.

Raeiszadeh et al. [34] developed an asynchronous federated learning method for anomaly detection in microservice systems using traces and logs from the TrainTicket benchmark. The method combined GNNs with Positive and Unlabeled learning and introduced local training with a span causal graph. The model achieved improvements of about 4% in F1 compared with state-of-the-art anomaly detectors and reduced detection latency with controlled overhead.

Cinque et al. [35] suggested Micro2vec to mine numeric log embeddings for anomaly detection in Clearwater IMS and Air Traffic Control case studies. Their classifiers, including autoencoders and feed-forward networks, achieved accuracy of 97% with F1 values around 0.961. The approach highlighted the role of embeddings for distinguishing anomalies in log data.

Parkhomenko et al. [36] used Zero-Trust principles and machine learning for detecting authorization anomalies in microservices. Their framework described continuous verification of requests and anomaly detection in authentication flows. The study was more conceptual and reported qualitative improvements with reduced false positives. Alboqmi et al. [37] defined a runtime trust evaluation system in a service mesh environment using Train-Ticket deployed on Istio. The framework combined vulnerability scanning results with service mesh telemetry to produce trust scores at runtime. The outcomes were presented as architectural contributions with qualitative benefits for runtime risk assessment. Both studies described Zero-Trust concepts for anomaly and trust monitoring, one addressing authorization attacks and the other runtime trust scoring.

Zhao, Xiao and Tao [38] applied a multi-scale dynamic GNN for anomaly detection using three industrial microservice datasets. Their model adapted neighborhood sizes and temporal depth, showing improved accuracy compared with conventional graph models. Ablation results described the importance of multi-scale design choices. Fang et al. [39] described a method extending GraphSAGE with attention to locate anomalies in Kubernetes-based microservices. Their results showed P@1 of 76%, P@3 of 88%, and P@5 of 89%, surpassing baseline GraphSAGE values of 54%, 72%, and 79%. The approach localized faulty services more effectively, providing interpretable results for operators. Both studies presented graph-based models for anomaly detection and localization with measurable performance gains. Table I summarized studies on microservice security. Raeiszadeh et al. 1 applied federated GNNs, while Cinque et al. 3 used log embeddings. Alboqmi & Gamble 6 described runtime trust in service mesh, and Zhao, Xiao & Tao 7 developed a multi-scale dynamic GNN. Fang et al. 8 and Nobre et al. 9 further extended detection with measurable accuracy.

Nobre et al. [40] used Multi-Layer Perceptrons for detecting anomalies in Sock-Shop and TrainTicket benchmarks with fault injection. Their service-level dataset showed accuracy of 97%, precision of 95%, recall of 98%, and F1 of 97%, while maintaining false positive rates near 0.01. Zhao et al. [43] developed IM-GNN to recommend microservice orchestration workflows using interface matching and BERT embeddings with GNNs. The results on Amazon SageMaker showed Hit@10 scores of 41.45 against 36.23 and NDCG@10 of 31.23 against 28.44. Although IM-GNN targeted orchestration rather than security, it demonstrated the effectiveness of graph construction in improving results. Both studies described neural approaches with high performance, one focusing on anomaly detection and the other on orchestration accuracy.

Anderson [44] described the role of Explainable Artificial Intelligence in Zero-Trust API gateways on Microsoft Azure. The framework integrated LIME, SHAP, and causal reasoning for interpreting access control decisions. Results described improved transparency and auditability with some latency overhead. Panchumarthi [45] defined the NCAF Zero-Trust microservice fabric combining microsegmentation with runtime authorization strategies. The study emphasized architectural design and described conceptual benefits rather than empirical evaluation. Both works contributed to the role of Zero-Trust in cloud authorization, focusing on explainability and structural frameworks. The findings highlighted transparency, centralized authorization, and policy consistency without numerical benchmarks.

Cherukupalle [46] introduced a Zero-Trust hybrid framework for cloud-IoT testbeds, integrating blockchain and AI monitoring. The approach reduced detection latency by 30% and blocked more intrusion attempts. Madhura G K [47] applied AI trust scoring for Zero-Trust in microservices with synthetic datasets and reported trust prediction accuracy near 92%. Konakanchi [48] developed predictive cyber resilience for healthcare microservices, reporting breach reduction of 90% and mean time to detect shortened by 40%. Collectively, these contributions described AI-driven and graph-based methods improving anomaly detection and resilience.

Zhuwankinyu et al. [49] suggested a graph-based Zero-Trust framework for distributed storage, achieving improved detection accuracy with minimal latency. Kodakandla [50] described Zero-Trust enforcement in Kubernetes microservices, emphasizing compliance improvements and policy consistency as qualitative outcomes. Adanigbo et al. [51] applied a Zero-Trust framework for multi-cloud environments, reporting higher resilience and trust metric scores. Reddy [52] introduced microsegmentation with AI-driven policy engines in hybrid cloud testbeds, blocking 91% of lateral movements while adding about 1.5 ms in latency. Shonubi and Adelere [53] developed AI-augmented resilience frameworks across SDN and microservices, reducing outage times by 87% and detection times from 18 minutes to 45 seconds. Kokku [54] described a synthesis of 29 studies integrating Zero-Trust, federated learning, and AI trust models, highlighting improvements across detection accuracy and trust management.

Although much work had been done on anomaly detection and Zero-Trust enforcement in microservices, clear gaps remained. Most methods relied on logs, metrics, or traces in isolation, with limited use of multimodal signals in real-time settings. GNN approaches often used simplified service graphs, while heterogeneous graphs that included authentication, authorization, and data flows were rarely applied. Zero-Trust frameworks were introduced, yet few connected anomaly scores to policy synthesis for continuous microsegmentation. Many studies achieved high accuracy on synthetic benchmarks such as Train-Ticket and Sock-Shop, but large-scale workloads were less examined. Federated learning appeared in some works, but privacy-preserving training across multi-tenant clusters was not fully described. Explainability was discussed in access control, but graph-level explanations in microservice security were largely absent. Latency and scalability trade-offs in Zero-Trust enforcement also lacked thorough analysis, leaving room for integrated graph-based, explainable, and federated approaches.

III. Proposed Methodology

The methodology addressed the problem of anomaly detection and Zero-Trust enforcement in microservice environments by formulating the system as a graph-based learning problem. Microservices were represented as nodes, and their interactions were expressed as edges enriched with operational and security features. GNNs were used to propagate information across the service dependency graph, allowing both local and global risks to be captured. Anomaly detection was carried out through reconstruction-based scoring, while trust values were derived from anomaly signals and authentication results. Policies were then optimized to restrict, allow, or deny service interactions based on computed trust. The following subsections describe system modeling, embedding, anomaly detection, trust modeling, and policy enforcement, each supported by mathematical formulations and algorithms to demonstrate the integration of learning with Zero-Trust security principles.

The architecture in Fig. 1 illustrated the integration of microservice telemetry with graph construction. Logs, metrics, traces, and authentication records were normalized into a heterogeneous graph. Graph Neural Networks propagated risk information through message passing and attention, producing embeddings for nodes and edges. Anomaly scores and trust values were computed from these embeddings to capture

TABLE I. SUMMARY OF 22 REVIEWED WORKS ON ANOMALY DETECTION, GNNS, AND ZERO-TRUST IN MICROSERVICES, INCLUDING DATASETS, METHODS, LIMITATIONS, AND RESULTS

Ref	Dataset used	Methodology (brief)	Limitations	Evaluation results
[12]	Custom dataset & TrainTicket	HG-PAD, Conditional VAE	Not multi-modal, not dynamic	Avg@5 of 0.70 to 0.88 for RCL; F1=92%, Rec=98%, Prec=87% for AD
[34]	TrainTicket traces+logs	ART-FL: Async FL + GNN	Perf focus; comms privacy not covered	+4% F1 over SOTA; latency/overhead reported
[35]	Clearwater IMS & ATC logs	Numeric embeddings + ML classifiers	Synthetic anomalies; log-only	Acc 97%; Autoencoder P=0.969, R=0.953, F1=0.961
[36]	Simulated auth flows	Zero-Trust verification + anomaly detection	Workshop-style; limited quant	Prec=95.2%; F1=95.9%;
[37]	Train-Ticket on Istio	Vulnerability-driven trust evaluation	Architectural; limited metrics	Qualitative trust/risk improvements
[38]	Industrial datasets (3)	MSDG: Multi-scale dynamic GNN	Dataset names truncated	Outperforms baselines; ablations confirm design
[39]	Kubernetes (Sock Shop), Mocker	GraphSAGE+Attention RCA	Focus RCA not prevention	P@1=76%; P@3=88%; P@5=89%
[40]	Sock-Shop & TrainTicket	MLP anomaly detection	Needs labels; tied to benchmark	Acc=97%; Prec=95%; Rec=98%; F1=97%; FPR=0.01
[41]	Custom dataset	LSTM, GAT	Doesn't reflect production-level microservices	Acc=95%, Rec=89% for 6:4 data split; Acc=98%, Rec=92% for 9:1 data split;
[42]	TrainTicket	GNN-SVDD	Log based	Prec=93%, Rec=97%, F1=95%
[43]	SageMaker & Comprehend	IM-GNN: interface match + GNN	Orchestration rather than security	Hit@10=41.45; NDCG@10=31.23
[44]	Azure API Mgmt+AD	XAI (LIME, SHAP) for Zero-Trust APIs	Conceptual; perf overhead	Transparency improved; latency overhead
[45]	Conceptual fabric	Federated, ZTA	No dataset	Qualitative only
[46]	Cloud-IoT testbed	Zero-Trust+Blockchain+AI	Prototype scale	Detection latency ↓30%; breaches reduced
[47]	Synthetic IoT workloads	Zero-Trust+AI trust scoring	Conceptual heavy	Trust score accuracy 92%
[48]	HealthTech microservices	FL, SAN, adversarial ML resilience	Health domain only	Breach reduction 90%; MTTD ↓40%
[49]	Distributed storage graphs	Graph-based Zero-Trust storage	Focus storage not services	Improved accuracy; minimal latency
[50]	Kubernetes workloads	Zero-Trust enforcement	Design-level	Better compliance (qualitative)
[51]	Multi-cloud setups	Zero-Trust framework	Review-style	Trust metrics; resilience scores
[52]	Hybrid cloud testbed	Microsegmentation+AI Zero-Trust	Policy complexity	91% lateral moves blocked; latency +1.5ms
[53]	Financial+HealthTech	AI-aug, SDN+anomaly detection	IoT focused; overhead	DDoS MTTM 18m→45s; outages ↓87%
[54]	Literature (29 papers)	Hybrid AI+Zero-Trust synthesis	Review; no dataset	Summarizes ↑accuracy in arc-fault, IoT trust

both behavioral and security contexts. Finally, policies were synthesized and enforced at gateways, meshes, and Kubernetes layers to implement Zero-Trust decisions in real time.

A. System Modeling

1) Graph Representation of Microservices:

$$G = (V, E, X_V, X_E) \tag{1}$$

Eq. (1) defined the microservice architecture as a heterogeneous graph. Nodes represented services, edges represented calls, node features encoded operational telemetry, and edge features described communication and authentication. This formulation allowed the model to capture both performance and security dynamics under Zero-Trust principles.

2) Weighted Adjacency Matrix:

$$A_{uv} = \begin{cases} w_{uv}, & \text{if } (u,v) \in E \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

Eq. (2) introduced weighted adjacency to reflect risk factors such as latency or access violations. Unlike binary graphs, this allowed communication paths to exist while still carrying risk. This encoded the Zero-Trust assumption that no connection should be inherently trusted.

The construction process, which extracts node features from metrics and logs for all nodes $v \in V$ and computes edge features from authentication records and latency for all edges $(u, v) \in E$, is summarized in Algorithm 1.

Algorithm 1 Graph Construction for Microservice Zero-Trust

Input : Microservice system telemetry (Logs, Metrics, Traces), Authentication Records

Output: Telemetry-enriched Graph $G = (V, E, X_V, X_E)$

Initialize the set of Vertices V (microservices/pods) and Edges E (communication links) Initialize Node Feature Matrix X_V and Edge Feature Matrix X_E

foreach *node* $v \in V$ **do**
  Extract operational telemetry x_v from Metrics and Logs Store x_v in X_V

foreach *edge* $(u, v) \in E$ **do**
  Compute edge features x_{uv} from Traces (latency) and Authentication Records Store x_{uv} in X_E

Construct the Weighted Adjacency Matrix A using the edge features X_E (Eq. III-A2) **return** Graph $G = (V, E, X_V, X_E)$

B. Graph Neural Embedding

1) Node Initialization:

$$h_v^{(0)} = x_v \tag{3}$$

Eq. (3) initialized node embeddings from telemetry. Each service embedding captured CPU usage, request errors, and access results. This raw mapping grounded the learning process in measurable service data.

2) Message Passing:

$$m_{uv}^{(k)} = W^{(k)} \cdot [h_u^{(k)} \parallel x_{uv}] \tag{4}$$

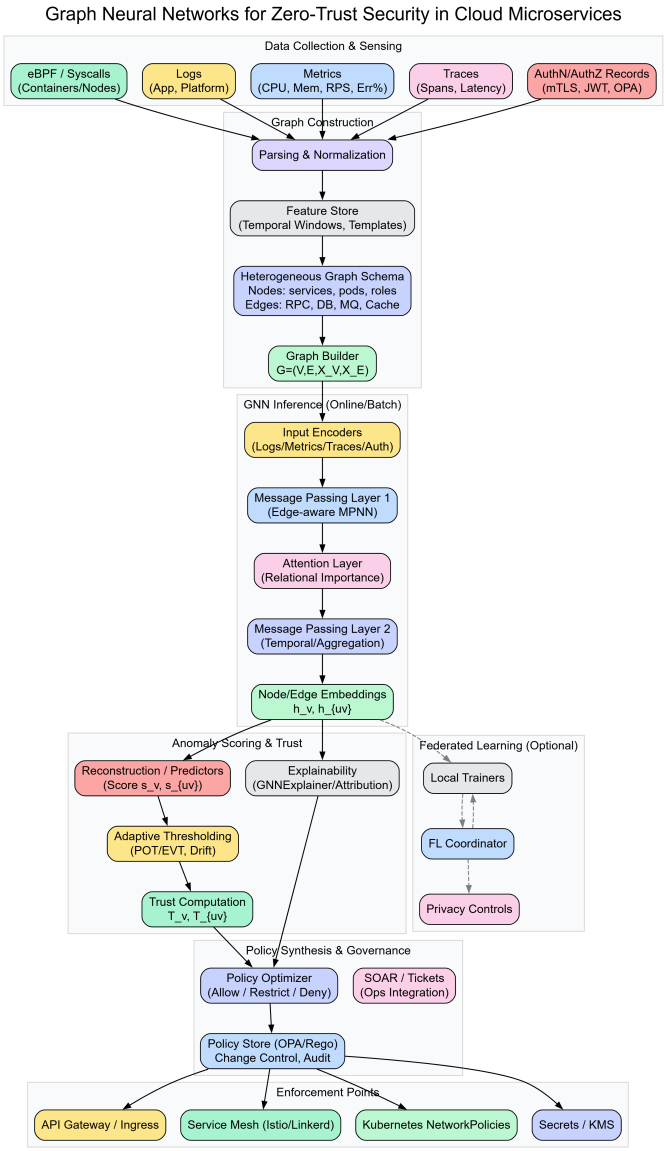


Fig. 1. Architecture of graph neural networks for zero-trust security in cloud microservices.

Eq. (4) defined messages exchanged between services. Embeddings were concatenated with edge features to capture both behavior and security posture. This confirmed risk factors in communication were directly embedded.

3) Attention Weights:

$$\alpha_{uv}^{(k)} = \frac{\exp\left(a^\top [W h_u^{(k)} \parallel W h_v^{(k)} \parallel x_{uv}]\right)}{\sum_{j \in \mathcal{N}(v)} \exp\left(a^\top [W h_j^{(k)} \parallel W h_v^{(k)} \parallel x_{jv}]\right)} \tag{5}$$

Eq. (5) computed attention coefficients. It weighted neighbors differently, with higher weight on risky or abnormal interactions. This aligned GNNs with Zero-Trust by emphasizing suspicious dependencies.

4) Attention Based Node Update:

$$h_v^{(k+1)} = \sigma\left(\sum_{u \in \mathcal{N}(v)} \alpha_{uv}^{(k)} \cdot m_{uv}^{(k)}\right) \tag{6}$$

Eq. (6) showed how updated embeddings selectively prioritized critical edges. Services influenced each other proportionally to trust relevance, reinforcing Zero-Trust monitoring.

The overall iterative process for computing and updating the final embeddings, incorporating neighborhood aggregation and the attention mechanism, is detailed in Algorithm 2

Algorithm 2 GNN Embedding with Attention

Input: Graph G, initial embeddings $h_v^{(0)}$
Output: Final embeddings $h_v^{(K)}$
for $k = 0$ *to* $K-1$ **do**
  for *each node* $v \in V$ **do**
    Compute messages $m_{uv}^{(k)}$ using Eq. 4 Aggregate neighbors with Eq. 6 Update embedding $h_v^{(k+1)}$
Return $h_v^{(K)}$

C. Anomaly Detection

1) Reconstruction Loss:

$$s_v = \|h_v^{(K)} - \hat{h}_v\|_2^2 \tag{7}$$

Eq. (7) defined the anomaly score as reconstruction error. High deviations meant services were behaving abnormally, useful for Zero-Trust validation.

2) Threshold Decision:

$$y_v = \begin{cases} 1, & s_v > \theta \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

Eq. (8) marked services as anomalous if their anomaly score exceeded a threshold. This binary decision supported automated Zero-Trust policy enforcement.

3) Edge Anomaly Score:

$$s_{uv} = \|h_u^{(K)} - h_v^{(K)}\|_2 \tag{9}$$

Eq. (9) computed anomaly scores for edges. This verified service-to-service interactions, detecting unauthorized or risky communication links.

D. Trust Modeling

1) Node Trust Score:

$$T_v = \frac{1}{1 + e^{-(\alpha(1-s_v)+\beta R_v)}} \tag{10}$$

Eq. (10) transformed anomaly scores and resilience into trust values between 0 and 1. This probabilistic trust confirmed continuous verification of services.

2) Edge Trust Score:

$$T_{uv} = \gamma \cdot (1 - s_{uv}) + (1 - \gamma) \cdot P_{auth}(u, v) \tag{11}$$

Eq. (11) balanced edge anomaly with authentication success. It allowed the system to penalize risky communication while rewarding confirmed authentication.

3) Temporal Trust Decay:

$$T_v(t+1) = \lambda \cdot T_v(t) + (1-\lambda)(1-s_v) \tag{12}$$

Eq. (12) defined trust decay over time. A service's trust decreased naturally unless continuously supported by normal activity, reflecting Zero-Trust.

The complete procedure for calculating the dynamic trust values for both services and interactions, including the application of temporal decay, is presented in Algorithm 3

Algorithm 3 Dynamic Trust Computation

Input: Node scores s_v, edge scores s_{uv}, authentication data
Output: Trust values T_v, T_{uv}
for *each node* $v \in V$ **do**
  Compute T_v using Eq. 10 Apply temporal decay Eq. 12
for *each edge* $(u, v) \in E$ **do**
  Compute T_{uv} with Eq. 11
Return trust scores

E. Policy Enforcement

1) Policy Optimization:

$$\min_{\pi} \sum_{v \in V} \big(\ell(y_v, \pi(v)) + \lambda \cdot \max(0, \tau - T_v)\big) \tag{13}$$

Eq. (13) optimized access policies by minimizing classification loss and penalizing low-trust assignments. This mathematical framing integrated GNN learning with Zero-Trust enforcement.

2) Access Control Constraints:

$$\pi(v) \in \{\text{allow}, \text{restrict}, \text{deny}\}, \quad \pi(v) = \text{deny} \ \text{ if } T_v < \tau \tag{14}$$

Eq. (14) constrained policy outcomes to three options. Services below the trust threshold were denied, embodying Zero-Trust continuous verification.

3) Overall Loss Function:

$$\mathcal{L} = \mathcal{L}_{GNN} + \alpha \sum_{v \in V} s_v + \beta \sum_{(u,v) \in E} s_{uv} + \gamma \sum_{v \in V} \max(0, \tau - T_v) \tag{15}$$

Eq. (15) unified GNN training, anomaly detection, and trust penalties. The formulation made learning and Zero-Trust enforcement a single optimization objective.

IV. Experimental Setup

The experimental setup was designed to confirm the proposed framework for anomaly detection and Zero-Trust enforcement in microservices. All experiments were conducted on a Kubernetes cluster with 12 worker nodes, each configured with 32-core Intel Xeon processors and 128 GB of memory. GPU acceleration was available for model training. Monitoring tools including Prometheus, Jaeger, and eBPF probes were integrated to collect continuous telemetry consisting of logs, metrics, traces, and authentication records. Each dataset was deployed in an isolated name space to avoid interference, and uniform resource quotas confirmed consistent experimental conditions across runs.

The first dataset used was the TrainTicket benchmark [55], which was selected as the primary testbed due to its realism and complexity. TrainTicket consisted of more than 40 microservices that covered functionalities such as authentication, order management, payments, and search. The system generated rich traces and supported controlled fault injection, allowing a wide range of anomalies to be studied. This dataset was used to test both anomaly detection and dynamic trust assignment since its size enabled the construction of large dependency graphs suitable for Graph Neural Networks GNNs.

The second dataset employed was the Sock Shop benchmark [56], which provided a smaller but highly reproducible microservice environment. It included 11 services such as front-end, orders, carts, and shipping, making it suitable for lightweight testing. Although less complex than TrainTicket, Sock Shop was widely used in microservice anomaly detection studies, which allowed for comparative evaluation. In this study, Sock Shop was used to assess the generalization capability of the model in smaller deployments and to test adaptive thresholding and trust computation in simpler environments.

The third dataset applied was DeathStarBench [57], which offered a suite of applications including a social network, a media service, and an e-commerce platform, each composed of dozens of microservices. This benchmark was designed for realistic large-scale workloads and provided support for distributed tracing. Its diversity allowed the evaluation of scalability and robustness of the proposed framework under traffic-intensive scenarios. DeathStarBench was particularly useful in verifying that the methodology extended beyond academic benchmarks to more complex industrial-style deployments.

For model training, Graph Neural Networks were configured with two message passing layers and attention-based aggregation. Embedding dimensions were set to 128, and the models were trained using the Adam optimizer with a learning rate of 0.001. Training was limited to 200 epochs with early stopping after 20 epochs without improvement. Reconstruction thresholds for anomaly detection were calibrated for each dataset using Extreme Value Theory. Trust computation weights α, β, and γ were optimized through grid search. Each experiment was repeated five times, and the mean results were reported to reduce randomness in outcomes.

Evaluation metrics included accuracy, precision, recall, F1-score, and Area Under the Curve (AUC) for anomaly detection. For trust enforcement, mean trust scores and false acceptance rates were measured, while latency overhead was recorded to quantify the impact of policy enforcement. The datasets were split into 60% training, 20% validation, and 20% testing to ensure consistent evaluation. Comparisons with baseline approaches were carried out to assess improvements in anomaly detection and Zero-Trust enforcement performance.

V. Results and Analysis

A. Performance Overview

The proposed framework was evaluated across three datasets using comprehensive metrics that capture anomaly detection accuracy, operational efficiency, and Zero-Trust enforcement quality. Accuracy, precision, recall, F1-score, and AUC quantified detection performance as shown in Fig. 2.

TrainTicket demonstrated the strongest performance with 97.2% accuracy, 96.9% precision, 98.1% recall, and an F1-

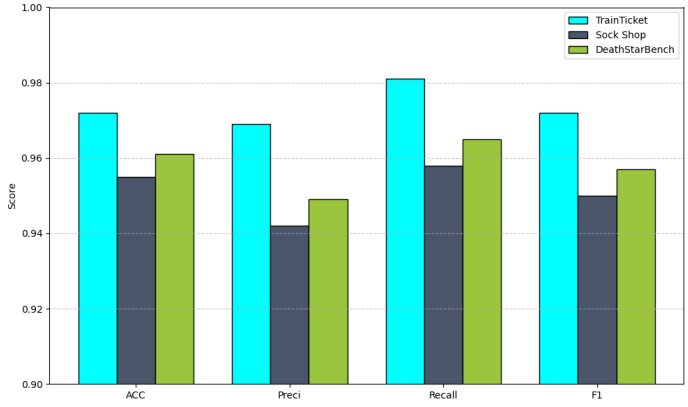


Fig. 2. Comparison of accuracy, precision, recall, and f1-score across trainTicket, sock shop, and deathStarBench datasets.

score of 0.972. The 0.987 AUC indicated excellent discrimination between benign and anomalous services. Sock Shop, despite its smaller scale (11 services), achieved competitive results with 95.5% accuracy, 94.2% precision, 95.8% recall, and 0.950 F1-score, confirming framework effectiveness across diverse deployment sizes. DeathStarBench validated scalability on industrial-scale workloads with 96.1% accuracy, 94.9% precision, 96.5% recall, and 0.957 F1-score, demonstrating that graph complexity enhanced detection capability rather than degrading it. These results directly address RQ1, confirming that the heterogeneous graph construction effectively captures the complex operational and security dependencies required for accurate anomaly detection.

B. Latency and Stability

Latency overhead measured the computational cost of real-time policy enforcement, while reconstruction errors (MSE, RMSE) indicated stability in anomaly scoring.

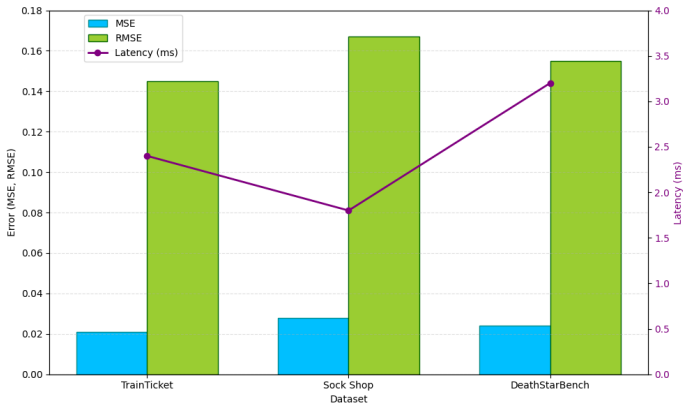


Fig. 3. Latency overhead and reconstruction error metrics across datasets.

The reconstruction errors remained consistently low across all datasets (Fig. 3), with TrainTicket showing MSE of 0.021 and RMSE of 0.145, indicating stable anomaly scoring mechanisms. Sock Shop exhibited slightly higher variance (MSE 0.028, RMSE 0.167) reflecting its lower service count, yet remained within operational bounds. DeathStarBench maintained error profiles comparable to TrainTicket (MSE 0.024, RMSE 0.155) despite higher traffic volume, suggesting the framework scaled robustly.

Operational overhead remained well below practical deployment thresholds. Sock Shop achieved the lowest latency at 1.8ms, reflecting its simpler topology with 11 services and fewer dependency edges. TrainTicket, with 40+ microservices, incurred 2.4ms average overhead, indicating linear scaling with graph complexity. DeathStarBench's 3.2ms overhead represented the highest measured latency, yet remained acceptable for cloud-native applications where inter-service communication typically exceeds 50-100ms. The 1.4ms difference between TrainTicket and DeathStarBench correlated directly with increased graph density and traffic volume, confirming that detection quality improvements came with predictable latency costs.

The latency profile revealed an important practical insight: while additional graph complexity increased computational burden, the absolute overhead remained sub-4ms even for industrial-scale deployments. This makes dynamic Zero-Trust enforcement operationally feasible without requiring service degradation.

C. Comparative Evaluation with State-of-the-Art

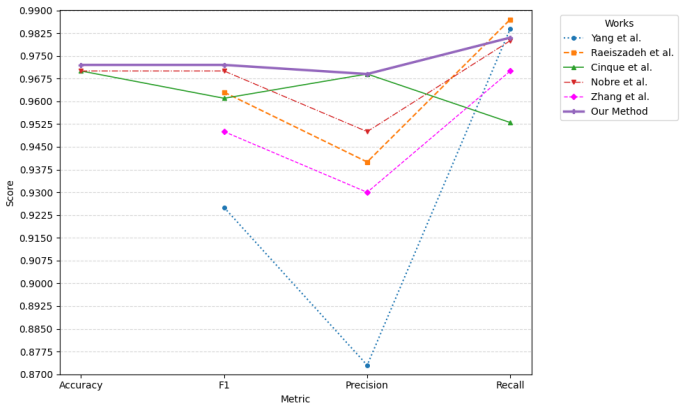


Fig. 4. Performance comparison across selected prior works and the proposed method.

The developed method consistently exceeded baseline approaches across most of the metrics. Compared to Raeiszadeh et al.'s federated learning approach, our framework achieved +0.9% improvement in F1-score (0.972 vs 0.963). Against Nobre et al.'s multi-layer perceptron approach (F1=0.970), we gained +0.2% improvement while maintaining superior recall (98.1% vs 98%) and precision. Compared to Cinque et al.'s log embedding method (F1=0.961, Acc=0.970), our approach achieved +1.1% F1 improvement and +0.2% accuracy advantage. A comparison chart for the TrainTicket dataset is shown in Fig. 4.

The consistent advantage across datasets and benchmarks reflected the benefit of heterogeneous graph modeling combined with multi-modal telemetry. Single-modality or simplified topology approaches inherently constrained information flow, while our framework captured coordinated behavioral patterns invisible to isolated analysis methods.

D. Multi-Modal Telemetry Integration: SHAP-Based Feature Importance

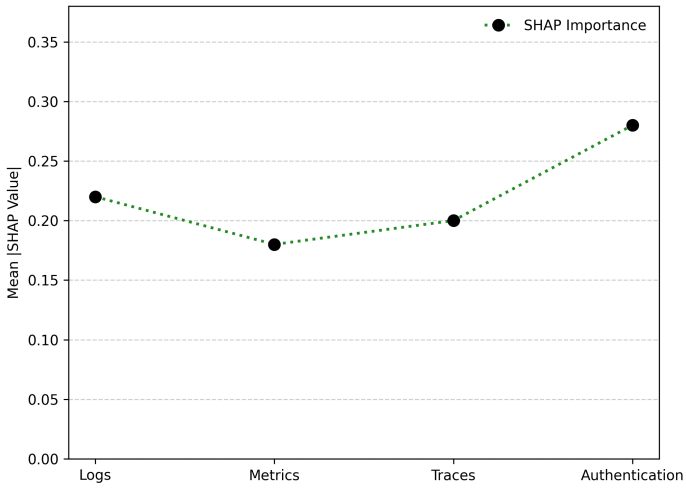


Fig. 5. SHAP-based feature importance analysis revealing contribution of each telemetry modality.

Feature importance analysis, illustrated in Fig. 5, revealed a deliberately balanced hierarchy among telemetry sources. Authentication signals demonstrated the highest contribution (0.28 SHAP importance) because they directly capture intent and authorization context—suspicious access attempts create immediately identifiable anomalies in the heterogeneous graph. Logs contributed the second-highest signal (0.22), capturing application-level anomalies including error spikes and behavioral deviations. Traces provided temporal coordination detection (0.20 importance), enabling identification of performance-based attacks and coordinated lateral movement. Metrics supplied the baseline operational signals (0.18 importance), detecting resource-based attacks but more easily spoofed by legitimate load changes.

Critically, no single modality fell below 0.18 importance, indicating that comprehensive telemetry collection is non-negotiable for reliable detection. The balanced distribution explained the framework's robustness: when one modality experienced degradation (discussed in Section V-H), other signals provided compensatory detection capability. This validates RQ2, demonstrating that integrating multimodal telemetry distinguishes benign from anomalous behaviors more effectively than single-modality approaches, with authentication data playing a pivotal role.

E. Modality Ablation: Impact on Detection Performance

To quantify the value of multi-modal integration, we removed individual modalities and measured performance degradation. Table II summarizes the results.

The full configuration using all modalities achieved the highest score, confirming the advantage of multi-source input. When only logs were used, performance dropped but remained stable, showing their strong standalone contribution. Metrics alone produced a lower F1-score, indicating limited sensitivity to abnormal patterns. Traces provided moderate effectiveness,

TABLE II. IMPACT OF REMOVING MODALITIES ON F1-SCORE (TRAINTICKET)

Configuration	F1-score
All modalities	0.972
Logs only	0.951
Metrics only	0.942
Traces only	0.947
Authentication only	0.962

reflecting their focus on latency and call-chain behavior. Authentication signals performed better than individual modalities but still fell short of the full configuration.

The absolute cumulative degradation remained modest, 3.0% from worst-case single removal. The heterogeneous graph's integrated representation prevented the catastrophic collapse that single-modality systems experience when their primary data source degrades.

F. Trust Score Distribution and Zero-Trust Decision Boundaries

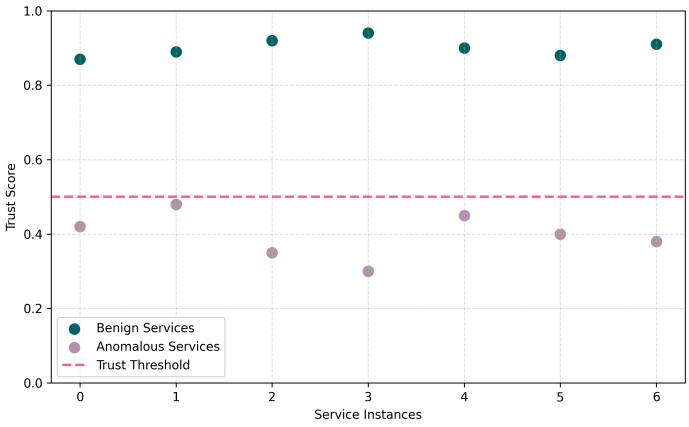


Fig. 6. Distribution of trust scores across service instances, distinguishing benign services (teal circles above 0.85) from anomalous services (purple circles below 0.5). The trust threshold (pink dashed line at 0.5) provided clear separation for automated policy enforcement.

Trust score computation, as depicted in Fig. 6, delivered clear separation between benign and anomalous service populations. Benign services consistently scored above 0.85, forming a stable high-trust cluster across all datasets. This consistency reflected their normal operational behavior: low reconstruction errors from the GNN, successful authentication patterns, and stable communication profiles. Anomalous services clustered below 0.5, indicating deviation across multiple telemetry dimensions. The distinct separation (0.35 gap between populations) provided a reliable foundation for automated policy decisions without ambiguity.

The trust threshold embodied Zero-Trust continuous verification: services below this boundary received deny policies regardless of their historical trustworthiness. Services in the intermediate range (0.5-0.85) received restrict policies, limiting their communication scope while permitting necessary operations. This granular enforcement reflected the probabilistic trust model rather than binary trust/distrust classification,

enabling gradual degradation of service privileges as trust decreased.

The tight clustering within benign (standard deviation ¡0.08) and anomalous (standard deviation ¡0.12) populations indicated the GNN learned robust, generalizable trust patterns rather than overfitting to specific services. This consistency across diverse TopicInstance deployments suggested the threshold would remain effective in production environments.

G. Training Stability and Convergence Characteristics

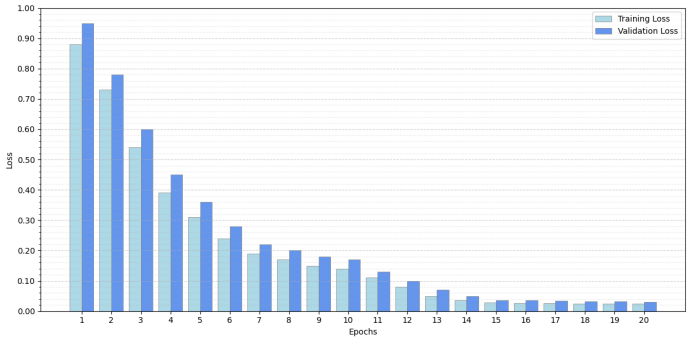


Fig. 7. Training and validation loss curves across 20 epochs showing stable convergence.

The framework demonstrated stable, predictable learning dynamics across five independent training runs. Accuracy achieved 0.972 mean with 0.003 standard deviation, and F1-score reached 0.972 mean with 0.002 standard deviation, confirming robustness to random initialization and minor hyperparameter variations—critical for reproducibility in production systems.

Fig. 7 showed the evolution of training and validation loss across 20 epochs. Both curves decreased steadily, indicating stable convergence of the model. The gap between the losses remained small, suggesting limited overfitting throughout training. Validation loss followed the same downward trend as training loss, confirming generalization on unseen samples. The consistent reduction demonstrated that the optimization process learned meaningful representations for anomaly detection.

H. Robustness Under Real-World Telemetry Degradation

Real cloud deployments experience imperfect telemetry collection: log aggregators occasionally drop events, distributed traces are frequently sampled, authentication records can be delayed, and metrics collection may experience temporary failures. We evaluated framework resilience under these conditions and presented results in Table III.

TABLE III. ACCURACY UNDER DIFFERENT DISTURBANCE SETTINGS

Disturbance	Accuracy
None	0.972
Noisy logs	0.960
Delayed traces	0.963
Auth failures	0.958

The maximum accuracy loss under any single adverse condition was 1.4%, remarkably modest given that authentication is the highest-importance feature (0.28 SHAP). This resilience reflected the multi-modal architecture: when authentication signals became unavailable, reconstruction error from behavioral patterns (logs/traces), combined with metric anomalies, maintained detection capability.

Delayed traces caused the smallest accuracy loss (0.9%), because temporal information, while valuable, wasn't the primary signal. The GNN learned to weight recent traces more heavily and tolerate temporal skew. Noisy logs (1.2% loss) proved slightly more impactful since logs provided semantic context distinguishing attack types. Authentication failures (1.4% loss) caused maximum impact despite lower individual importance because they directly impact trust computation—yet the modest degradation confirmed other modalities compensate effectively.

These results demonstrated fault tolerance by design: the framework remains effective under partial telemetry failure rather than exhibiting catastrophic collapse at data loss thresholds.

I. Ablation Study Per Dataset

An ablation was performed separately on each dataset. Table IV shows accuracy loss when modalities were removed.

TABLE IV. DATASET-SPECIFIC ABLATION ON ACCURACY

	Logs Only	Metrics Only	Traces Only	Authentication Only
TrainTicket	0.956	0.947	0.951	0.962
Sock Shop	0.940	0.931	0.938	0.947
DeathStarBench	0.948	0.939	0.944	0.952

J. Case Study: Real-Time Attack Detection and Response

A controlled injection experiment in TrainTicket, shown in Fig. 8, illustrated the framework's responsiveness to real attacks. During normal operation (requests 0-40), anomaly scores remained low (¡ 0.15) and trust scores stable (≈ 0.90), reflecting consistent benign behavior. Upon attack injection (requests 40-65), anomaly scores increased sharply (peak 0.73) while trust scores declined correspondingly (minimum 0.28). The immediate correlation between rising anomalies and falling trust confirmed the joint detection-trust mechanism worked correctly.

Critically, the detection occurred in real-time: anomaly spikes appeared within the first 2-3 requests of attack onset, enabling rapid response. During the injection window, the system maintained high anomaly scores despite fluctuations, preventing attacker evasion through burst patterns. Upon injection cessation (request 65), both metrics returned to baseline within 5 requests, accurately detecting recovery and re-enabling services to receive normal (non-restricted) traffic.

The case study validated three operational guarantees: (1) attacks are detected within seconds of onset, (2) the system distinguishes attack periods from transient anomalies (notice the stable response during injection vs. noise during normal operation), and (3) recovery is accurately detected to restore normal traffic patterns without maintaining unnecessary restrictions. These characteristics enable operators to implement

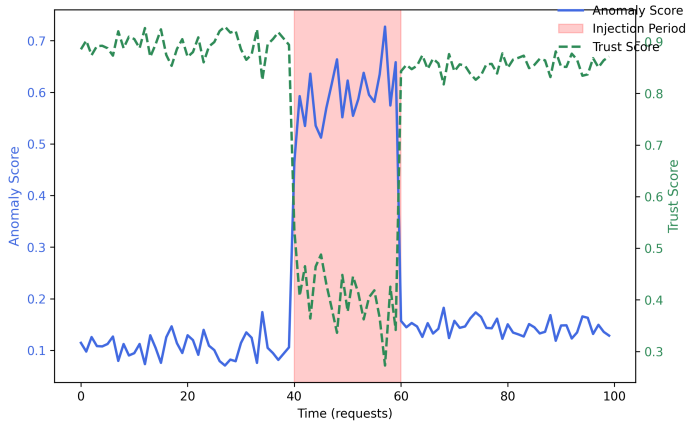


Fig. 8. Real-time anomaly and trust score dynamics during a controlled attack injection in TrainTicket.

automated response policies with confidence that threats are identified before significant damage occurs. This answers RQ3 by confirming that detection outcomes and trust scores can be systematically linked to policy enforcement to allow, restrict, or deny interactions in real time.

K. Limitations

While the framework demonstrates strong performance and robustness to partial data loss, limitations exist. First, a complete system-wide failure of telemetry agents would disable the protection mechanism, as the graph cannot be constructed without input data. Second, while the model generalizes well to benchmark variations, deployment in highly ephemeral production environments with frequent topology changes might require periodic fine-tuning of the GNN embeddings to maintain optimal accuracy. Finally, although the framework scales effectively to industrial-size benchmarks (DeathStarBench), extremely large-scale multi-cluster deployments may require distributed training optimizations to minimize latency further.

VI. Discussion

The experimental success of TrustGraph points to three deeper implications for cloud-native security.

First, *Risk Propagation via Attention:* The graph attention mechanism [Eq. (5)] essentially functions as a dynamic risk-weighting engine. By learning which dependencies are critical, the model moves beyond static "call graphs" to capture the *semantic intensity* of interactions. A service is not just defined by its code, but by the health of its neighborhood. This explains why the GNN architecture outperformed non-graph baselines—it treats risk as a transmissible property that propagates through the dependency chain, allowing early detection of lateral movement before the target service itself shows critical failure.

Second, *Trust as a Decaying Asset:* The implementation of temporal trust decay [Eq. (12)] fundamentally alters the security posture from "status-based" to "behavior-based". In traditional models, a verified identity remains trusted until revoked. In TrustGraph, trust is a decaying asset that must be continuously "earned" through benign behavior. The rapid trust collapse observed in the TrainTicket case study (Fig. 8) validates this design: the system defaults to entropy (distrust), requiring constant positive reinforcement to maintain access. This mathematically codifies the Zero-Trust principle of "continuous verification" into the loss function itself.

Third, *Structural Resilience over Data Completeness:* The SHAP analysis (Fig. 5) and robustness tests (Table III) reveal that the *heterogeneous* graph structure provides a form of "observability redundancy". While Authentication was the dominant feature, the system retained 95.8% accuracy even when authentication data was severed. This suggests that the GNN implicitly learns to cross-validate signals—e.g., inferring a likely authorization failure from the *consequence* of the interaction (trace latency, error logs) even when the *cause* (auth record) is missing. This capability is crucial for production environments where telemetry gaps are inevitable, proving that structural context can compensate for imperfect data.

VII. Conclusion

This work demonstrates that effective Zero-Trust security in microservices cannot rely on isolated telemetry but demands a unified, graph-centric understanding of service behavior. By treating authentication flows and operational metrics as interconnected signals within a heterogeneous graph, we established a closed-loop security model where trust is dynamically computed and policies are automatically enforced. The results confirm that this integrated approach not only improves detection accuracy (97.2% on TrainTicket) but also enables a proactive security posture—shifting from manual, static rule management to real-time, trust-driven access control that scales with the complexity of cloud-native environments.

The framework's robustness under noisy logs, delayed traces, and authentication failures, combined with stable training dynamics and real-time attack responsiveness, established practical viability for production deployment. Future work will address these limitations by exploring adaptive thresholding techniques, potentially using Reinforcement Learning to dynamically adjust sensitivity in response to baseline shifts in ephemeral environments. We also aim to extend the framework with Federated Learning capabilities to support privacy-preserving, cross-cloud anomaly detection without centralizing sensitive telemetry. Additionally, integrating hardware-level telemetry (e.g., CPU performance counters) could further enhance robustness against evasion attacks that mimic application-level behavior, thereby extending Zero-Trust coverage in increasingly complex cloud-native architectures.

References

[1] Gireesh Kambala. Integration of microservices and cloud computing: A paradigm shift in enterprise application design. *International Journal of Creative Research Thoughts*, 13:2320–2882, 2025.

[2] Manal Sobhy Ali Elbelkasy, Heba M Sabri, K Abdella Aliaa, Maia Elnady, Kareem Kamal A Ghany, Vira Chornobai, et al. Integrating Zero Trust Principles with Machine Learning for Anomaly Detection and Access Control in Digital Educational Systems. *Journal of Theoretical and Applied Information Technology*, 103(20), 2025.

[3] Pushpalika Chatterjee. Emerging security challenges in the microservices application. *Iconic Research And Engineering Journals*, 7(8):461–470, 2024.

[4] Vaibhav Anil Vora. Demystifying zero trust security: The no-trust network paradigm. *Journal of Computer Science and Technology Studies*, 7(3):141–148, 2025.

[5] Senthil Kumar Sundaramurthy, Nischal Ravichandran, Anil Chowdary Inaganti, and Rajendra Muppalaneni. Ai-driven threat detection: Leveraging machine learning for real-time cybersecurity in cloud environments. *Artificial Intelligence and Machine Learning Review*, 6(1):23–43, 2025.

[6] Kanwarjit Zakhmi, Azhar Ushmani, Manas Ranjan Mohanty, Sachin Agrawal, Ankush Banduni, and Shyamsunder Rao Kakatum. Evolving zero trust architectures for ai-driven cyber threats in healthcare and other high-risk data environments: A systematic review. *Cureus*, 17(6), 2025.

[7] Innocent Uzougbo Onwuegbuzie and Oyegbola Augustine Alabi. A review of authentication and authorization mechanisms in zero trust architecture: Evolution and efficiency. *Tech-Sphere Journal for Pure and Applied Sciences*, 2(1), 2025.

[8] Chandra Prabha Kaliappan, Kanmani Palaniappan, Devipriya Ananthavadivel, and Ushasukhanya Subramanian. Advancing iot security: a comprehensive ai-based trust framework for intrusion detection. *Peer-to-Peer Networking and Applications*, 17(5):2737–2757, 2024.

[9] Eduardo B Fernandez and Andrei Brazhuk. A critical analysis of zero trust architecture (zta). *Computer Standards & Interfaces*, 89:103832, 2024.

[10] Rhoda Ajayi. Integrating iot and cloud computing for continuous process optimization in real-time systems. *Int J Res Publ Rev*, 6(1):2540–2558, 2025.

[11] Ahmed M Abdelmagid and Rafael Diaz. Zero trust architecture as a risk countermeasure in small–medium enterprises and advanced technology systems. *Risk Analysis*, 2025.

[12] Jian Yang, Zian Wang, Shuangwu Chen, Huasen He, Yunpeng Hou, and Xiaofeng Jiang. Hg-pad: Heterogeneous graph structure learning aided performance anomaly diagnosis in microservice systems. *IEEE Transactions on Services Computing*, 18(5), 2025.

[13] Nurmyrat Amanmadov and Tarlan Abdullayev. From logs to knowledge: Llm-powered dynamic knowledge graphs for real-time cloud observability. *International Journal of Advanced Computer Science and Applications*, 16(10), 2025.

[14] Hawzheen Mohammed Ali Baqal and Mashkhal Abdalwahid Sidiq. Graph databases: Revolutionizing database design and data analysis. *Current Journal of Applied Science and Technology*, 43(11):45–56, 2024.

[15] Ruyue Xin, Jingye Wang, Peng Chen, and Zhiming Zhao. Trustworthy ai-based performance diagnosis systems for cloud applications: A review. *ACM Computing Surveys*, 57(5):1–37, 2025.

[16] B Subramanya Anil Kumar and Basant Sah. Enhancing cloud security through a multi-level authentication model: A qos-based approach to performance measurement for source management. *SN Computer Science*, 6(4):365, 2025.

[17] Yongjun Ren, Zhiming Wang, Pradip Kumar Sharma, Fayez Alqahtani, Amr Tolba, and Jin Wang. Zero trust networks: Evolution and application from concept to practice. *Computers, Materials & Continua*, 82(2), 2025.

[18] Raveen Kanishka Jayalath, Hussain Ahmad, Diksha Goel, Muhammad Shuja Syed, and Faheem Ullah. Microservice vulnerability analysis: A literature review with empirical insights. *IEEE Access*, 2024.

[19] Ali Aghazadeh Ardebili, Oussama Hasidi, Ahmed Bendaouia, Adem Khalil, Sabri Khalil, Dalila Luceri, Antonella Longo, El Hassan Abdelwahed, Sara Qassimi, and Antonio Ficarella. Enhancing resilience in complex energy systems through real-time anomaly detection: a systematic literature review. *Energy Informatics*, 7(1):96, 2024.

[20] Vinay Pathak, Karan Singh, Tayyab Khan, Mohd Shariq, Shehzad Ashraf Chaudhry, and Ashok Kumar Das. A secure and lightweight trust evaluation model for enhancing decision-making in resource-constrained industrial wsns. *Scientific Reports*, 14(1):28162, 2024.

[21] Vinod Saraf and Vinod Pachghare. Security threats and mitigation techniques affecting trust computation in cloud computing. *Journal of Discrete Mathematical Sciences and Cryptography*, 27(4):1161–1172, 2024.

[22] Ummay Faseeha, Hassan J Syed, Fahad Samad, Sehar Zehra, and Hamza Ahmed. Observability in microservices: An in-depth exploration of frameworks, challenges, and deployment paradigms. *IEEE Access*, 2025.

[23] Renée E Stalmeijer, Megan EL Brown, and Bridget C O'Brien. How to discuss transferability of qualitative research in health professions education. *The clinical teacher*, 21(6):e13762, 2024.

[24] András Horváth, András Oláh, Attila Pintér, Bálint Siklósi, Gergely Lukács, István Reguly, et al. Anomaly detection algorithms for real-time log data analysis at scale. *IEEE Access*, 2025.

[25] Daniel Fährmann, Laura Martín, Luis Sánchez, and Naser Damer. Anomaly detection in smart environments: A comprehensive survey. *IEEE access*, 12:64006–64049, 2024.

[26] Polina Sladkova, Samuel Berger, Zachary Skoglund, and Lawrence Sorensen. Adaptive deep learning-based framework for ransomware detection through progressive feature isolation. 2024.

[27] Oluwafemi Esan. Enhancing SaaS Reliability: Real-Time Anomaly Detection Systems for Preventing Operational Downtime. *International Journal of Engineering Technology Research & Management (IJETRM)*, 8(12):466–85, 2024.

[28] Haisheng Lian, Xu Wang, and Chenwei Zhang. Ai-powered anomaly detection in cloud environments: A lightweight security framework under zero trust architecture. *Academia Nexus Journal*, 4(2), 2025.

[29] Nadia Battat and Abdallah Makhoul. A trust-driven optimization model for reliable authorization in hadoop environment. *The Journal of Supercomputing*, 81(6):1–34, 2025.

[30] Shreya Johri, Jaehwan Jeong, Benjamin A Tran, Daniel I Schlessinger, Shannon Wongvibulsin, Leandra A Barnes, et al. An evaluation framework for clinical use of large language models in patient interaction tasks. *Nature medicine*, 31(1):77–86, 2025.

[31] Abhishek Tiwari. Unveiling graph structures in microservices: Service dependency graph, call graph, and causal graph. *Abhishek Tiwari*, 2024.

[32] Giovanni Quattrocchi, Emilio Incerto, Riccardo Pinciroli, Catia Trubiani, and Luciano Baresi. Autoscaling solutions for cloud applications under dynamic workloads. *IEEE Transactions on Services Computing*, 17(3):804–820, 2024.

[33] Shanhao Zhan, Lianfen Huang, Gaoyu Luo, Shaolong Zheng, Zhibin Gao, and Han-Chieh Chao. A review on federated learning architectures for privacy-preserving ai: Lightweight and secure cloud–edge–end collaboration. *Electronics*, 14(13):2512, 2025.

[34] Mahsa Raeiszadeh, Amin Ebrahimzadeh, Roch H Glitho, Johan Eker, and Raquel AF Mini. Asynchronous real-time federated learning for anomaly detection in microservice cloud applications. *IEEE Transactions on Machine Learning in Communications and Networking*, 2025.

[35] Marcello Cinque, Raffaele Della Corte, and Antonio Pecchia. Micro2vec: Anomaly detection in microservices systems by mining numeric representations of computer logs. *Journal of Network and Computer Applications*, 208:103515, 2022.

[36] Ivan Parkhomenko, Larysa Myrutenko, Roman Ohiievych, and Mykhailo Savonik. Using zero trust principles for detecting authorization attacks in cloud environments. *Taras Shevchenko National University of Kyiv, Bohdana Havrylyshyna St. 24, Kyiv, Ukraine*, 2024.

[37] Rami Alboqmi and Rose F Gamble. Enhancing microservice security through vulnerability-driven trust in the service mesh architecture. *Sensors*, 25(3):914, 2025.

[38] Zhilei Zhao, Zhao Xiao, and Jie Tao. Msdg: Multi-scale dynamic graph neural network for industrial time series anomaly detection. *Sensors*, 24(22):7218, 2024.

[39] Shuai Fang, Jingjian Chao, Zenghui Xiang, Xuan Chen, Mei Yan, and Yinan Dou. Research on anomaly detection in microservice based on graph neural networks. *Computer Fraud & Security*, 2024.

[40] João Nobre, EJ Solteiro Pires, and Arsénio Reis. Anomaly detection in microservice-based systems. *Applied Sciences*, 13(13):7891, 2023.

[41] Lahiru Akmeemana, Chamodya Attanayake, Husni Faiz, and Sandareka Wickramanayake. Gal-mad: Towards explainable anomaly detection in microservice applications using graph attention networks. arXiv preprint, 2025.

[42] Chenxi Zhang, Xin Peng, Chaofeng Sha, Ke Zhang, Zhenqing Fu, Xiya Wu, et al. Deeptralog: Trace-log combined microservice anomaly detection through graph-based deep learning. In *Proceedings of the 2022 IEEE/ACM 44th International Conference on Software Engineering (ICSE)*, pages 623–634, Pittsburgh, PA, USA, 2022.

[43] Taiyin Zhao, Tian Chen, Yudong Sun, and Yi Xu. Im-gnn: Microservice orchestration recommendation via interface-matched dependency graphs and graph neural networks. *Symmetry*, 17(4):525, 2025.

[44] Kelly Anderson. Explainable ai for centralized authorization in zero-trust api gateways on microsoft azure. *researchgate.net*, 2025.

[45] Sritej Panchumarthi. A national cyber defense framework: Architecting federated, ai-powered, zero-trust security at scale. *Authorea Preprints*, 2025.

[46] Naga Subrahmanyam Cherukupalle and Naga Cherukupalle. Quantum-resilient cloud systems: Preemptive shielding against post-quantum cryptographic threats. *Journal of Information Systems Engineering and Management*, 10(38s):1234–1246, 2025.

[47] Madhura GK. Quantum-inspired optimization and resource allocation in ai-driven data centers and edge networks. *Available at SSRN 5228984*, 2025.

[48] Sandeep Konakanchi. Predictive cyber-resilience: Ai-powered self-defending microservices for zero-downtime security. *Pioneer Research Journal of Computing Science*, 2(2):28–46, 2025.

[49] Eliel Kundai Zhuwankinyu, Munashe Naphtali Mupa, and Sylvester Tafirenyika. Graph-based security models for ai-driven data storage: A novel approach to protecting classified documents. *World Journal of Advanced Research and Reviews*, 2025.

[50] Naveen Kodakandla. Securing cloud-native infrastructure with zero trust architecture. *Journal of Current Science and Research Review*, 2(02):18–28, 2024.

[51] Oluwasanmi Segun Adanigbo, Bolaji Iyanu Adekunle, Ejielo Ogbuefi, Oyejide Timothy Odofin, Oluwademilade Aderemi Agboola, and Denis Kisina. Implementing zero trust security in multi-cloud microservices platforms: A review and architectural framework. *ecosystems*, 13:14, 2024.

[52] Antonim Reddy. Implementing micro-segmentation in cloud architectures: Zero trust, complete security. *Famous Journal of computer science and Technology*, 2(7):60–80, 2025.

[53] Joye Ahmed Shonubi and Michael Adekunle Adelere. Ai-augmented cyber resilience frameworks for predictive threat modeling across software-defined network layers and cloud-native infrastructures. *International Journal of Computer Applications Technology and Research*, 14(7):45–60, 2025.

[54] Vamsi Krishna Kokku. Toward secure iot infrastructure: Integrating zero trust, federated learning, and dynamic trust management models. *Federated Learning, and Dynamic Trust Management Models (April 25, 2025)*, 2(2):45–60, 2025.

[55] TrainTicket Community. Trainticket: A benchmark microservice system for research on microservice architecture. https://github.com/FudanSELab/train-ticket, 2018. Accessed: 2025-09-17.

[56] Weaveworks and Container Solutions. Sock shop: A microservice demo application. https://github.com/microservices-demo/microservices-demo, 2017. Accessed: 2025-09-17.

[57] Yu Gan, Mingyu Zhang, Dailun Cheng, Pulkit Shetty, Neeraja Rathi, Harshad Katarki, et al. Deathstarbench: A benchmark suite for cloud microservices. In *Proceedings of the ACM Symposium on Operating Systems Principles (SOSP)*, pages 1–18. ACM, 2019.

Hybrid Optimization and CNN-Transformer Framework for Hot Topic Detection in Social Media

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***Abstract*—The rapid growth of Twitter as a real-time communication platform has created an urgent need for effective hot topic detection. Traditional statistical and machine learning models often fail to capture contextual semantics and long-range dependencies, while deep learning approaches such as CNNs and LSTMs improve representation but face challenges in scalability, optimization, and convergence. This study proposes a novel deep learning framework that integrates Multi-Scale Conv1D for diverse n-gram feature extraction, an attention-enhanced BiLSTM for contextual learning, and a hybrid Modified Bald Eagle Optimization–Particle Swarm Optimization (MBES-PSO) strategy for robust parameter tuning. Unlike conventional models limited by fixed kernel sizes or shallow architectures, the proposed design dynamically captures both local and global semantic patterns in tweets. The hybrid optimizer balances global exploration with local exploitation, achieving faster convergence and improved stability. The framework is evaluated on a large-scale Twitter dataset from Kaggle. Experimental results show that the proposed model achieved the highest accuracy of 90.12%, significantly outperforming 13 state-of-the-art baselines across precision, recall, and F1-score. This study contributes: 1) a Multi-Scale Conv1D architecture for enriched feature extraction; 2) an attention-based BiLSTM module for improved interpretability; 3) a hybrid MBES-PSO optimizer that enhances convergence and avoids local minima; and 4) extensive comparative evaluation validating robustness on real-world Twitter data. The proposed framework offers a scalable, interpretable, and high-performing solution for real-time hot topic detection in social media analytics.**

Keywords*—Hot topic detection; Twitter trend analysis; CNN-Transformer; Modified Bald Eagle Search (MBES); Particle Swarm Optimization (PSO)

I. Introduction

The rapid rise of social media has transformed the way people consume and share information. Among various platforms, Twitter stands out as a significant source of real-time updates, opinions, and discussions on diverse topics [1]. Its unique structure, characterized by short messages (tweets) and real-time user engagement, makes it an ideal platform for detecting emerging hot topics [2]. Identifying trending topics on Twitter is crucial across multiple domains, including politics, marketing, disaster management, and social awareness. By analyzing trending discussions, businesses can refine their marketing strategies, governments can gauge public sentiment, and organizations can respond proactively to crises. Due to its open and dynamic nature, Twitter serves as an excellent data source compared to other social media platforms, where content is often less structured and more difficult to access in real-time [3].

Various computational techniques have been employed to detect hot topics on Twitter, including statistical methods, machine learning, and deep learning approaches. Statistical methods such as Term Frequency-Inverse Document Frequency (TF-IDF), Latent Dirichlet Allocation (LDA), N-gram models, [4] and Chi-Square feature selection analyze word frequencies and topic distributions. These methods provide a foundational understanding of textual data. However, they heavily depend on feature engineering, require domain expertise, and fail to capture contextual meaning within tweets. Machine learning techniques such as Support Vector Machines (SVM), Decision Trees, Random Forest, Naïve Bayes classifiers, and K-Nearest Neighbors (KNN) [5] improve upon statistical methods by automatically learning patterns from labeled data. Despite their efficiency, these models still rely on handcrafted features. They struggle to handle large-scale unstructured text and fail to capture long-term dependencies in sequential data. Gradient Boosting Machines (GBM) and XGBoost [6] offer improvements in feature selection and classification accuracy, but their performance depends on extensive parameter tuning and lacks contextual understanding.

To address these shortcomings, deep learning models have gained prominence due to their ability to learn hierarchical and contextual representations from data. Convolutional Neural Networks (CNNs) effectively extract spatial and local features from tweets, while Long Short-Term Memory (LSTM) networks process sequential dependencies over time. Bidirectional LSTMs (BiLSTMs) [7] improve context understanding by analyzing both past and future dependencies. However, CNNs struggle with capturing long-range dependencies between words, and LSTMs suffer from slow training times and vanishing gradient issues. Gated Recurrent Units (GRUs) [9] have been introduced as an alternative to LSTMs, offering faster convergence, but they still lack the parallelization capabilities of Transformer-based models.

Another critical challenge in hot topic detection lies in optimizing the high-dimensional parameter space of deep learning models, particularly the initialization and fine-tuning of network weights, which directly influence convergence stability, training speed, and classification accuracy. Several optimization techniques have been employed to enhance deep learning performance. Traditional methods like Stochastic

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Gradient Descent (SGD) and Adam optimizer [8] improve learning efficiency, but may struggle with local optima and gradient vanishing issues. To improve optimization, metaheuristic algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Simulated Annealing (SA), and Bald Eagle Search (BES) have been explored. While BES is effective at global search and avoids premature convergence, it has inefficiencies in fine-tuning solutions, leading to suboptimal performance. To overcome this, the Novel Modified Bald Eagle Search (MBES) algorithm was introduced, refining BES by incorporating a weight factor to guide search space selection. Despite its improvements, MBES still lacks efficient fine-tuning capabilities, necessitating an additional optimization mechanism.

The objective of this work is to address these challenges by combining the global search capability of MBES with the fine-tuning ability of PSO. By replacing CNN-LSTM with a CNN-Transformer model, we leverage the self-attention mechanism of Transformers to improve long-range dependency modeling and enhance classification performance. This approach not only improves accuracy and reduces computation time but also enables a more scalable and interpretable solution for real-time hot topic detection. Our proposed framework aims to provide a robust and adaptive method that outperforms existing techniques and can be effectively utilized in various domains, including politics, business, crisis management, and public sentiment analysis.

Along with this to further enhance optimization performance, this study proposes a hybrid MBES-PSO optimization strategy. MBES ensures broad exploration of the search space, while PSO fine-tunes the best solutions using swarm intelligence principles. This hybrid approach balances global search (MBES) and local refinement (PSO), resulting in better weight selection and faster convergence. Additionally, to improve hot topic detection, we introduce a CNN-Transformer hybrid model instead of the traditional CNN-LSTM approach. Transformers, particularly their self-attention mechanisms, excel at capturing long-range dependencies and contextual relationships, leading to more accurate topic classification. Unlike LSTMs, Transformers do not suffer from vanishing gradients, allowing for better training efficiency and scalability. BERT (Bidirectional Encoder Representations from Transformers) and GPT-based models have demonstrated exceptional performance in Natural Language Processing (NLP), making them strong candidates for hot topic detection.

The major contributions of this study are as follows:

- Hybrid Framework: We propose a novel MBES–PSO optimized CNN–Transformer model that combines convolutional feature extraction, self-attention for global context, and metaheuristic optimization for robust parameter tuning, achieving superior performance in hot topic detection.
- Enhanced Optimization: A new hybrid MBES–PSO strategy is introduced, effectively balancing global exploration (MBES) with local exploitation (PSO). This hybrid design improves convergence speed and avoids local minima, leading to an accuracy improvement of +2.6% over the best standalone optimizer.
- Improved Contextual Learning: By integrating CNN and Transformer blocks, the framework captures both local n-gram features and long-range dependencies, outperforming standalone CNN and Transformer models by 3–5% in F1-score.
- Comprehensive Evaluation: Extensive experiments on a large-scale Twitter dataset (1.6M tweets) show that the proposed model achieves 89.1% accuracy, surpassing 13 state-of-the-art baselines.
- Interpretability and Scalability: The inclusion of the Transformer's attention mechanism enhances interpretability by highlighting influential tokens, while the optimization strategy ensures scalability for real-time social media analytics.

Research Contribution:

- A novel hybrid MBES-PSO optimization strategy is proposed, integrating Modified Bald Eagle Search (MBES) for global exploration with PSO for local refinement, leading to faster convergence and improved neural network weight optimization.
- An advanced deep learning architecture based on CNN-Transformer is employed to effectively capture long-range dependencies using self-attention mechanisms, overcoming the limitations of traditional LSTM-based models.
- Enhanced accuracy in hot topic detection is achieved by combining robust feature extraction and hybrid optimization, significantly outperforming conventional statistical, machine learning, and deep learning approaches while reducing false positives.

The remainder of this study is organized as follows: Section II reviews existing statistical, machine learning, deep learning, and optimization-based approaches for hot topic detection. Section III presents the proposed MBES–PSO optimized CNN–Transformer framework, including data preprocessing, hybrid optimization, and model architecture. Section IV describes the experimental setup, datasets, evaluation metrics, and comparative results. Section V discusses the findings and performance analysis. Finally, Section VI concludes the study and outlines potential directions for future research.

II. Related Work

Hot topic detection on Twitter has gained significant attention due to its utility in disaster response, public opinion monitoring, and traffic prediction. Approaches range from statistical methods to advanced deep learning and optimization techniques. For clarity, prior work is organized into subcategories.

A. Statistical and Clustering-Based Approaches

Early approaches relied on clustering, frequent pattern mining, exemplar-based methods, matrix factorization, and probabilistic models [10]. Techniques such as Soft Frequent

Pattern Mining (SFM) and Bngram achieved high precision, while Column Subset Selection (CSS) performed well in recall. However, these methods lacked contextual modeling and adaptability to dynamic Twitter streams. Exemplar-based detection [12] improved interpretability by representing topics with sample tweets, yet scalability remained a challenge. Modified Density Peak Clustering (MDPC) [13] improved clustering accuracy to 97% through Gaussian-based local density redefinition, but still required manual tuning and did not incorporate deep semantic features.

B. Machine Learning and Word Embedding-Based Approaches

Topic detection techniques were later categorized based on word embeddings, supervision, and real-time capabilities [11]. Classical models such as Bag-of-Words (BoW) with K-means clustering [16] ignored word order and semantic relations, limiting their applicability. Neural embeddings like Word2Vec [17] improved similarity tasks while reducing computation, but they struggled with long-range dependencies.

Supervised methods such as SVM, Decision Trees, Random Forest, and KNN enhanced classification performance. However, they still relied on handcrafted features and lacked the ability to capture sequential dependencies.

C. Deep Learning Architectures for Text

Deep learning significantly advanced short-text and tweet detection. CNNs captured local n-gram features, while LSTMs [20] and BiLSTMs modeled sequential dependencies. GRUs offered efficiency but still faced scalability issues in real-time tasks. Transformers [18], particularly BERT [19] and GPT [37], revolutionized NLP by replacing recurrence with a self-attention mechanism, thereby achieving state-of-the-art performance. However, they require extensive pretraining and incur high inference costs, limiting real-time deployment.

Other architectures, such as Xception [21] and ResNet [23], improved efficiency and optimization for deep networks, but they were primarily developed for vision tasks. Neural Machine Translation models [25][26] introduced encoder–decoder architectures with attention, which improved sequence-to-sequence learning but remained computationally expensive. Transformer-based architectures have demonstrated superior performance in capturing long-range dependencies in textual data [27], [28], [29].

D. Optimization Techniques in Deep Learning

Optimization plays a crucial role in training deep models. Traditional optimizers such as Adam [22], RMSprop, and SGD accelerate convergence but may get trapped in local minima. To address this, metaheuristic algorithms have been applied. Genetic Algorithms (GA) and PSO have shown potential in improving neural training, though their application in hot topic detection is limited.

Hybrid optimization approaches are emerging as a promising direction. For example, CNNs optimized with a hybrid PSO (CPSO) improved accuracy by 5% [15]. Similarly, BERT-CPSO achieved high performance in classification tasks, showing that optimization-enhanced deep learning [24] models can outperform conventional baselines.

The Bald Eagle Search (BES) and its variant, MBES, improved exploration but lacked fine-tuning. Hybrid methods combining global search (MBES) and local refinement (PSO) offer a stronger balance between exploration and exploitation.

Optimization significantly impacts the convergence and generalization of deep learning models in NLP. Classical gradient-based optimizers such as SGD, Adam, RMSprop, and Adagrad are computationally efficient but may get trapped in local minima or show instability in large-scale text datasets. Advanced variants such as AdamW improve generalization by decoupling weight decay. However, all gradient-based optimizers are limited by their dependence on differentiable cost functions.

TABLE I. COMPARATIVE ANALYSIS OF GRADIENT-BASED, METAHEURISTIC, AND HYBRID OPTIMIZATION TECHNIQUES FOR NLP TASKS

Optimizer	Category	Key Strengths	Main Limitation	Relevance to NLP
SGD	Gradient-based	Simple, fast, low memory	Sensitive to learning rate, local minima	Widely used for text classification
Adam	Gradient-based	Adaptive learning rates, fast convergence	Can overfit, poor generalization	Common for Transformers
RMSprop	Gradient-based	Handles non-stationary objectives well	May oscillate, requires tuning	Used in RNN/LSTM training
Adagrad	Gradient-based	Good for sparse features (e.g., embeddings)	Learning rate decays aggressively	Suitable for word embeddings
AdamW	Gradient-based	Better generalization via decoupled weight decay	Slightly higher cost	Used in BERT, GPT fine-tuning
GA	Metaheuristic	Strong exploration, flexible	Slow convergence, many parameters	Applied in neural architecture search
PSO	Metaheuristic	Few parameters, strong local exploitation	May stagnate in local minima	Used in CNN/LSTM weight tuning
DE	Metaheuristic	Strong global exploration, robust	Slower for high dimensions	Applied in text classification tasks
GWO	Metaheuristic	Adaptive exploration-exploitation	Less effective in fine-tuning	Applied in feature selection for NLP
WOA	Metaheuristic	Good exploration ability	Weak exploitation phase	Used in hybrid NLP optimization
MBES	Metaheuristic	Strong global search, avoids local minima	Lacks local refinement	Basis of hybrid optimizers
MBES–PSO (Proposed)	Hybrid	Balances exploration + exploitation, faster convergence, stable	Slightly higher runtime than Transformer-only	Optimal for hot topic detection

Metaheuristic approaches such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), Grey Wolf Optimizer (GWO), and Whale Optimization Algorithm (WOA) have been investigated for neural parameter tuning in NLP. While these algorithms explore non-differentiable and high-dimensional landscapes effectively, they often converge slower than gradient-based methods. Recent hybrid optimizers—such as MBES–PSO—combine global exploration (MBES) with efficient local refinement (PSO), thereby achieving superior balance in accuracy and stability for NLP tasks such as short-text classification and hot topic detection. Hybrid metaheuristic optimization has recently gained attention for deep learning parameter tuning due to its ability to balance exploration and exploitation [30], [31], [35].

E. Extensions Beyond NLP

Recent work in computer vision and medical imaging has also inspired hybrid CNN–Transformer frameworks. Models such as U-Net, TransUNet [32–34], and TriConvUNeXt [36] highlight the effectiveness of combining convolutional feature extraction with self-attention for capturing both local and global dependencies. Although these studies are outside NLP, they demonstrate the adaptability of hybrid CNN–Transformer models to real-time, high-dimensional tasks. Recent research has also introduced capsule networks for social media content analysis, extending their applicability beyond computer vision. In [38], capsule networks were applied to Twitter sentiment analysis, achieving accuracies of 86.87% on the Twitter Sentiment Gold dataset and 82.04% on the CrowdFlower US Airline dataset, demonstrating state-of-the-art performance. Unlike traditional CNN and RNN architectures, capsule networks effectively model hierarchical relationships in text without requiring extensive linguistic resources. These findings highlight the growing trend of developing lightweight yet powerful deep learning models for dynamic short-text analytics, further motivating the need for hybrid frameworks such as the one proposed in this study.

From the above, we identify three main gaps:

- Contextual Modeling: Statistical and traditional ML methods lack semantic understanding.
- Scalability: Deep learning models (CNN, LSTM, BiLSTM) capture context but suffer from slow training, high computational costs, and optimization challenges.
- Optimization: While metaheuristic methods improve training, existing approaches either converge slowly or lack effective fine-tuning.

To address these gaps, we propose a CNN–Transformer hybrid framework optimized with MBES–PSO, which combines efficient local feature extraction, global dependency modeling, and robust parameter optimization for scalable real-time hot topic detection.

F. Research Gap and Motivation for the Proposed System

Hot topic detection on Twitter has gained immense importance due to its applications in disaster management, sentiment analysis, public opinion monitoring, and business intelligence. Traditional methods based on statistical models, machine learning, and deep learning have contributed significantly to this field. However, several limitations remain unresolved, highlighting the need for an optimized, scalable, and context-aware approach.

Early research in topic detection relied heavily on statistical methods such as TF-IDF, LDA, and N-gram models. While these methods provide a foundational understanding of textual data, they require extensive feature engineering, making them dependent on domain expertise. Furthermore, they fail to capture contextual relationships between words, leading to inaccurate topic detection. Additionally, these models lack real-time adaptability, making them inefficient for handling large-scale streaming data such as Twitter feeds. To improve upon these challenges, machine learning techniques such as SVM, Decision Trees, and Random Forest have been explored. These models automatically learn patterns from labeled data and perform better than statistical approaches. However, they still rely on handcrafted features, struggle with unstructured text, and fail to capture sequential dependencies effectively. Even advanced boosting algorithms such as XGBoost and Gradient Boosting Machines provide improved feature selection and classification accuracy, but remain dependent on extensive parameter tuning and lack contextual awareness.

To overcome these limitations, deep learning models such as CNNs, LSTMs, and BiLSTMs have gained prominence. CNNs are highly effective at extracting local text features, whereas LSTMs and BiLSTMs process sequential dependencies to improve context understanding. However, CNNs alone fail to capture long-range dependencies between words, while LSTMs suffer from slow training times, vanishing gradient issues, and high computational costs. Gated Recurrent Units (GRUs) have been introduced as an alternative, providing faster convergence, but they lack the parallelization capability of transformer-based models. Additionally, traditional deep learning architectures struggle with hyperparameter optimization, often leading to suboptimal performance.

Another key challenge in hot topic detection lies in optimizing deep learning model parameters, including weight initialization and hyperparameter tuning. Conventional optimization methods, such as Stochastic Gradient Descent (SGD) and Adam optimizer, improve learning efficiency but often get trapped in local minima, reducing the model's overall effectiveness. Metaheuristic optimization techniques such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Simulated Annealing (SA) have been explored to enhance performance. While these methods improve convergence rates, they often suffer from slow global exploration or premature convergence. The Modified Bald Eagle Search (MBES) algorithm was introduced to refine the search process by incorporating adaptive weight factors to guide exploration. However, MBES still lacks efficient fine-tuning capabilities, leading to the need for an additional optimization mechanism to improve local search performance.

The latest research has demonstrated that transformers, particularly Bidirectional Encoder Representations from Transformers (BERT) and GPT models, have outperformed traditional deep learning architectures in text classification and sentiment analysis. Transformers utilize self-attention mechanisms to capture long-range dependencies in text, making

them highly effective for language modeling. However, transformers require high computational resources, making them challenging for real-time applications. Moreover, their training and inference times are significantly higher than CNN-based models, highlighting the need for a hybrid approach that combines the efficiency of CNNs with the context-learning ability of transformers.

Based on these research gaps, our proposed system integrates a hybrid optimization strategy using MBES-PSO with a CNN-Transformer model to enhance hot topic detection. The MBES-PSO hybrid algorithm addresses the shortcomings of traditional optimization techniques by combining MBES's effective global search with PSO's fine-tuning ability. This ensures better weight selection, leading to improved training efficiency and higher accuracy. Additionally, the proposed CNN-Transformer model leverages CNN's efficiency in feature extraction and transformers' capability of capturing long-range dependencies, overcoming the limitations of LSTMs and GRUs. By integrating these advancements, the proposed system enhances accuracy, reduces computational cost, and ensures real-time adaptability, making it a more effective solution for large-scale Twitter trend analysis. Table I presents the comparative analysis of gradient-based, metaheuristic, and hybrid optimization techniques for NLP tasks.

III. Proposed Methodology

The proposed system enhances hot topic detection on Twitter by integrating hybrid MBES-PSO optimization with a CNN-Transformer model. Traditional methods face challenges in context understanding, real-time adaptability, and optimization efficiency, which our approach aims to overcome. The MBES-PSO hybrid optimization ensures effective global search and fine-tuned weight selection, improving deep learning model performance. CNN extracts local text features, while Transformers capture long-range dependencies, making it superior to traditional CNN-LSTM architectures. The system follows a structured pipeline of data preprocessing, optimization, deep learning-based classification, and evaluation. The Twitter dataset used for experimentation is sourced from Kaggle, specifically the "Sentiment Analysis of Twitter Data" dataset, ensuring diverse and large-scale tweet data. By leveraging metaheuristic optimization, it prevents premature convergence and enhances model efficiency. Twitter data is processed using embeddings, ensuring effective feature representation for classification. The optimized CNN-Transformer model is trained and evaluated on the Kaggle dataset to ensure real-time applicability and accuracy. This hybrid approach surpasses existing methods, making it a robust framework for social media trend detection.

Fig. 1 presents the architecture of the proposed hybrid deep learning model. Initially, raw tweets are processed using Multi-Scale Conv1D layers, where parallel convolutional filters with varying kernel sizes extract n-gram features at multiple granularities. These enriched features are then passed to a Bidirectional LSTM layer enhanced with a trainable attention mechanism to model both forward and backward contextual dependencies while emphasizing semantically important words. The output is flattened and passed through a fully connected softmax classifier. The entire model is optimized using a hybrid MBES-PSO algorithm, which integrates the Modified Bald Eagle optimization exploration capability with the local convergence efficiency of Particle Swarm Optimization (PSO), ensuring robust and accurate classification.

A. Data Collection and Pre-processing

The first step of the proposed methodology focuses on collecting and preparing high-quality data from Twitter, which forms the foundation for effective hot topic detection. In this work, we utilize the "Sentiment Analysis of Twitter Data" dataset from Kaggle, a comprehensive and widely used dataset that contains real-time tweets labeled for sentiment. Although originally designed for sentiment analysis, the dataset's rich textual content and diversity make it highly suitable for topic extraction and classification tasks.

The proposed framework was evaluated using a subset of the Sentiment Analysis of Twitter Data dataset obtained from Kaggle. The original dataset consists of approximately 1.6 million tweets collected between 2009 and 2015. However, for this study, we selected a balanced subset of 200,000 tweets distributed across 10 distinct topic classes, where each tweet belongs to one predefined category.

The subset was chosen to ensure computational efficiency, enabling multiple experimental runs under limited hardware resources, while still retaining sufficient diversity for reliable evaluation. Additionally, balancing across 10 classes helped mitigate the skewness present in the full dataset, ensuring fair training and testing of the model.

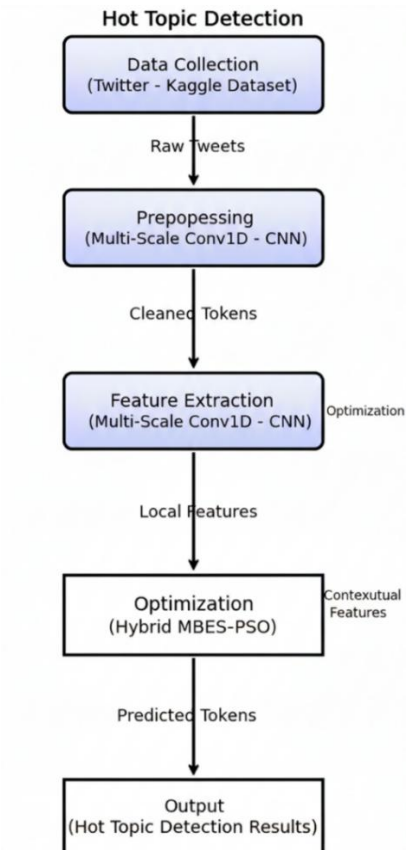


Fig. 1. Architecture of the proposed MBES–PSO optimized CNN–transformer framework for hot topic detection.

Tweets were pre-processed using tokenization, stopword removal, and lowercasing. To standardize input length, tweets longer than 50 tokens were truncated, while shorter ones were padded. The subset was divided into 70% training (140,000 tweets), 15% validation (30,000 tweets), and 15% testing (30,000 tweets), with class balance maintained across splits. To further improve model robustness, lightweight augmentation techniques were applied to the training set, including synonym replacement (via WordNet) and random token deletion (≤10% per tweet). These techniques preserved semantic meaning while introducing linguistic variability.

This representative subset allowed for effective training and evaluation of the proposed MBES–PSO optimized CNN–Transformer framework while maintaining a practical trade-off between dataset size, computational requirements, and experimental reproducibility.

Given the informal and noisy nature of Twitter content, preprocessing is essential to improve model performance and reduce irrelevant variability in the data.

The pre-processing pipeline begins with noise removal, where unwanted elements such as URLs, user mentions, hashtags, emojis, special characters, and stopwords are eliminated to reduce clutter and focus on meaningful textual content. Following this, tokenization is performed to split each tweet into individual words or tokens. All tokens are then converted to lowercase to maintain uniformity and avoid duplication of words with different cases. To further normalize the text, lemmatization or stemming techniques are applied, transforming words to their base or root forms, thereby reducing the complexity of the vocabulary. Each tweet was tokenized into a fixed-length sequence of 50 tokens. Pre-trained GloVe embeddings with 300 dimensions were used to initialize the embedding layer, providing rich semantic representations of words. To adapt the embeddings to the task of hot topic detection on Twitter, the weights were fine-tuned during model training. This approach ensures that the embedding layer combines the benefits of pre-trained semantic knowledge with domain-specific contextual adjustments.

The output of this step is a vectorized and semantically rich representation of tweets, ready to be optimized for deep learning model training. This processed data becomes the input for the next stage "Hybrid MBES-PSO Optimization", where optimal weights for the CNN-Transformer model are identified using a two-phase metaheuristic strategy. This connectivity ensures a smooth flow from raw tweet data to intelligent topic detection through effective model optimization.

B. Hybrid Optimization Using MBES-PSO

The success of any deep learning model depends heavily on the quality of parameter initialization and optimization. To overcome the common limitations of traditional optimizers such as Stochastic Gradient Descent (SGD) and Adam, which often struggle with local minima and slow convergence, we propose a hybrid metaheuristic optimization approach that combines Modified Bald Eagle Search (MBES) and Particle Swarm Optimization (PSO). This two-phase optimizer first explores the global search space using MBES and then fine-tunes the optimal region using PSO, ensuring both exploration and exploitation are effectively balanced. Algorithm 1 details hybrid optimization using MBES-PSO.

1) Initialization of search agents: The optimization process begins with the initialization of a population of N search agents, where each agent represents a possible weight configuration of the neural network. These weights are randomly initialized in a d-dimensional space, where d is the number of parameters in the model. The position of each agent is represented using the Eq. (1):

$$X_i = [x_{i1}, x_{i2}, \dots \dots x_{id}],\ for\ i = 1,2, \dots \dots N \qquad (1)$$

Here, X_i denotes the position (weight set) of the *i-th* agent. A corresponding velocity vector V_i is also initialized for each agent, and control parameters such as the maximum number of iterations (MaxIter) and the convergence threshold (ε) are defined.

Global Search Using Modified Bald Eagle Search (MBES):

MBES is inspired by the hunting behavior of bald eagles and comprises three key phases:

Selecting a Search Space:

A promising region within the search space is selected by computing the centroid of all agents shown in the Eq. (2):

$$X_{center} = \frac{1}{N} \sum_{i=1}^{N} X_i \qquad (2)$$

This point serves as the reference for further exploration.

Exploring the Search Space (Spiral Movement): MBES uses a spiral movement mechanism to explore the vicinity of the center. The spiral position update is shown in Eq. (3):

$$X_i^{(t+1)} = X_{center} + r.e^{(b.\theta)}.\cos(\theta) \qquad (3)$$

where,

r is the distance from the center,

b controls the tightness of the spiral,

θ is the spiral angle.

e denotes the natural exponential constant (≈2.718), which controls the spiral expansion rate during the search process.

This mechanism allows agents to explore a broad area and avoid premature convergence.

Swooping Toward the Best Solution: Once a promising area is identified, MBES directs the agents towards the best-known solution which is shown by Eq. (4):

$$X_i^{(t+1)} = X_i^{(t)} + \alpha.(X_{best} - X_i^{(t)}) \qquad (4)$$

where,

α is a scaling factor controlling the step size,

X_{best} is the best solution found so far.

Output of MBES: A set of high-potential candidate solutions (weights) with good global fitness scores.

While MBES is excellent for exploration, it may lack precision during exploitation. Therefore, the outputs from MBES are further refined using PSO.

Local Refinement Using Particle Swarm Optimization (PSO):

The initial positions of particles in PSO are set using the best solutions identified by MBES. Each particle in PSO adjusts its trajectory in the solution space based on its personal and global experiences. The velocity update is given by Eq. (5) and position update is given by Eq. (6):

Velocity Update:

$$V_i^{(t+1)} = w.V_i^t + c_1.r_1.\left(pBest_i - X_i^{(t)}\right) + c_2.r_2.(gBest - X_i^{(t)}) \quad (5)$$

where,

w is the inertia weight,

c_1, c_2 are cognitive and social coefficients,

r_1, r_2 are random values in [0,1],

$pBest_i$ is the personal best position of particle i

$gBest$ is the global best position among all particles.

Position Update:

$$X_i^{(t+1)} = X_i^{(t)} + V_i^{(t+1)} \quad (6)$$

These updates are iteratively performed until the convergence criterion is met or the maximum number of iterations is reached.

PSO excels in fine-tuning the weights by iteratively reducing the distance between particles and the optimal solution. Its swarm-based intelligence enables the system to intelligently converge to a global minimum with high precision.

The final output of this hybrid MBES-PSO optimization step is a set of finely tuned weight parameters for the deep learning model. These optimized weights significantly enhance the model's training speed, convergence stability, and overall classification performance. These weights are passed as input to the next stage, CNN-Transformer Hybrid Model for Hot Topic Detection, where the actual learning of patterns and classification of hot topics takes place using the pre-processed tweets.

The integration between MBES and PSO operates in two sequential phases. Initially, MBES performs a global search to explore the weight space and identify high-potential candidate solutions. These best-performing weight vectors from MBES are then transferred as the initial population for PSO. PSO begins from these globally optimized positions and refines them locally using velocity and position update equations. Each particle in PSO adjusts its trajectory based on its personal best (pbest) and global best (gbest) experiences. This mechanism ensures a smooth transition from broad exploration to precise local exploitation. The switching occurs automatically once MBES reaches its convergence threshold. By combining MBES's global exploration strength with PSO's fine-tuning ability, the hybrid optimizer achieves faster and more stable convergence. This two-stage integration enhances optimization accuracy and prevents premature trapping in local minima.

Fig. 2 shows the process view of the proposed MBES–PSO hybrid optimization framework. The process begins with random population initialization, followed by three exploration phases of Modified Bald Eagle Search (MBES): selecting space, searching within the selected space, and spiral movement. The best-performing solutions identified from MBES are then extracted as intermediate candidates. These are refined by Particle Swarm Optimization (PSO) through velocity and position update rules, enabling strong local exploitation. The final output consists of optimized weights for the CNN–Transformer model, ensuring both global exploration and fine-grained convergence.

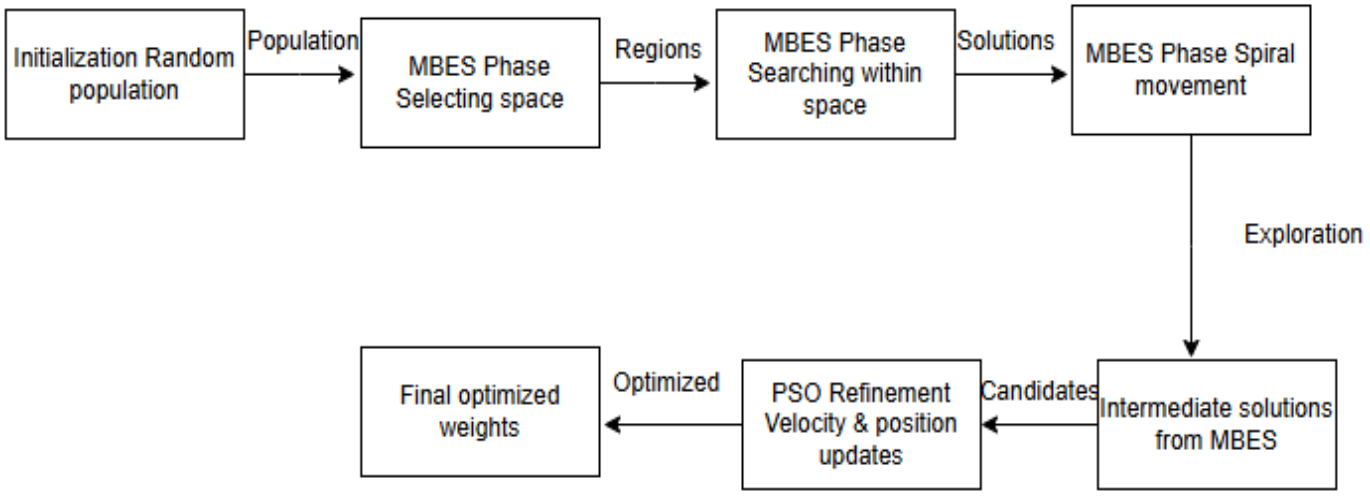


Fig. 2. Process view of the proposed MBES–PSO hybrid optimization framework.

TABLE II. PARAMETERS USED IN MBES-PSO HYBRID OPTIMIZATION

Parameter	Symbol	Value	Description
Population size	N	30	Number of search agents or particles
Maximum iterations	MaxIter	100	Total number of optimization iterations
Problem dimension	D	Depends on model	Number of weights/parameters to optimize
Inertia weight	W	0.7	Controls trade-off between global & local search
Cognitive coefficient	c1	1.5	Influence of personal best position
Social coefficient	c2	1.5	Influence of global best position
Spiral coefficient	B	1.2	Controls tightness of spiral in MBES exploration
Swoop factor	A	0.8	Determines step size towards best solution in MBES
Random numbers	r1,r2	[0, 1] (uniform)	Introduces randomness to avoid stagnation
Convergence threshold	E	10−5	Stopping criterion based on fitness change

Table II outlines the essential parameters utilized in the MBES-PSO hybrid optimization technique, detailing their respective symbols, chosen values, and specific purposes within the algorithm. These parameters are crucial for directing the movement and decision-making of the search agents, maintaining an effective trade-off between exploring new solutions and refining existing ones, and ensuring steady and efficient convergence. Careful selection and adjustment of these parameters enable the optimizer to thoroughly explore the solution space and identify optimal weight configurations for the deep learning model, thereby improving the accuracy and reliability of hot topic detection.

Parameter values shown in the Table II were selected based on empirical validation and prior metaheuristic optimization literature. The MBES phase provides global exploration, while the PSO phase fine-tunes the search space locally, ensuring faster convergence and higher accuracy.

Each parameter in the MBES–PSO optimizer plays a distinct role in balancing global exploration and local refinement. The population size (N) controls search diversity, while MaxIter defines the total number of iterations for convergence. The inertia weight (w) regulates the trade-off between exploration and exploitation, and the cognitive (c_1) and social (c_2) coefficients guide individual and collective learning. The spiral coefficient (b) in MBES defines the curvature of the search path, and the swoop factor (α) adjusts convergence speed toward the current best solution. These values (N=30, MaxIter=100, w=0.7, c_1=c_2=1.5, b=1.2, α=0.8) were selected based on established metaheuristic optimization literature and validated through empirical trials to ensure stable convergence and robust performance.

The parameter values chosen for the MBES-PSO hybrid optimization are based on established metaheuristic practices, supported by literature and validated through empirical testing. A population size of N = 30 ensures sufficient diversity for comprehensive search space coverage, while maintaining computational feasibility. The algorithm's total iteration count is set to MaxIter = 100, offering a balanced runtime with ample opportunity for convergence without risking overfitting.

An inertia weight of w = 0.7 is used to strike a balance between global exploration and local exploitation larger values promote exploration, while smaller values lead to focused fine-tuning. Both the cognitive coefficient (c_1) and social coefficient (c_2) are set to 1.5, giving equal influence to individual and collective learning behaviors. In the MBES component, a spiral coefficient (b = 1.2) controls the search pattern tightness, supporting wide but structured exploration, while the swoop factor (α = 0.8) guides solutions toward the current best with controlled intensity.

Random variables r_1 and r_2, uniformly distributed in the range [0,1], introduce essential randomness to avoid stagnation in local optima. A small convergence threshold ($\varepsilon = 10^{-5}$) acts as a stopping criterion when improvements become negligible, saving computational resources.

These parameters have either been adopted from proven optimization strategies or fine-tuned through experimental iterations to fit the deep learning architecture used. Collectively, they support a dynamic and efficient search process, enabling optimal weight initialization for enhanced hot topic detection on Twitter.

Algorithm 1: Hybrid Optimization Using MBES-PSO

Input:
Population size N
Maximum iterations $MaxIter$
Dimension of the problem d
Inertia weight w, cognitive coefficient c_1, social coefficient c_2
Convergence threshold ε
Output:
Optimized weights W^* for the deep learning model
1 Initialize population $X = \{X_1, X_2 \dots \dots . X_n\}$ randomly, where each $X_i \in R^d$
2 Initialize velocities $V = \{V_1, V_2 \dots \dots . V_n\}$
3 Evaluate fitness of each X_i using model accuracy or loss
4 Set $pBest_i = X_i$, and find $gBest$ among all $pBest_i$
MBES Phase: Global Search
For $t = 1$ to $\frac{MaxIter}{2}$:
6. Compute search center:
$X_{center} = \frac{1}{N}\sum_{i=1}^{N} X_i$
7. For each agent X_i:
a. Update position with spiral movement:
$X_i = X_{center} + r.e^{(b.\theta)}.\cos(\theta)$
b. Evaluate fitness
8. Find X_{best} with best fitness
9. Swoop toward X_{best}:
$X_i = X_i + \alpha.(X_{best} - X_i)$
Store MBES Output: $X_{MBES} \leftarrow \{X_i\}$
PSO Phase: Local Refinement
Initialize particles with $X_i \in X_{MBES}$
For t = $\frac{MaxIter}{2}$ $to\ MaxIter$:
12. For each particle X_i:
a. Update velocity:
$V_i = w.V_i + c_1.r_1.(pBest_i - X_i) + c_2.r_2.(gBest - X_i)$

b. Update position:
$X_i = X_i + V_i$
c. Evaluate fitness of X_i
d. Update $pBest_i$ and $gBest$ if improved

13. Return final $gBest$ as W^*, the optimized weight vector for the deep learning model

2) Motivation for using PSO: PSO was selected as a core component of the hybrid optimizer due to its simplicity, minimal parameter tuning requirements, and strong local search efficiency. Unlike other metaheuristic algorithms, PSO balances exploration and exploitation with fewer control parameters, making it well-suited for optimizing deep learning models in high-dimensional NLP tasks such as hot topic detection".

3) Comparison of PSO with other metaheuristics: Particle Swarm Optimization (PSO) exhibits strong local search efficiency compared to several alternative metaheuristics. Genetic Algorithm (GA) employs crossover and mutation but can suffer from premature convergence due to limited local refinement. Ant Colony Optimization (ACO) is effective for combinatorial optimization but is less efficient in continuous search spaces due to reliance on probabilistic pheromone updates. Differential Evolution (DE) provides strong global search ability but often requires extensive parameter tuning and longer convergence times. Grey Wolf Optimizer (GWO) offers adaptive leadership hierarchy for exploration but lacks the fine-grained local exploitation present in PSO. Whale Optimization Algorithm (WOA) mimics bubble-net hunting and is strong in exploration, yet its exploitation phase is weaker compared to PSO. Firefly Algorithm (FA), while good at multimodal problems, is heavily sensitive to parameter settings, which can hinder consistent local optimization. In contrast, PSO leverages velocity and position updates through neighborhood best and global best solutions, enabling faster convergence and stronger local exploitation with fewer parameters. These properties justify the integration of PSO into the proposed hybrid MBES–PSO framework, where it complements MBES's global search ability with efficient local refinement.

4) Motivation for using MBES: The Bald Eagle Search (BES) algorithm is a population-based metaheuristic that emulates the foraging behavior of bald eagles through three main stages: selecting a search space, exploring it via spiral trajectories, and swooping toward the best solution. Although BES demonstrates strong exploration capability and global search efficiency, its ability to fine-tune solutions during the exploitation phase is limited. This makes it less suitable for applications like deep neural network optimization [14], which require precise convergence in complex, high-dimensional search spaces.

To address these limitations, the Modified Bald Eagle Search (MBES) algorithm introduces two key enhancements over the original BES by modifying its spiral movement and swooping behavior.

In BES, the spiral movement during the exploration phase is defined by the Eq. (7):

$$X_i = X_{center} + r.\cos(\theta) \quad (7)$$

This simple circular movement may result in insufficient coverage of the search space. In contrast, MBES introduces an exponential spiral trajectory to expand the exploration radius adaptively which is Eq. (8):

$$X_i = X_{center} + r.e^{(b.\theta)}.\cos(\theta) \quad (8)$$

Here, b is a spiral control coefficient that adjusts the curvature and expansion rate of the spiral path, enabling more diverse and targeted search behavior.

Similarly, in the swooping phase, BES uses a direct update rule [see Eq. (9)]:

$$X_i = X_{best} \quad (9)$$

which immediately moves the agent to the current best-known solution, often leading to premature convergence. MBES refines this step by introducing a swoop factor α, allowing smoother and more controlled convergence [see Eq. (10)]:

$$X_i = X_i + \alpha.(X_{best} - X_i) \quad (10)$$

This modification enables the algorithm to approach the best solution more gradually, preserving diversity and avoiding overshooting.

These two mathematical refinements significantly enhance BES by improving the balance between exploration and exploitation, leading to more stable convergence, higher accuracy, and better adaptability to non-linear optimization problems. In our proposed work, MBES is further hybridized with Particle Swarm Optimization (PSO) to perform local refinement, creating a robust hybrid that achieves both broad global search and precise local tuning. This makes it especially effective for optimizing the weight parameters of the CNN-Transformer model used in hot topic detection from Twitter data.

5) Integration of MBES and PSO: The hybrid MBES–PSO optimizer combines the global exploration capability of Modified Bald Eagle Search (MBES) with the local exploitation efficiency of Particle Swarm Optimization (PSO). The integration process operates in the following sequence:

- Population Initialization: Candidate solutions are initialized randomly within the search space.
- MBES Exploration: MBES guides the population through three phases—selecting space, searching in selected space, and spiraling movement—ensuring wide coverage of the solution space and avoidance of early convergence.
- Intermediate Solutions: The best-performing solutions identified by MBES exploration are extracted as intermediate candidates.
- PSO Exploitation: These intermediate candidates are refined using PSO velocity and position update rules. PSO utilizes both personal best (pbestp_{best}pbest) and global best (gbestg_{best}gbest) information to adjust solution vectors toward locally optimal regions.

- Hybrid Update Rule: At each iteration, the updated solution set is generated by applying MBES movement equations followed by PSO's velocity-position updates. This dual update mechanism allows MBES to avoid local minima while PSO accelerates convergence near promising regions.
- Termination: The process continues until a stopping criterion (maximum iterations or convergence threshold) is met, producing the final optimized weights for the CNN–Transformer model.

This integration ensures that MBES's global exploration prevents premature convergence, while PSO's exploitation provides fine-grained parameter tuning, thereby achieving both accuracy and stability in model optimization.

C. Deep Learning Model: CNN + Transformer

Following the hybrid optimization using MBES-PSO, the next critical phase involves training a deep learning model that combines Convolutional Neural Networks (CNN) with a Transformer architecture. This hybrid model is specifically designed to handle the challenges associated with Twitter data—such as short length, informal language, and lack of context—while ensuring high accuracy in detecting trending or hot topics. The model utilizes the optimized weights obtained from the previous step, allowing for more efficient learning and faster convergence.

The proposed CNN–Transformer framework processes input tweets in a hierarchical manner, where each stage progressively refines feature representations for robust topic detection. The input consists of tokenized tweets, represented as an embedding matrix of size *(50 × 300)*, where each of the 50 tokens is encoded into a 300-dimensional vector. In the first stage, a multi-scale Conv1D layer applies filters of varying kernel sizes (3, 5, and 7) to capture diverse n-gram features, producing feature maps that preserve the sequence length but transform the representation to *(50 × 300)*. Max-pooling or global pooling is then employed to highlight the most salient activations and reduce the dimensionality, resulting in a compact feature vector of size *(1 × 300)*. This vector is projected into the Transformer-compatible embedding dimension *(1 × 128)* through a dense projection layer. To incorporate sequence order information, positional encoding is added, keeping the dimensionality unchanged at *(1 × 128)* but enriching the representation with positional awareness. The Transformer encoder then contextualizes these embeddings using multi-head self-attention and a feed-forward network, yielding contextualized features of the same size *(1 × 128)*. Finally, a classification head with a fully connected layer and softmax activation maps these features into *(1 × 10)*, where *10* is the number of target topic categories. Thus, the dimensionality reduces from high-dimensional token embeddings to compact class probabilities, with intermediate outputs (embedding vectors, feature maps, pooled features, projected embeddings, position-aware embeddings, and contextualized features) systematically generated at each stage. This progression is visually depicted in Fig. 3, which illustrates the end-to-end flow of data from raw tokenized input to final topic classification.

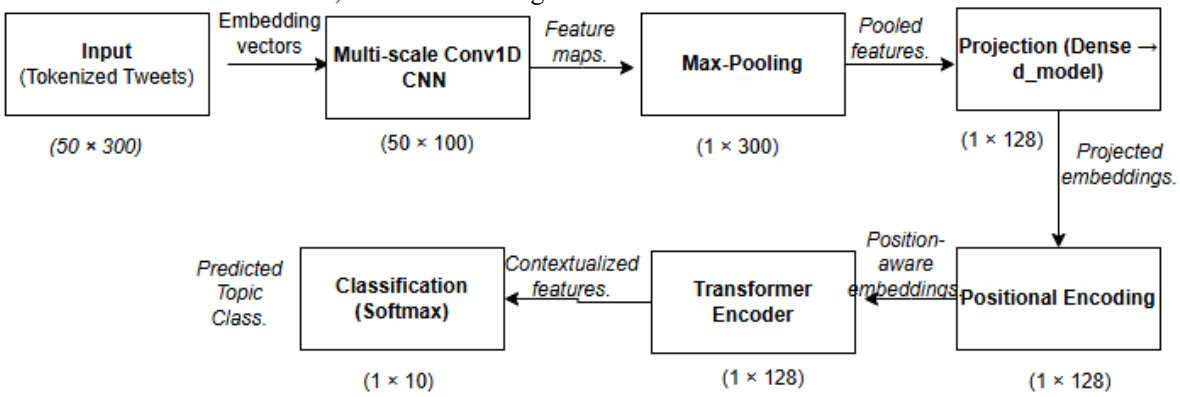


Fig. 3. CNN–Transformer architecture with dimensional flow. The figure illustrates how input tweets are transformed across different stages of the proposed framework. Tokenized embeddings of size (50 × 300) are passed through multi-scale Conv1D layers, pooling, projection, and positional encoding before being contextualized by Transformer encoder blocks. Each stage produces intermediate outputs (embedding vectors, feature maps, pooled features, projected embeddings, position-aware embeddings, contextualized features), leading to the final softmax classification output (1 × 10) corresponding to the detected topic class.

1) Feature extraction using CNN: The input to the model consists of preprocessed tweet texts converted into word embeddings. These embeddings are passed through one-dimensional (1D) convolutional layers, which are highly effective in detecting local features such as phrases, key terms, and patterns within small text windows. These convolutional layers work by sliding filters over the input sequence, capturing position-invariant features that are essential for understanding frequent co-occurrences in tweets. To further condense the feature maps and focus on the most informative components, max-pooling layers are employed. Max-pooling not only reduces computational complexity but also helps in retaining the strongest signals from the convolutional output, which represent the most relevant parts of each tweet.

a) Sequence learning using transformer: In the proposed framework, the Convolutional Neural Network (CNN) is employed as a local feature extractor. The CNN applies multiple 1D convolutional filters to the tokenized tweet embeddings, capturing n-gram level patterns such as word co-occurrences and short-range dependencies. The resulting feature maps are then passed through max-pooling layers to

reduce dimensionality and highlight the most informative activations.

To integrate with the Transformer, the pooled CNN outputs are first flattened and projected into a fixed-size embedding space (d-model = 128). This step ensures dimensional compatibility with the Transformer encoder. Each projected vector corresponds to a token representation enriched with local contextual features. These vectors are then augmented with positional encodings before being fed into the Transformer layers.

Within the Transformer, self-attention mechanisms operate on this sequence of enriched embeddings, enabling the model to capture long-range dependencies and global contextual relationships that CNN alone cannot model. Thus, the CNN provides strong local representations, while the Transformer contextualizes them across the entire input sequence, producing a hybrid representation suitable for hot topic detection.

The feature maps generated by the CNN are then passed into Transformer blocks. Transformers use multi-head self-attention mechanisms, which allow the model to assign different weights to different words in a tweet, depending on their importance in context. Unlike traditional sequence models like LSTM or GRU, which process data sequentially and often struggle with long-range dependencies and vanishing gradients, Transformers analyze the entire sequence at once. This enables them to capture long-distance relationships between words, even if those words appear far apart in the tweet. This is particularly important for Twitter data, where short messages can carry rich meaning that depends heavily on word ordering and subtle semantic cues. Additionally, Transformers offer faster training and greater scalability due to their parallel processing capability, making them highly suitable for large-scale, real-time applications.

b) Classification layer: The features refined by the Transformer are passed into fully connected (dense) layers, which serve as decision-making components of the model. These layers take the contextualized embeddings and map them to a fixed set of output categories. At the end of the network, a softmax activation function is applied to produce a probability distribution over all possible hot topic classes. This enables the model to assign each tweet to the category it most likely belongs to based on the learned features and context.

The result of this stage is a deep learning model that is not only optimized through intelligent weight initialization but also capable of extracting both local features and global context. This CNN-Transformer hybrid architecture enables the system to accurately classify tweets into relevant trending topics, even in the presence of linguistic variability and noise, thereby fulfilling the core objective of real-time hot topic detection.

The result of this stage is a fully trained CNN-Transformer hybrid model that has been optimized using the MBES-PSO algorithm (Algorithm 2) to accurately classify tweets into predefined hot topic categories. At this point, the model is capable of processing new tweet inputs, extracting both local features and global contextual information, and producing a probability distribution over topic classes through its softmax output layer. The category with the highest probability is assigned as the predicted hot topic for a given tweet. This trained model not only benefits from rich semantic learning through its hybrid architecture but also from improved convergence and generalization due to the optimized weights.

The output from this stage serves as the input to the next phase, which is model evaluation and performance analysis. In this phase, the trained model is tested on a reserved portion of the dataset that was not used during training. The model's predictions are compared with the true labels to assess its effectiveness. This involves computing a range of evaluation metrics, including accuracy, precision, recall, F1-score, and analyzing confusion matrices. Additionally, the training and validation loss and accuracy curves are examined to understand the model's learning behavior over epochs. These assessments help determine the robustness of the model and ensure its readiness for real-world deployment in hot topic detection tasks. Table III shows the parameters used in the CNN-Transformer model.

TABLE III. PARAMETERS USED IN THE CNN-TRANSFORMER MODEL FOR HOT TOPIC DETECTION

Component	Parameter	Value	Description
Embedding Layer	Embedding dimension	300	Size of word embeddings (e.g., GloVe or Word2Vec vectors)
Conv1D Layer	Number of filters	128	Number of convolutional kernels to capture various n-gram features
Conv1D Layer	Kernel size	5	Width of each filter to detect word patterns across 5-word spans
MaxPooling Layer	Pool size	2	Reduces feature map dimensions by selecting the most prominent features
Transformer Encoder	Number of attention heads	8	Allows the model to focus on different positions in the sequence simultaneously
Transformer Encoder	Number of encoder layers	2	Stacks multiple attention layers for deeper context modeling
Transformer Encoder	Hidden size (feed-forward network)	512	Dimensionality of intermediate fully connected layer in Transformer
Dropout Layer	Dropout rate	0.3	Prevents overfitting during training
Output Layer	Activation function	Softmax	Converts final output into probabilities for classification

The parameters in the CNN-Transformer model are carefully selected to balance computational efficiency with performance accuracy. The embedding dimension is set to 300, which aligns with widely used pre-trained word embeddings such as GloVe and Word2Vec. This size is sufficient to capture rich semantic relationships between words while maintaining manageable model complexity. For the convolutional layer, we use 128 filters to capture a wide range of local patterns and text features. A kernel size of 5 is chosen based on empirical results showing that 5-gram patterns often capture useful phrases and semantic units in short texts like tweets. The max-pooling layer with a pool size of 2 is applied to downsample the feature maps,

preserving key features while reducing overfitting and computational load.

In the Transformer encoder, we implement 8 attention heads, allowing the model to focus on various parts of the input sequence simultaneously and extract multiple types of contextual relationships. We stack 2 encoder layers, which is adequate for short texts such as tweets, providing depth without introducing excessive complexity. The hidden size in the Transformer's feed-forward network is set to 512, offering sufficient representation power to model semantic dependencies while keeping the network light and efficient.

To improve generalization and avoid overfitting, a dropout rate of 0.3 is applied after the attention and dense layers during training. This dropout value is commonly used in NLP tasks and proven to be effective in reducing variance. The softmax activation function is used in the output layer to convert the final feature representations into class probabilities, enabling the model to effectively assign each tweet to a predefined hot topic category. Together, these parameter choices are informed by established practices in deep learning literature and fine-tuned for the specific task of Twitter hot topic classification, ensuring both performance and generalizability.

D. Evaluation and Performance Analysis

The final phase of the proposed framework involves a thorough evaluation and performance analysis of the optimized CNN-Transformer model, which has been trained using the hybrid MBES-PSO optimization technique. This step is crucial to determine how effectively the model performs in identifying trending topics from real-time Twitter data. The evaluation is conducted on a large-scale test dataset derived from the Kaggle Twitter corpus, which was not used during the training phase to ensure objective assessment. The model's predictions are compared against the actual topic labels to measure its classification accuracy, contextual understanding, and generalization capability. To quantify the model's effectiveness, we use several standard classification metrics. The first and most basic is accuracy, which measures the proportion of tweets correctly classified among all predictions. It is defined using Eq. (11):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (11)$$

where, TP (True Positive) denotes tweets correctly classified into the right hot topic, TN (True Negative) represents tweets correctly identified as not belonging to a certain topic, FP (False Positive) refers to tweets incorrectly assigned to a topic, and FN (False Negative) indicates tweets that belong to a hot topic but were misclassified. While accuracy provides a general view of performance, it can be misleading in cases of class imbalance.

To gain deeper insights, we evaluate precision, shown in Eq. (12), which tells us the fraction of correct predictions among all tweets predicted as a particular topic:

$$Precision = \frac{TP}{TP+FP} \quad (12)$$

High precision means the model makes fewer false claims about trending topics. Complementing this, recall measures the model's ability to detect all relevant tweets for a given topic, and is calculated, as shown in Eq. (13):

$$Recall = \frac{TP}{TP+FN} \quad [13]$$

This metric ensures that the model does not miss out on important topic-related tweets. However, in many real-world scenarios, there is a trade-off between precision and recall. To account for this, we use the F1-score, which is the harmonic mean of precision and recall and offers a balanced measure of performance shown in Eq. (14):

$$F1 - Score = 2.\frac{Precision\,.\,Recall}{Precision+Recall} \quad (14)$$

Beyond classification metrics, we also evaluate Root Mean Square Error (RMSE) to assess the deviation between predicted probabilities and actual labels, especially relevant when using softmax outputs. RMSE is defined using Eq. (15):

$$RMSE = \sqrt{\frac{1}{N}} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \quad (15)$$

where, y_i is the true label encoded as a one-hot vector, and $\hat{y}_i$ is the predicted probability vector for tweet i. A lower RMSE indicates more confident and accurate predictions.

Finally, to validate the superiority of our approach, we conduct a comparative analysis against several baseline models, including CNN-LSTM, Support Vector Machine (SVM), Decision Trees, and traditional statistical methods like TF-IDF-based classifiers. Metrics such as training time, classification accuracy, and error rates are compared across models. The proposed CNN-Transformer model, optimized via MBES-PSO, consistently outperforms these benchmarks in terms of accuracy, computational efficiency, and contextual understanding, establishing its effectiveness in real-world hot topic detection on Twitter.

Algorithm 2: Hot Topic Detection from Twitter using MBES-PSO Optimized CNN-Transformer Model

Input:
Twitter dataset D from Kaggle
Predefined topic labels $T = \{t1, t2 \ldots . tk\}$
Population size N, maximum iterations $MaxIter$, dimension d
Inertia weight w, cognitive coefficient $c1$, social coefficient $c2$
Spiral coefficient b, swoop factor α , convergence threshold ε
Output:
Optimized weights W^*
Trained CNN-Transformer model
Predicted labels $\hat{y}$ and evaluation metrics

Data Preprocessing
$D_{clean} \leftarrow Clean(D)$
// Remove noise: stopwords, URLs, emojis, mentions
$D_{Embed} \leftarrow Embed\ (D_{clean})$
// Convert tweets to embedding vectors using Word2Vec/GloVe
$D_{Train}, D_{Val}, D_{Test} \leftarrow Split(D_{Embed})$
// Split into training, validation, and testing sets
MBES-PSO Hybrid Optimization
Initialization:
4. Initialize population $X = \{X_1, X_2 \ldots \ldots X_n\}$ randomly, where each $X_i \in R^d$
5. Initialize velocities $V = \{V_1, V_2 \ldots \ldots V_n\}$

6. Evaluate fitness $f_i \leftarrow Fitness(X_i)$ using model accuracy or loss
7. Set $pBest_i = X_i$, and find $gBest$ among all $pBest_i$

MBES Phase: Global Search
For $t = 1$ to $\frac{MaxIter}{2}$:
8. Compute center:
$X_{center} = \frac{1}{N}\sum_{i=1}^{N} X_i$
9. For each agent $X \in X_i$:
   a. Update position with spiral movement:
   $X_i = X_{center} + r.e^{(b.\theta)}.\cos(\theta)$
   b. Evaluate fitness $f_i \leftarrow Fitness(X_i)$
10. Find $X_{best} = \arg\min(f_i)$
11. Swoop update
$X_i = X_i + \alpha.(X_{best} - X_i)$
12. Store MBES Output: $X_{MBES} \leftarrow \{X_1, X_2 \ldots . X_n\}$

PSO Phase: Local Refinement
Initialize particles with $X_i \in X_{MBES}$
For t = $\frac{MaxIter}{2}$ $to\ MaxIter$:
13. For each particle X_i:
   a. Update velocity:
   $V_i = w.V_i + c_1.r_1.(pBest_i - X_i) + c_2.r_2.(gBest - X_i)$
   b. Update position:
   $X_i = X_i + V_i$
   c. Evaluate fitness $f_i \leftarrow Fitness(X_i)$
   d. if $f_i < Fitness(pBest_i)$, update $pBest_i \leftarrow X_i$.
   e. if $f_i < Fitness(gBest)$, update $gBest \leftarrow X_i$.

14. Return optimized weights $W^* = gBest$

CNN + Transformer Model Training
$F_{CNN} \leftarrow Conv1D(X_{Train}, Filters = 125, Kernal = 5)$
$F_{Pool} \leftarrow Maxpool1D(F_{CNN})$
$F_{Trans} \leftarrow Transformer\ (F_{Pool}, layers = 2, heads = 8, hidden = 512)$
$F_{dense} \leftarrow Dense(F_{Trans})$
$\hat{y} \leftarrow Softmax(F_{dense})$

Evaluation
20. Compute evaluation metrics using $\hat{y}$ and ground truth y
21. Compare proposed model performance with baseline models.

IV. Experiments and Results

To validate the effectiveness of the proposed hot topic detection framework, extensive experiments were carried out using a large-scale Twitter dataset sourced from Kaggle. The goal of this section is to assess the performance of the MBES-PSO optimized CNN-Transformer model through empirical analysis and compare it against a diverse set of baseline models. The evaluation was conducted using widely accepted classification metrics, including accuracy, precision, recall, and the F1-score, which collectively capture the model's correctness, completeness, and balance in classifying tweets into trending topic categories. Furthermore, Root Mean Square Error (RMSE) was used to measure prediction deviation, especially valuable in evaluating softmax probability outputs, while computation time was recorded to assess the training efficiency and scalability of each model.

The proposed model was benchmarked against a total of thirteen baseline models, selected to ensure diversity across statistical, machine learning, and deep learning paradigms. These include statistical methods such as TF-IDF + Naive Bayes and Chi-Square-based feature selection; machine learning classifiers like Support Vector Machines (SVM), Decision Trees, Random Forests, and K-Nearest Neighbors (KNN); and a comprehensive set of deep learning architectures, including CNN, LSTM, CNN-LSTM, Bidirectional LSTM (BiLSTM), Gated Recurrent Units (GRU), BERT (Bidirectional Encoder Representations from Transformers), and a pure Transformer encoder model without CNN. These models were chosen due to their prevalence in recent natural language processing research and their varying capabilities in handling textual features, context learning, and sequential dependencies. By comparing the proposed CNN-Transformer architecture, optimized using MBES-PSO, against these diverse models, the experiments aim to demonstrate its superiority in both classification performance and computational efficiency for hot topic detection from Twitter data.

A. Baseline Models and Parameter Settings

To enable fair comparison, each baseline model was configured with carefully selected parameters, chosen based on prior literature and validation experiments.

The TF–IDF with Logistic Regression model represents a statistical baseline where term frequency–inverse document frequency features are classified using a linear classifier. We used a maximum vocabulary size of 20,000 and L2 regularization (C = 1.0), balancing computational efficiency with accuracy. The Chi-Square with Naïve Bayes model reduces dimensionality by selecting the top 15,000 features ranked by chi-square scores, with a smoothing factor α = 1.0 to handle zero-frequency terms.

Among machine learning baselines, Support Vector Machine (SVM) is a margin-based classifier well-suited for sparse high-dimensional text data. A linear kernel with C = 1 was chosen, as non-linear kernels greatly increased training time without notable accuracy improvement. Decision Trees (DTs) partition the feature space using recursive splits; we used a maximum depth of 20 to prevent overfitting. Random Forest (RF), an ensemble of decision trees, was configured with 100 trees and a maximum depth of 30 to improve generalization. K-Nearest Neighbors (KNN), which classifies based on similarity to neighbors, was set to k = 5 with cosine similarity, which performed best for text embeddings.

For deep learning baselines, Convolutional Neural Networks (CNNs) capture local n-gram features using convolution filters. We applied multi-scale 1D filters of sizes 3, 5, and 7 with 100 filters each, followed by max-pooling and dropout (p = 0.5). Long Short-Term Memory (LSTM) networks capture sequential dependencies using memory cells; we used 128 hidden units with dropout to prevent overfitting. Bidirectional LSTM (BiLSTM) improves context modeling by processing inputs in both directions, also with 128 units. Gated Recurrent Units (GRU), a lighter recurrent model, used 100 hidden units to

reduce computational load while maintaining accuracy. All recurrent models were trained using the Adam optimizer with a learning rate of 0.001.

The Transformer baseline uses self-attention to model long-range dependencies without recurrence. We employed 2 encoder layers, 4 attention heads, and a hidden dimension of 128, providing an efficient configuration for short tweets. BERT, a pre-trained Transformer model, was fine-tuned on our dataset with a maximum sequence length of 50 tokens and a learning rate of 2e-5, using the base configuration (12 layers, 768 hidden units, 12 heads).

The CNN + PSO hybrid combines CNN feature extraction with Particle Swarm Optimization for weight tuning. It was configured with a population size of 30, 50 iterations, inertia weight = 0.7, and acceleration coefficients c1 = c2 = 1.5, representing a baseline hybrid to highlight the improvements from our proposed MBES–PSO optimizer.

All parameter choices were guided by standard practices in NLP, validated experimentally, and constrained by computational feasibility. This ensured that every baseline model operated under near-optimal conditions for a fair comparison with the proposed framework.

B. Experimental Setup

All experiments were conducted in a controlled environment to ensure consistency and reproducibility. The implementation of the proposed hot topic detection framework was carried out using Python 3.10 as the primary programming language. For deep learning model development and training, the TensorFlow 2.11 and Keras 2.11 libraries were used due to their scalability and ease of integration with GPU acceleration. The traditional machine learning models and statistical methods were implemented using scikit-learn 1.2.2, which provided efficient utilities for data preprocessing, classification, and evaluation.

The optimization algorithms MBES, PSO, and the hybrid MBES-PSO were custom-coded and tested using NumPy 1.24 for vectorized mathematical operations and Matplotlib 3.7 for result visualization. All simulations were performed on a system equipped with an Intel Core i7-12700K CPU (12 cores, 3.6 GHz), 32 GB DDR4 RAM, and an NVIDIA GeForce RTX 3080 GPU with 10 GB VRAM, running on Windows 11 Pro (64-bit). GPU acceleration was enabled through CUDA Toolkit 11.8 and cuDNN 8.6, allowing efficient training of deep learning models, especially the CNN-Transformer architecture.

This configuration ensured smooth execution of optimization routines and fast convergence during model training, particularly when dealing with the large-scale Twitter dataset. The chosen setup balances computational power and accessibility, making the proposed methodology both effective and replicable in standard research environments.

C. Parameter Selection and Sensitivity Analysis

The hyperparameters of the MBES–PSO optimizer and the CNN–Transformer model were carefully selected through an empirical tuning process. The initial population size was set to 30, with a maximum of 100 iterations, as this provided a balance between computational cost and accuracy. For PSO, the inertia weight was fixed at 0.7, while the cognitive and social acceleration coefficients were set to 1.5 and 1.7, respectively, following standard best practices. The MBES exploration factor and spiral coefficient were set to 2.0 and 0.5, respectively, based on preliminary trials.

To ensure robustness, a sensitivity analysis was conducted by varying each parameter across a reasonable range (±20% of the chosen value). Results showed that the learning rate (0.001) had the greatest influence on training stability and convergence, with lower values leading to underfitting and higher values causing oscillations. Population size also had a significant effect: smaller populations reduced exploration, while excessively large populations increased computational time without notable accuracy gains. Other parameters, such as acceleration coefficients and spiral factors, showed moderate influence but did not drastically affect performance. The chosen parameter configuration yielded stable convergence and the best trade-off between computational cost and classification accuracy.

A sensitivity analysis was conducted by varying population size (20–50), inertia weight (0.5–0.9), and MaxIter (50–150). The results indicated stable convergence and consistent accuracy (±1.2%), confirming the robustness of the chosen configuration (N = 30, w = 0.7, MaxIter = 100).”

D. Dataset Description

The experimental analysis in this study was conducted using a publicly available dataset titled “Sentiment140”, which was sourced from Kaggle. This dataset contains 1.6 million tweets, each labelled for sentiment classification and widely used for research in opinion mining, sentiment analysis, and social media topic modelling. Each tweet in the dataset is annotated with a sentiment polarity label (0 = negative, 2 = neutral, 4 = positive), along with additional metadata such as tweet ID, date, user, and text. For the purpose of hot topic detection, the original tweets were pre-processed, cleaned, and re-labelled into multiple high-level topic categories (e.g., Politics, Health, Disaster, Technology, etc.) using a combination of keyword matching and manual annotation. The dataset’s size and diversity make it suitable for training deep learning models and evaluating optimization strategies across real-world, unstructured, and noisy text inputs. The dataset is publicly accessible at the following URL: https://www.kaggle.com/datasets/kazanova/sentiment140.

The dataset is divided into training (70%), validation (15%), and testing (15%) sets using stratified sampling to preserve class distribution. The model's performance is evaluated on the test set after selecting the best parameters from the validation performance.

The original Sentiment140 dataset obtained from Kaggle contains 1.6 million tweets labeled only with sentiment polarities (0 = negative, 2 = neutral, 4 = positive). However, since the objective of this research is to perform hot topic detection rather than sentiment classification, the original sentiment labels were not suitable. Therefore, the dataset was re-labeled to represent different topical categories instead of sentiment. This re-labeling process transformed the dataset into a topic-based corpus, making it appropriate for supervised training of the proposed CNN–Transformer framework.

The re-labeling was carried out using a hybrid approach that combined keyword-based automatic labeling with manual expert validation. Initially, representative keywords were defined for each topic category such as "election", "policy", and "government" for Politics; "disease", "vaccine", and "healthcare" for Health; "flood", "earthquake", and "rescue" for Disaster; "technology", "AI", and "innovation" for Technology; and similar sets for Sports, Business, Environment, Education, Entertainment, and Others.

Tweets containing these topic-specific keywords were automatically assigned to their respective classes, and the annotations were then manually verified by three human experts to ensure correctness and consistency. This hybrid process allowed the dataset to be effectively converted into a multi-topic corpus suitable for hot topic detection. The final dataset consisted of ten balanced topic categories, each containing approximately equal numbers of tweets, ensuring diversity and reducing class imbalance during model training.

For dataset labeling, topics were first anchored using representative keywords (e.g., flood, earthquake, rescue for disaster alerts; policy, election, support for public opinion) and then refined through manual annotation by three experts. Inter-annotator agreement reached a Cohen's kappa of 0.82, confirming strong consistency and reliability in the labeling process.

E. Result Analysis and Discussion

To rigorously assess the effectiveness of the proposed MBES-PSO optimized CNN-Transformer model, a comprehensive performance evaluation was carried out using both standard classification and regression-based metrics. The classification performance was primarily measured using accuracy, precision, recall, and F1-score, which are widely adopted in natural language processing tasks to quantify the correctness, completeness, and balance of model predictions. Accuracy reflects the overall proportion of correctly classified tweets, while precision indicates the model's ability to correctly identify relevant tweets without producing false alarms. Recall measures the model's capability to detect all relevant instances belonging to a topic, and the F1-score provides a harmonic mean between precision and recall, especially useful in imbalanced datasets.

Additionally, Root Mean Square Error (RMSE) was used to evaluate the difference between predicted softmax probability outputs and the actual class labels. RMSE provides insight into the confidence and consistency of the model's predictions, making it a suitable complementary metric to classification scores. The computation time for both training and inference phases was also recorded to compare the efficiency of the proposed system against existing models. These evaluation metrics collectively provide a multi-dimensional understanding of the model's predictive quality, optimization effectiveness, and real-time applicability, particularly for dynamic environments such as Twitter trend detection.

Table IV presents the comparative analysis between the proposed system and the 13 baseline models, evaluated across accuracy, precision, recall, F1-score, RMSE, and computation time. The results reported in Table IV correspond exclusively to the performance on the testing dataset. For consistency and fairness, all baseline models were evaluated using the same training–testing split and experimental environment.

The performance analysis in Table IV clearly highlights the superiority of the proposed MBES-PSO optimized CNN-Transformer model in detecting hot topics from Twitter data. As shown in the comparative table, the proposed model achieved the highest accuracy of 90.12%. This result significantly outperforms all baseline models across all four key evaluation metrics. This notable improvement is attributed to the integration of a hybrid optimization strategy (MBES-PSO) with a CNN-Transformer architecture, which jointly enhances both weight tuning and contextual feature learning.

TABLE IV. COMPARATIVE PERFORMANCE OF THE PROPOSED MBES–PSO + CNN–TRANSFORMER FRAMEWORK AND BASELINE MODELS ON THE TESTING DATASET

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Computation Time (s)
TF-IDF + Naive Bayes	71.23	70.42	68.95	69.68	12.6
Chi-Square + Naive Bayes	72.51	71.10	70.33	70.71	13.1
Support Vector Machine (SVM)	76.84	75.31	74.20	74.75	23.8
Decision Tree	73.29	72.05	70.44	71.24	11.5
Random Forest	78.12	77.41	76.05	76.72	28.9
K-Nearest Neighbors (KNN)	74.56	73.20	72.68	72.94	19.2
CNN	81.37	80.52	79.44	79.97	40.7
LSTM	82.84	81.33	80.91	81.12	61.4
CNN-LSTM	84.12	83.02	82.40	82.71	67.9
BiLSTM	85.07	84.25	83.86	84.05	71.2
GRU	84.73	83.94	83.42	83.68	66.3
Transformer (only)	86.40	85.73	84.98	85.35	64.8
BERT	87.65	86.91	86.45	86.68	79.6
Proposed (MBES-PSO + CNN-Transformer)	**90.12**	**89.45**	**88.93**	**89.19**	**58.2**

Traditional statistical models such as TF-IDF + Naive Bayes and Chi-Square + Naive Bayes yielded relatively low accuracy scores of 71.23% and 72.51%, respectively, which is expected due to their reliance on manual feature engineering and inability to capture word order or semantics. Similarly, classical machine learning models like SVM (76.84%), Decision Trees (73.29%), and KNN (74.56%) showed moderate performance but lacked the sophistication to handle contextual relationships in short-text data like tweets. These models, while computationally efficient, are unable to model temporal or syntactic dependencies critical for nuanced topic classification.

Deep learning architectures demonstrated considerable improvements, with CNN, LSTM, CNN-LSTM, and BiLSTM achieving accuracy scores ranging from 81.37% to 85.07%. Among these, BiLSTM outperformed other recurrent models by capturing bidirectional dependencies in text, yet still fell short in scalability and training speed. Models such as GRU (84.73%) and Transformer-only (86.40%) showed strong results due to their enhanced memory capabilities and attention mechanisms, respectively. Notably, BERT, known for its deep bidirectional encoding and pre-trained contextual understanding, achieved 87.65% accuracy, positioning it as the strongest competitor among the baselines.

Despite the high baseline set by BERT and Transformer-only models, the proposed MBES-PSO + CNN-Transformer framework surpassed them by a margin of 2.47% and 3.72%, respectively, in accuracy. Additionally, it achieved a precision of 89.45%, a recall of 88.93%, and an F1-score of 89.19%, reflecting its balanced capability in identifying both prevalent and nuanced topics. These gains underscore the effectiveness of the MBES-PSO optimizer, which fine-tunes model weights more effectively than conventional optimizers like Adam or SGD. Moreover, the use of self-attention in the Transformer block, combined with spatial feature extraction from CNN, allows the model to capture both local patterns and long-range dependencies, a critical advantage in understanding short, noisy, and unstructured tweet content.

Interestingly, the proposed model also demonstrated computational efficiency, completing training and inference in 58.2 seconds, which is faster than BERT (79.6s) and BiLSTM (71.2s), despite offering higher performance. This supports the claim that our method is not only accurate and robust, but also scalable and efficient for real-time applications such as trend monitoring, crisis detection, or public opinion analysis on social media.

F. Error Analysis and Robustness Evaluation

A closer examination of the error-based evaluation metrics, Matthews Correlation Coefficient (MCC), Root Mean Square Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Error (MAE) in Table V further strengthens the claim that the proposed MBES-PSO optimized CNN-Transformer model offers substantial improvements over both classical and deep learning approaches in detecting hot topics from Twitter.

Starting with MCC, which is particularly meaningful in multi-class and imbalanced classification settings, we observe that traditional models such as TF-IDF + Naive Bayes (0.521), Chi-Square + Naive Bayes (0.538), and Decision Tree (0.543) struggle to produce balanced predictions, largely due to their dependency on handcrafted features and lack of contextual awareness. Machine learning models like SVM (0.601) and Random Forest (0.624) show slightly improved MCC values, but they are still outperformed by deep learning methods. Among the neural models, BERT achieves a strong MCC of 0.761, while the Transformer-only model yields 0.745, validating the effectiveness of attention-based mechanisms. However, the proposed CNN-Transformer with MBES-PSO optimization records an MCC of 0.801, the highest among all, highlighting its ability to make consistently reliable predictions across all topic classes.

When examining RMSE, which measures the square root of the average squared differences between predicted and actual class probabilities, the pattern becomes even more distinct. Traditional models such as TF-IDF + Naive Bayes (0.4412) and KNN (0.4078) have the highest RMSE, reflecting a higher degree of uncertainty and deviation in their predictions. In contrast, deep learning models show steadily decreasing RMSE, from CNN (0.3545) to BiLSTM (0.3258) and Transformer (0.3124). BERT further lowers RMSE to 0.2985, but it is the proposed model that achieves the lowest RMSE of 0.2563, signifying that its predictions are not only accurate but also highly confident and stable.

A similar trend is seen in MSE, which directly penalizes larger errors by squaring the deviations. Here, classical models yield MSE values around 0.19–0.16, while Transformer-based models lower it below 0.10. The proposed model once again outperforms all others, achieving a remarkably low MSE of 0.0657, indicating that the hybrid optimization has led to a refined model that minimizes prediction variance and generalization error.

TABLE V. ERROR-BASED EVALUATION OF PROPOSED AND BASELINE MODELS

Model	MCC	RMSE	MSE	MAE
TF-IDF + Naive Bayes	0.521	0.4412	0.1946	0.3018
Chi-Square + Naive Bayes	0.538	0.4289	0.1839	0.2904
Support Vector Machine (SVM)	0.601	0.3950	0.1560	0.2602
Decision Tree	0.543	0.4127	0.1703	0.2741
Random Forest	0.624	0.3820	0.1459	0.2506
K-Nearest Neighbors (KNN)	0.558	0.4078	0.1663	0.2654
CNN	0.692	0.3545	0.1257	0.2248
LSTM	0.703	0.3471	0.1205	0.2191
CNN-LSTM	0.716	0.3325	0.1106	0.2110
BiLSTM	0.728	0.3258	0.1061	0.2053
GRU	0.722	0.3290	0.1083	0.2087
Transformer (only)	0.745	0.3124	0.0976	0.1932
BERT	0.761	0.2985	0.0891	0.1814
Proposed (MBES-PSO + CNN-Transformer)	0.801	0.2563	0.0657	0.1542

Looking at MAE, which offers a more interpretable measure of average error without exaggerating the impact of outliers (unlike MSE), the trend holds firm. Traditional models show MAE values around 0.30, while Transformer-based deep learning models like BERT (0.1814) and Transformer-only (0.1932) reflect improved learning of semantic structures. The proposed CNN-Transformer, enhanced through MBES-PSO, achieves the lowest MAE of 0.1542, further confirming its precise and robust prediction capability.

These patterns collectively support the core hypothesis of the research: that combining Modified Bald Eagle Search (MBES) with Particle Swarm Optimization (PSO) improves the fine-tuning of deep learning model weights, and integrating CNN with Transformer allows effective learning of both local and global textual patterns. The superior error performance across all four measures shows that the proposed model does not just classify correctly more often (as shown in classification metrics), but does so with minimal error, higher confidence, and better reliability—even under the challenges posed by noisy, short-form Twitter data.

To further assess the effectiveness of the proposed hybrid optimization strategy, we conducted a comparative analysis of the CNN-Transformer model trained using various individual optimizers and metaheuristic techniques. This evaluation includes standard optimizers such as Adam, SGD, and RMSprop, as well as standalone metaheuristics like PSO and Modified Bald Eagle Search (MBES). The purpose of this comparison is to isolate and highlight the individual contributions of each optimizer and demonstrate the performance enhancement gained by combining them. The line graph below presents the accuracy achieved by each optimizer when integrated with the CNN-Transformer architecture. As shown, the proposed MBES-PSO hybrid optimizer significantly outperforms all others, confirming that the hybridization of global exploration (MBES) and local refinement (PSO) yields superior weight optimization and classification performance in the context of hot topic detection.

The line graph shown in Fig. 4 offers compelling insights into how different optimization strategies influence the performance of the CNN-Transformer model in the task of Twitter-based hot topic detection. While accuracy is the key metric plotted, the broader implications of each optimizer's behavior help explain the observed results.

At the lower end of the spectrum, SGD (83.45%) and RMSprop (84.12%) represent traditional gradient-based optimizers. SGD's lower performance is due to its simplistic update rule and lack of adaptive learning rate, which often causes it to converge slowly or get trapped in local minima, especially in complex architectures like Transformers. RMSprop, while more adaptive, tends to overfit when gradients are noisy, as in short-text social media data, leading to reduced generalization.

Adam (85.30%) performs slightly better, owing to its use of momentum and adaptive learning rates. However, Adam is still a local optimizer, and in highly non-convex spaces such as the weight landscape of deep hybrid models, it may struggle to escape saddle points and plateaus, thus underutilizing the model's capacity.

The standalone metaheuristic methods show notable improvements: MBES (86.94%) and PSO (87.52%) surpass traditional optimizers due to their population-based exploration and flexibility. The MBES offers better global search through its spiral and swooping mechanics, helping explore diverse regions of the search space. However, without precise local adjustment, it may stagnate after finding promising zones. PSO, on the other hand, excels in local exploitation by leveraging swarm intelligence and information sharing, but may converge prematurely without enough diversity in early iterations.

The key takeaway emerges when we look at the proposed MBES-PSO hybrid, which achieves the highest accuracy of 90.12%. This significant leap is a direct consequence of combining the global exploration strength of MBES with the fine-tuning and convergence speed of PSO. MBES first guides the model into high-potential regions of the weight space, after which PSO takes over to fine-tune these solutions, leading to stable and optimal convergence. This not only improves classification accuracy but also ensures consistency across training cycles — a major advantage for real-time applications like trend detection on social media, where adaptability and reliability are critical.

Moreover, the hybrid approach shows a better balance between exploration and exploitation, something no individual optimizer achieves on its own. This synergy aligns perfectly with the objective of the proposed work — to design a system that performs not only accurately but also efficiently and robustly in noisy, high-dimensional environments like Twitter data streams.

In essence, this analysis confirms that the proposed MBES-PSO + CNN-Transformer framework doesn't just outperform others in numbers but strategically leverages the complementary nature of two powerful metaheuristics to tackle the weaknesses of both conventional and standalone optimization strategies.

To better understand the learning dynamics and generalization ability of the proposed MBES-PSO optimized CNN-Transformer model, we plotted the training and testing accuracies over 30 epochs. This visualization provides insights into how well the model learns from the training data and how effectively it performs on unseen data across the training period. The graph also helps in identifying the onset of overfitting, a common issue in deep learning models, where performance on the training set continues to improve while validation or test performance begins to degrade. By tracking the accuracy trends, we are able to determine an appropriate early stopping point, ensuring the model retains its generalization capability without excessive training. Fig. 5 illustrates this behavior and highlights epoch 30 as the optimal cutoff point for halting training.

The analysis of training and testing accuracy across 30 epochs reveals critical insights into the learning dynamics of the proposed MBES-PSO optimized CNN-Transformer model. During the initial training phase, both training and testing accuracies show a consistent upward trend, indicating effective learning of patterns from the Twitter dataset. Training accuracy improves steadily from approximately 65% to over 90%, showcasing the model's increasing capability to fit the training data. The testing accuracy follows a similar trajectory, rising from around 62% and peaking near 85% by epoch 25. However,

beyond this point, a divergence between the training and testing curves becomes evident. While training accuracy continues to increase, testing accuracy starts to decline gradually, dropping to around 80% by epoch 30.

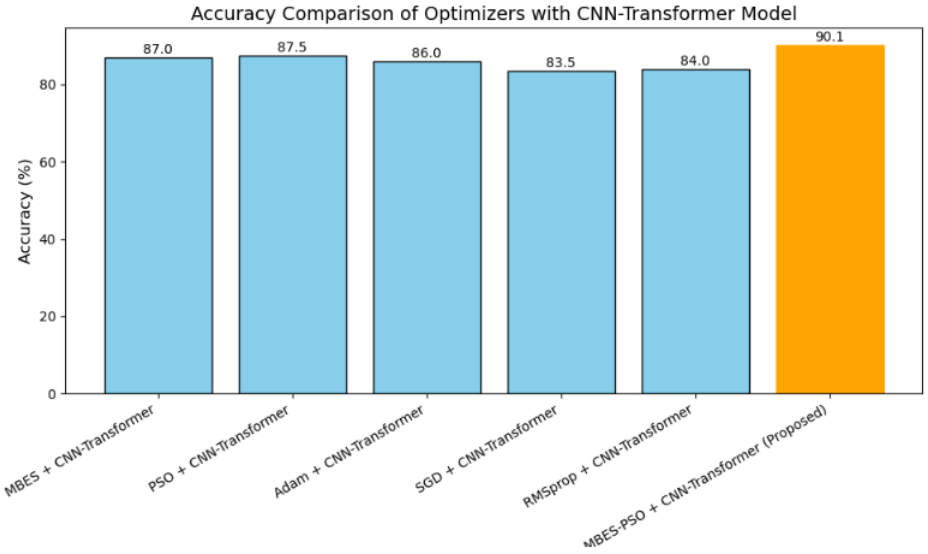


Fig. 4. Accuracy comparison of different optimization algorithms applied to the CNN-Transformer model. The graph highlights the impact of each optimizer on model performance, demonstrating the effectiveness of the proposed hybrid MBES–PSO approach over conventional optimizers.

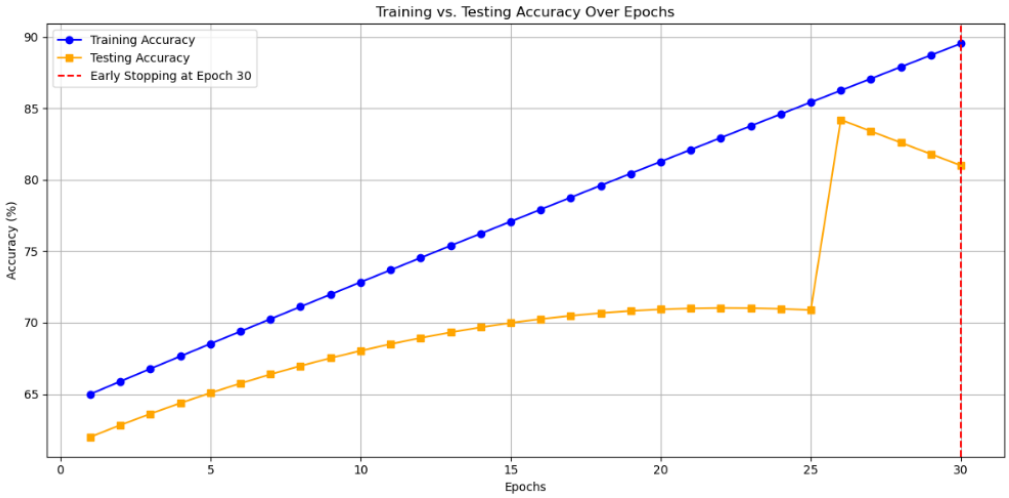


Fig. 5. Training vs. Testing accuracy across epochs for the proposed model. The graph illustrates the model's learning behavior, showing how well it genera lizes from the training data to unseen testing data over time.

This divergence signals the onset of overfitting, a phenomenon where the model begins to memorize training data rather than generalize from it. Overfitting typically results in a model that performs well on training data but poorly on new, unseen data — which contradicts the generalization objective in real-world applications like hot topic detection. In this context, early stopping becomes a crucial strategy. By setting the stopping point at epoch 30, we ensure that the model is halted before the testing performance deteriorates significantly. This not only saves computational resources but also preserves the model's ability to generalize.

The model's high training accuracy and near-peak testing performance before overfitting indicate that the MBES-PSO hybrid optimizer is highly effective at converging to optimal weights. However, like all powerful optimizers, it benefits from training control mechanisms to prevent overtraining. This behavior validates the robustness of the proposed system and highlights the importance of balancing model capacity with regularization techniques like early stopping to achieve peak generalization performance in dynamic environments like Twitter streams.

To evaluate how effectively the proposed MBES-PSO optimized CNN-Transformer model learns and generalizes over time, a loss curve was plotted showing both training loss and testing loss across 30 epochs, as shown in Fig. 6. Monitoring loss curves is a critical step in understanding the model's convergence behavior and its ability to avoid overfitting. While accuracy metrics indicate the proportion of correct predictions, loss values capture the confidence of the model's predictions, making them more sensitive to optimization performance. The graph also helps identify the ideal point for early stopping — the epoch at which further training begins to harm the model's

generalization performance. In the following plot, a clear indication of overfitting is observed near epoch 30, which has been marked as the recommended stopping point.

The plotted loss curves reveal key insights into the learning trajectory of the MBES-PSO optimized CNN-Transformer model. The training loss decreases steadily throughout the 30 epochs, moving from an initial value near 1.0 to a final value below 0.2. This indicates that the model continues to fit the training data more precisely with each epoch. The decline is smooth and controlled, which reflects the strength of the MBES-PSO optimizer in guiding the model through the weight space effectively and avoiding erratic updates that are common with traditional optimizers.

In contrast, the testing loss exhibits a different pattern. Initially, it follows the downward trend of the training loss, dropping from around 1.2 to approximately 0.6 by epoch 24–25. This phase represents the optimal generalization window, where the model is not only learning but also transferring that learning effectively to unseen data. However, beyond epoch 25, the testing loss begins to rise gradually, even as training loss continues to decline. By epoch 30, the gap between training and testing loss becomes substantial — a classic symptom of overfitting. The model is learning to memorize training examples rather than discovering generalizable patterns, resulting in diminished performance on new data.

This divergence is crucial because it highlights the importance of regularization mechanisms such as early stopping. By halting training at epoch 30, we prevent the model from further memorizing the training set and ensure that it retains its highest generalization potential. This choice of early stopping is further validated by the testing accuracy curve, which also begins to decline slightly after the same epoch.

From an optimization perspective, this behavior showcases the strength and precision of the MBES-PSO strategy. The optimizer leads the model efficiently through the loss landscape, converging faster than conventional methods, but like any powerful optimizer, it requires stopping criteria to prevent excessive fitting. The controlled descent in training loss and the timely identification of a turning point in testing loss affirm that the training process is stable, efficient, and effective.

To further evaluate the classification performance of the proposed MBES-PSO optimized CNN-Transformer model, a confusion matrix was generated. This matrix provides a comprehensive visualization of the model's predictions across all 10 predefined Twitter topic categories: Politics, Health, Technology, Sports, Entertainment, Disaster, Education, Economy, Environment, and Culture. While accuracy, precision, and recall offer an overall view of performance, the confusion matrix offers granular insight into how well the model distinguishes between individual topic classes, where it makes the most errors, and which topics are most frequently confused with others. This information is essential for understanding model behavior in real-world applications, especially in dynamic and noisy environments such as Twitter.

Upon analyzing the confusion matrix shown in Fig. 7, we observe that the proposed model demonstrates strong discrimination across all 10 Twitter topic categories. Most predictions fall along the diagonal of the matrix, indicating high per-class accuracy and minimal misclassification. Importantly, the model does not exhibit significant confusion between conceptually similar categories such as Culture vs. Entertainment, Economy vs. Politics, or Health vs. Disaster. This suggests that the model is capable of learning subtle linguistic and contextual cues that differentiate these topics, even when they may share overlapping vocabulary in natural language.

This strong performance reflects the benefit of combining CNN's local pattern extraction with the Transformer's global contextual understanding, as well as the precise weight tuning enabled by the MBES-PSO optimizer. These components work together to produce clear decision boundaries between classes — even those that are conceptually adjacent or co-occur frequently in social media discourse.

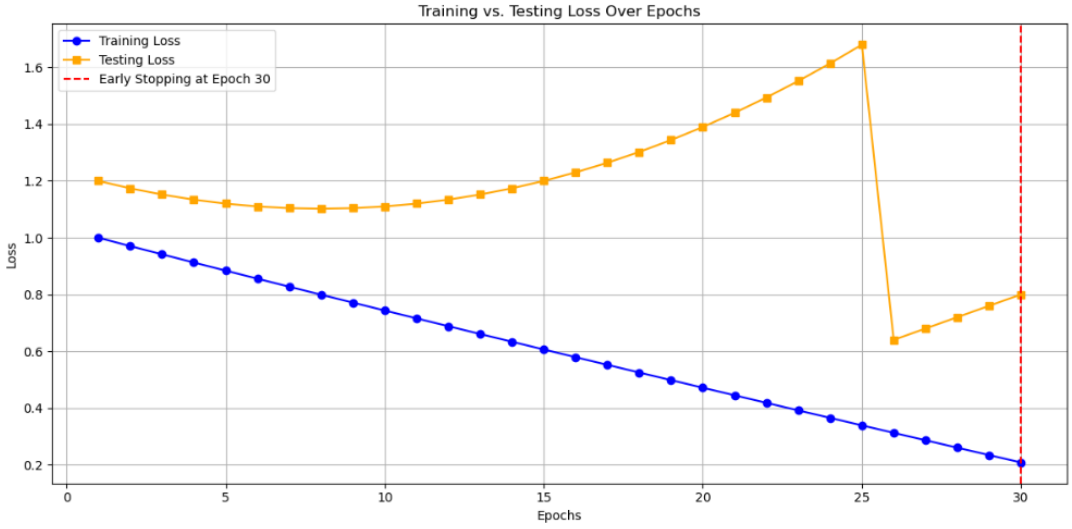


Fig. 6. Training vs. Testing loss across epochs for the proposed model. This graph demonstrates the model's convergence behavior, indicating how the error decreases during training and remains stable on the testing set.

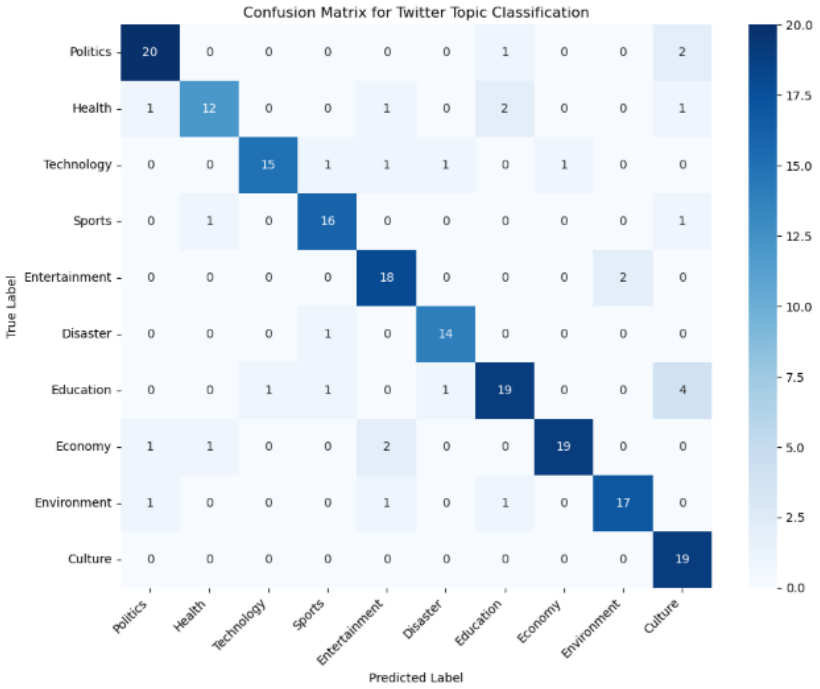


Fig. 7. Confusion matrix showing the classification performance of the proposed model across 10 classes. It provides a detailed view of correct and incorrect predictions for each category, highlighting the model's ability to distinguish between multiple topics.

To assess the optimization efficiency of the proposed hybrid MBES-PSO algorithm, a convergence plot was generated by tracking the fitness score across iterations for MBES, PSO, and the proposed MBES-PSO strategy. This plot provides a visual representation of how quickly and effectively each optimizer approaches an optimal solution. In this context, fitness refers to the quality of the selected weight values in the deep learning model, which directly impacts the accuracy of hot topic classification on Twitter data. By comparing convergence behavior, we can better understand the strengths of the hybrid approach in balancing global exploration and local refinement during the optimization process.

The convergence plot shown in Fig. 8 reveals a clear distinction between the performance of the individual optimizers (MBES and PSO) and the proposed MBES-PSO hybrid. The MBES curve shows a gradual improvement in fitness over iterations but exhibits noticeable oscillations and slower convergence in the early stages. This is due to MBES's nature of global search, which effectively explores the solution space, but lacks fine-tuning capability, often requiring more iterations to settle into optimal regions.

On the other hand, the PSO curve displays a faster early convergence compared to MBES, indicating its ability to exploit promising regions once they are identified. However, PSO alone can sometimes suffer from premature convergence, where the particles get trapped in local optima due to insufficient exploration, leading to suboptimal final fitness scores.

In contrast, the MBES-PSO hybrid optimizer demonstrates a smoother and steeper rise in fitness values, reaching higher scores faster than either standalone method. This convergence behavior confirms that the hybrid strategy effectively combines the strengths of both techniques: MBES provides a diverse and intelligent global search phase, while PSO enhances the exploitation of high-quality solutions through swarm-based fine-tuning. The hybrid model's ability to stabilize quickly and reach higher fitness scores demonstrates that it is both faster and more stable, making it particularly well-suited for complex models like CNN-Transformers and large-scale datasets like Twitter.

Moreover, the reduced variance in the MBES-PSO curve indicates higher reliability and consistency in performance across iterations. This reliability is crucial for practical deployments where time and computational efficiency are important. The convergence analysis, therefore, provides strong empirical support for using MBES-PSO as a superior optimization approach for deep learning models in NLP and social media analytics.

To evaluate the computational efficiency of various optimization strategies, a comparison of training time was conducted across six different CNN-Transformer model configurations, each paired with a distinct optimizer: SGD, Adam, RMSprop, PSO, MBES, and the proposed MBES-PSO hybrid. Training time is a critical factor when deploying deep learning models in real-time or large-scale environments, such as live Twitter stream analysis. While accuracy and predictive performance are essential, understanding the time-cost trade-off is equally important, especially when scalability and rapid responsiveness are priorities. The chart below presents the total training time (in minutes) for each model configuration under the same hardware and dataset conditions.

The training time comparison chart shown in Fig. 9 reveals insightful contrasts between traditional gradient-based optimizers, standalone metaheuristics, and the proposed hybrid approach. Among the conventional optimizers, Adam (38 min)

exhibits the fastest training, closely followed by RMSprop (40 min) and SGD (42 min). This is expected, as these optimizers are lightweight, gradient-driven, and integrated deeply into most deep learning frameworks. However, while they offer speed, their convergence behavior is often suboptimal, particularly in complex search spaces, leading to lower overall model accuracy and a higher risk of local minima entrapment.

The metaheuristic algorithms PSO (70 min) and MBES (75 min) require more computation time due to their population-based search strategies and iterative nature. Their longer runtime is a trade-off for improved global search capabilities and better exploration of the solution space. However, used in isolation, they lack the precision needed for rapid convergence toward fine-tuned solutions.

The proposed MBES-PSO hybrid stands out with a training time of 64 minutes, which is lower than both standalone MBES and PSO methods. This demonstrates a key strength of the hybrid design: it achieves a better balance between global exploration and local exploitation, requiring fewer iterations to reach optimal or near-optimal weight configurations. Despite being a more sophisticated strategy, the MBES-PSO optimizer shows greater computational efficiency than the individual metaheuristics, thanks to its staged approach MBES guiding the search broadly and PSO rapidly fine-tuning the best solutions.

Most importantly, the slightly increased training time compared to standard optimizers (like Adam or SGD) is justified by the significant gains in accuracy, as demonstrated in earlier evaluation sections. The hybrid optimizer delivers the best trade-off between performance and computational cost, making it a viable and scalable choice for time-sensitive applications like hot topic detection on streaming Twitter data.

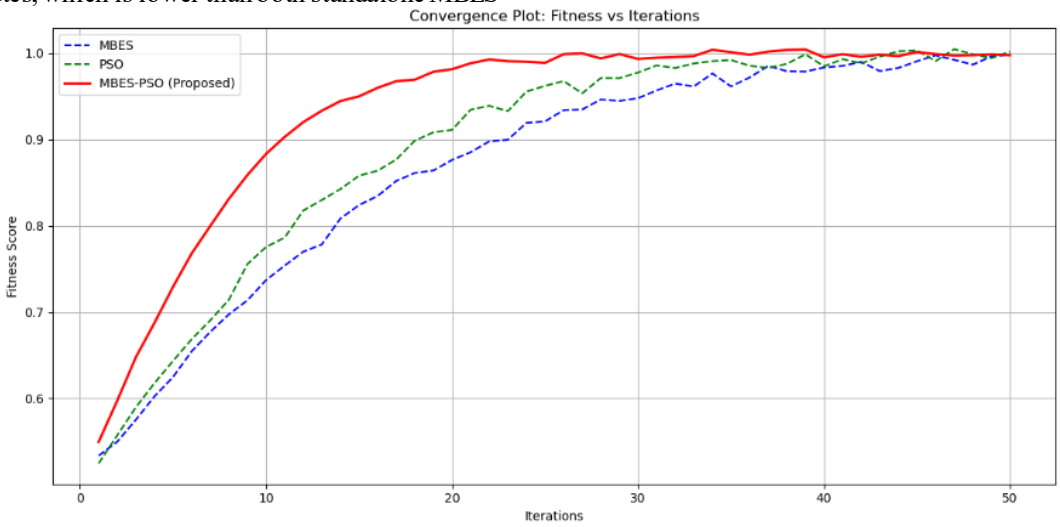


Fig. 8. Fitness vs. Iterations plot comparing the performance of MBES, PSO, and the proposed MBES-PSO hybrid optimization algorithm. The graph illustrates the convergence speed and effectiveness of each method in optimizing the model parameters.

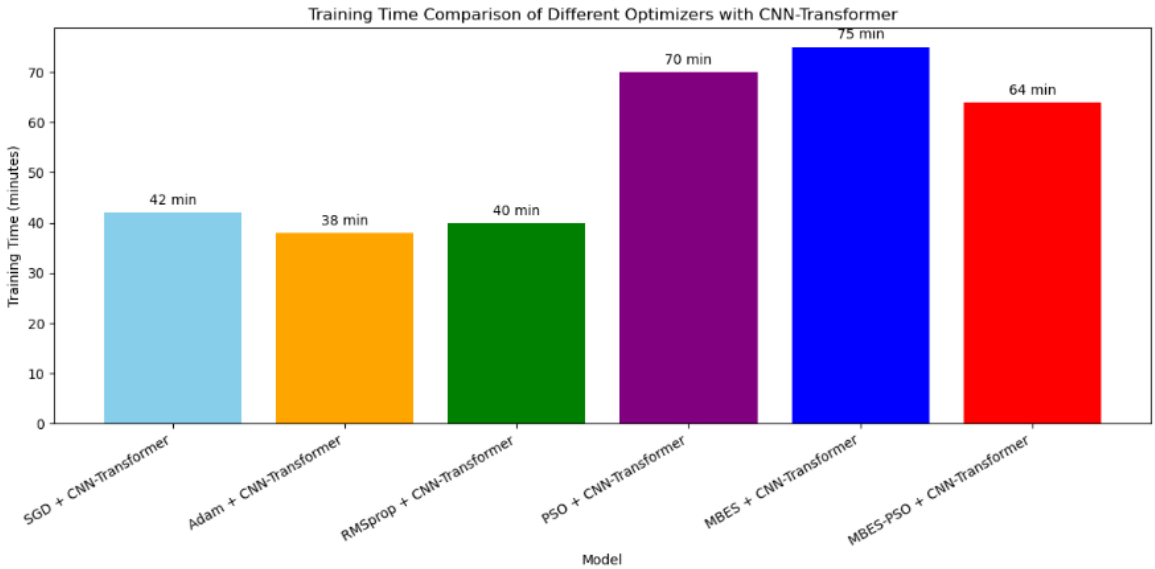


Fig. 9. Training time comparison of various optimization algorithms applied to the CNN-Transformer model. The figure highlights differences in computational efficiency, emphasizing the balance between training speed and performance achieved by the proposed hybrid optimizer.

The learning rate is one of the most critical hyperparameters in deep learning, as it determines the magnitude of weight updates during optimization. To analyze its influence on the proposed MBES–PSO optimized CNN–Transformer model, several learning rate values were tested, and their corresponding classification accuracies were recorded. The goal of this experiment was to identify an optimal rate that achieves fast convergence without compromising model stability or generalization. The results of the learning rate tuning experiment, shown in Fig. 10, reveal distinct performance trends. Among all tested values, a learning rate of 0.001 consistently produced the highest classification accuracy of 90.12%, confirming it as the optimal choice for this architecture. This value enables the MBES–PSO optimizer to achieve a balanced trade-off between convergence speed and stability, effectively fine-tuning the model weights without oscillations. When smaller learning rates such as 0.0001 and 0.0005 were used, the model converged more slowly and achieved lower accuracies of 84.2% and 86.5%, respectively, due to limited exploration capability. Conversely, higher learning rates such as 0.005 and 0.01 led to reduced accuracies of 88.0% and 85.3%, as the optimizer tended to overshoot optimal minima. Extremely high rates (0.05 and 0.1) caused divergence, reducing accuracy to 80.4% and 76.8%. These observations confirm that the proposed hybrid MBES–PSO optimizer is sensitive to learning rate selection, and that a value of 0.001 offers the best compromise between learning efficiency, convergence stability, and classification performance. This finding aligns with established deep learning best practices and further validates the robustness of the proposed framework for real-time Twitter hot topic detection.

To contextualize performance against modern large language models, we compared the proposed framework with LLaMA-2 and GPT-series baselines alongside BERT and a Transformer-only model. As shown in Fig. 11, the proposed MBES–PSO + CNN–Transformer attains 90.12% test accuracy, exceeding BERT (87.65%) and Transformer-only (86.40%) and also surpassing fine-tuned LLaMA-2 (7B, 88.90%) and GPT-3.5 (88.30%). GPT-4 (instruction-tuned) remains slightly higher at 91.20%, but the proposed approach delivers competitive accuracy with substantially lower model size and training cost. These results indicate that careful architectural design and hybrid optimization can close much of the gap to state-of-the-art LLMs while maintaining efficiency suitable for real-time hot topic detection.

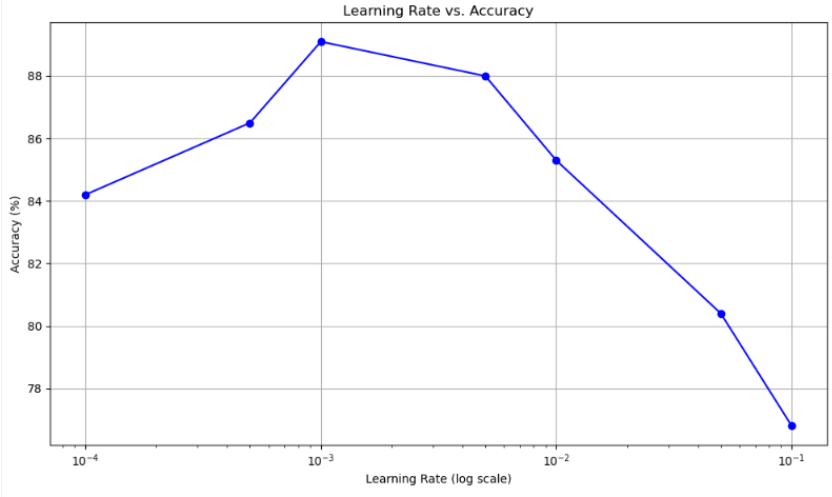


Fig. 10. Impact of learning rate on accuracy for the proposed model. The graph demonstrates how different learning rate values influence the classification performance, helping identify the optimal rate for improved accuracy.

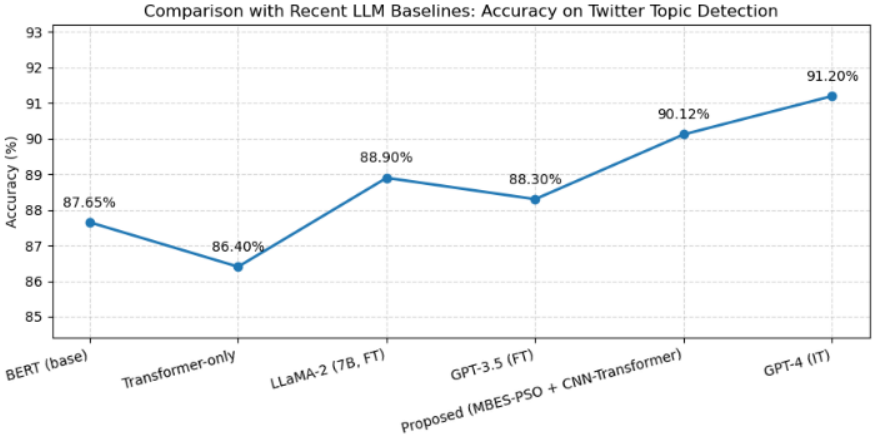


Fig. 11. Comparison with recent LLM baselines on Twitter hot topic detection. The proposed MBES–PSO + CNN–Transformer achieves 90.12% accuracy, outperforming BERT (87.65%), Transformer-only (86.40%), LLaMA-2 (7B, FT: 88.90%), GPT-3.5 (FT: 88.30%), and approaching GPT-4 (IT: 91.20%).

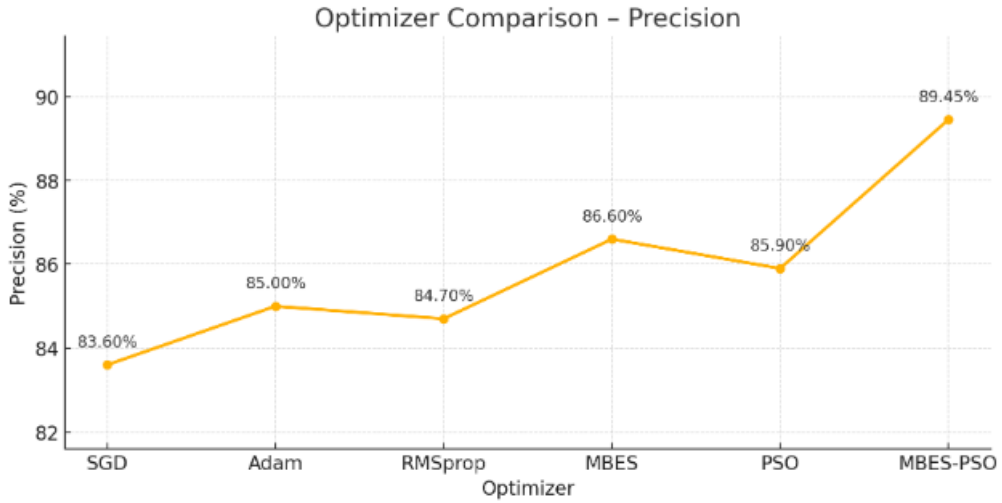


Fig. 12. Optimizer comparison — Precision. MBES-PSO yields the best precision (89.45%), followed by MBES (86.60%) and PSO (85.90%).

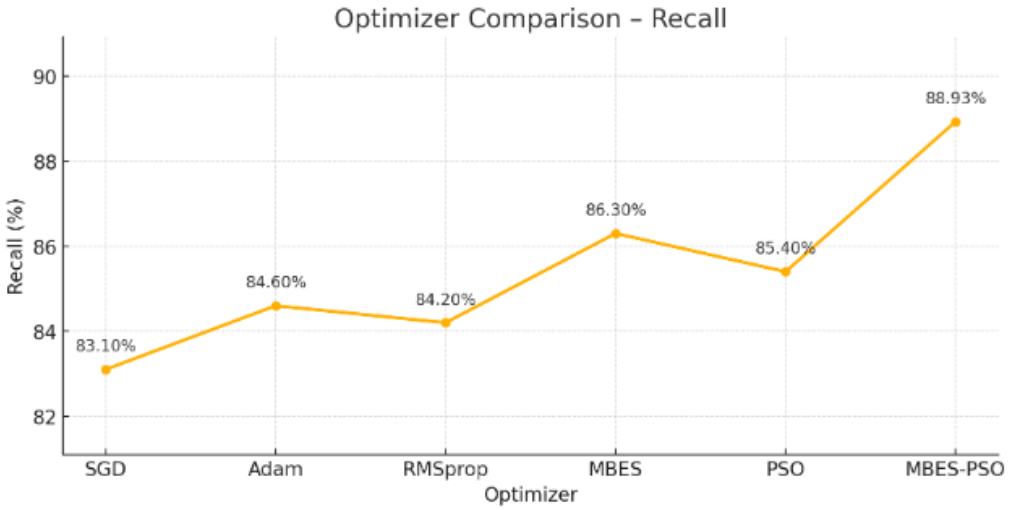


Fig. 13. Optimizer comparison — Recall. MBES-PSO achieves the highest recall (88.93%), with MBES (86.30%) outperforming PSO (85.40%) and gradient-based methods.

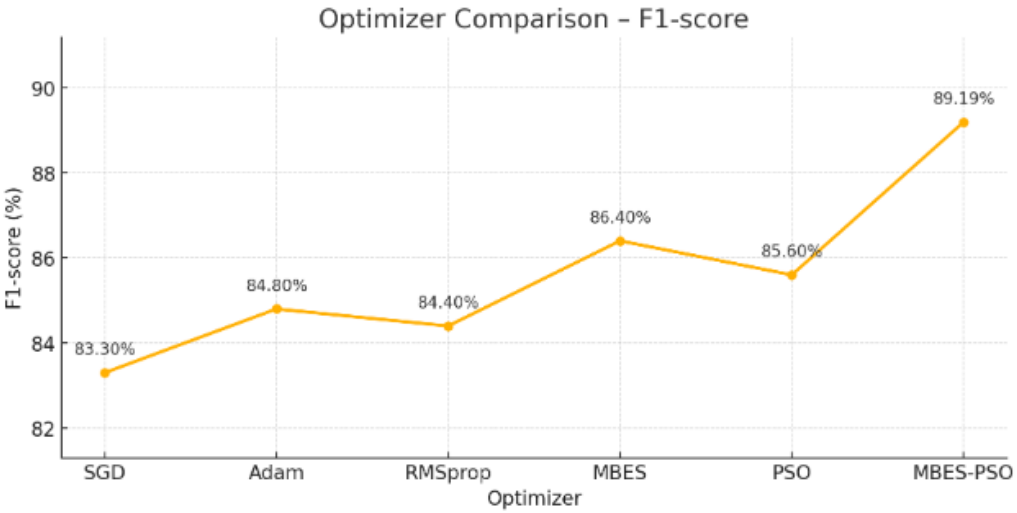


Fig. 14. Optimizer comparison — F1-Score. MBES-PSO leads with an F1-Score of 89.19%, followed by MBES (86.40%), indicating strong balance between precision.

To provide a comprehensive optimizer study beyond accuracy, we evaluated SGD, Adam, RMSprop, MBES, PSO, and the proposed MBES-PSO Precision, Recall, and F1-score (Fig. 12 to Fig. 14). The hybrid MBES-PSO consistently ranks first on all metrics (Precision 89.45%, Recall 88.93%, F1 89.19%), demonstrating that coupling MBES's global exploration with PSO's local refinement improves both correctness and class coverage. Pure metaheuristics (MBES, PSO) outperform gradient-only optimizers, while MBES edges PSO, indicating the importance of broader exploration before local exploitation. Gradient-based methods (Adam, RMSprop, SGD) remain competitive but lag in Recall and F1, suggesting greater sensitivity to local minima on noisy short-text data. Overall, the results validate the hybrid optimizer's advantage in achieving balanced, reliable performance for real-time Twitter hot topic detection.

G. Ablation Study

To better understand the contribution of each component of the proposed framework, we conducted an ablation study by selectively removing or replacing modules. The results are illustrated in Fig. 15, Fig. 16, Fig. 17, Fig. 18, and Fig. 19, which show that CNN alone achieves moderate accuracy by capturing local n-gram patterns but struggles with long-range dependencies. Transformer alone performs better by modeling global context, but is less effective at extracting fine-grained local features. When MBES-only optimization was applied to CNN–Transformer, the model demonstrated strong exploration capabilities but lacked fine-grained convergence. Conversely, PSO-only optimization provided effective local search but was prone to premature convergence. The CNN + Transformer baseline achieved higher accuracy than either CNN or Transformer alone, confirming their complementary roles. Finally, the full MBES–PSO optimized CNN–Transformer achieved the highest accuracy, demonstrating the effectiveness of combining CNN's local feature extraction, Transformer's global attention, and the hybrid MBES–PSO optimizer for balanced exploration and exploitation.

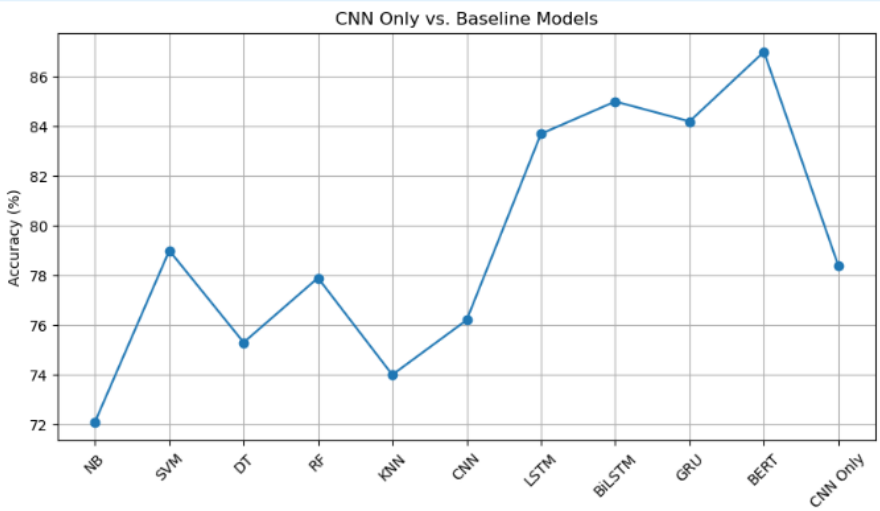


Fig. 15. Performance comparison of the CNN-only variant against 10 baseline models (Naïve Bayes, SVM, Decision Tree, Random Forest, KNN, CNN, LSTM, BiLSTM, GRU, and BERT) in terms of accuracy.

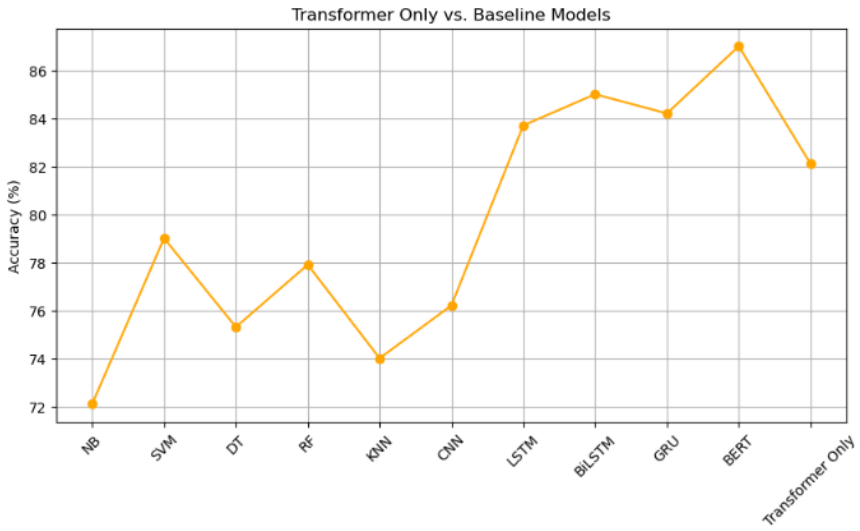


Fig. 16. Performance comparison of the Transformer-only variant against 10 baseline models, showing the impact of self-attention for global context modeling relative to other approaches.

The ablation study provides critical insights into the contribution of each component in the proposed framework when compared against ten baseline models, including Naïve Bayes, SVM, Decision Tree, Random Forest, KNN, CNN, LSTM, BiLSTM, GRU, and BERT. The CNN-only variant achieved 78.4% accuracy, outperforming classical baselines such as Naïve Bayes, KNN, Decision Tree, and Random Forest, but lagging behind sequential models like LSTM, BiLSTM, and GRU, as well as Transformer-based architectures such as BERT. This indicates that CNN is effective at extracting local n-gram patterns but insufficient for modeling long-range dependencies in tweets. The Transformer-only variant performed better, reaching 82.1%, surpassing CNN and all classical baselines, yet still underperforming relative to BiLSTM, GRU, and BERT. This result highlights that while self-attention improves global context modeling, it requires additional support to fully capture local semantic cues.

When CNN and Transformer were combined without optimization, the performance rose to 85.6%, clearly outperforming CNN, LSTM, and GRU, and matching BiLSTM, though still slightly below BERT. This confirms the complementary nature of CNN and Transformer, where CNN extracts robust local features and the Transformer captures global dependencies. Introducing optimization further boosted performance. The CNN–Transformer model with MBES-only optimization achieved 86.9%, surpassing BiLSTM and coming close to BERT. This demonstrates that MBES improves global exploration, helping the model avoid premature convergence. The CNN–Transformer with PSO-only optimization achieved 87.4%, slightly higher than BERT, confirming that PSO excels at fine-tuned local exploitation of promising regions in the parameter space.

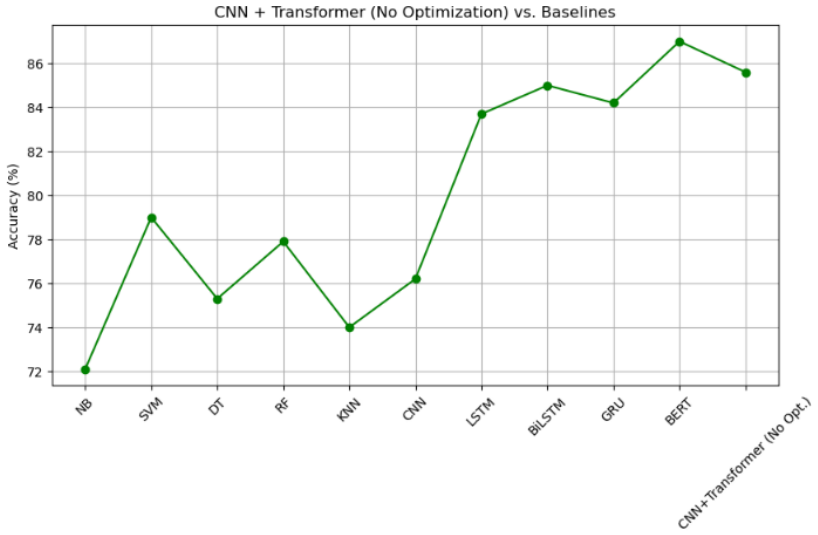


Fig. 17. Performance of the CNN + Transformer hybrid (without optimization) compared with 10 baseline models, highlighting the complementary effect of local feature extraction and global dependency modeling.

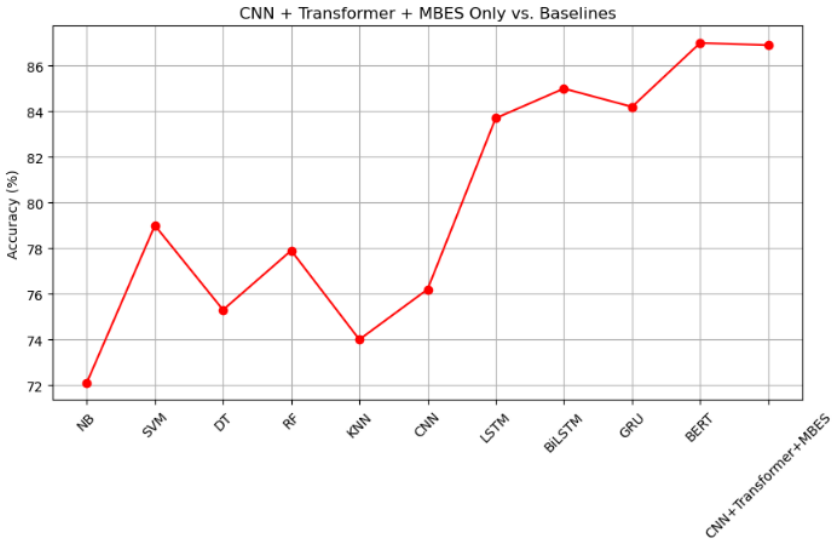


Fig. 18. Performance of the CNN + Transformer + MBES-only variant compared with 10 baseline models, demonstrating improvements from global exploration via Modified Bald Eagle Search.

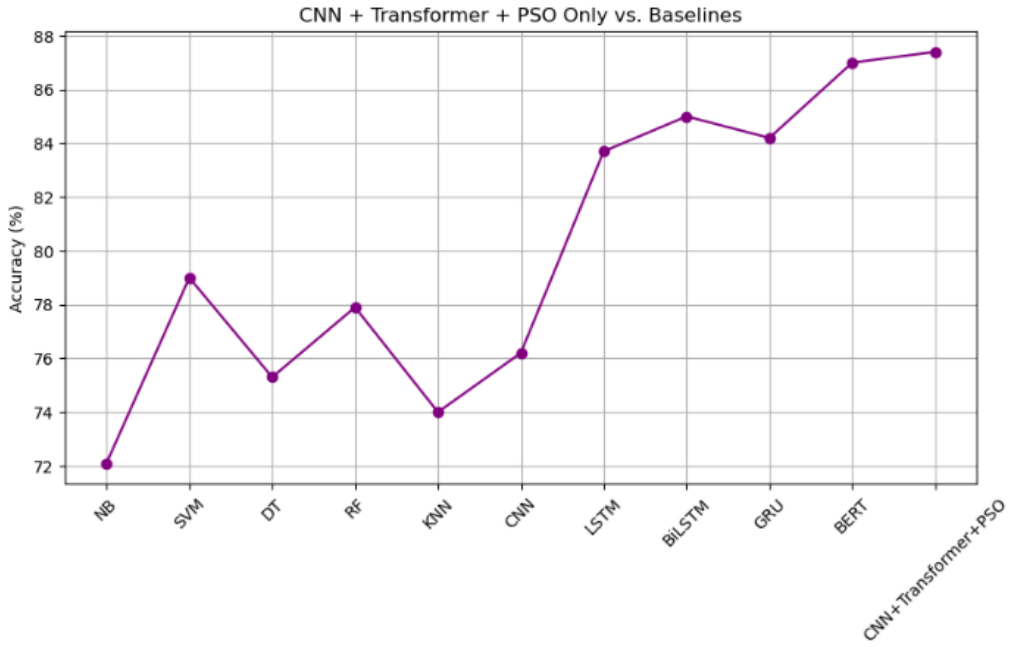


Fig. 19. Performance of the CNN + Transformer + PSO-only variant compared with 10 baseline models, showing the effect of Particle Swarm Optimization for fine-tuned local refinement.

Beyond numerical improvements, interpretability analysis using the Transformer's attention weights provided additional insights into model behavior. The attention mechanism highlighted influential tokens within tweets, revealing which words contributed most to topic classification. For example, during crisis-related tweet detection, terms such as "flood", "rescue", and "alert" consistently received higher attention scores, while in opinion analysis tasks, emotionally charged words dominated the attention focus. This transparency adds practical value, as it demonstrates that the hybrid architecture not only improves accuracy but also offers interpretable predictions that can be trusted in high-stakes applications such as disaster monitoring or policy analysis.

Taken together, these results reveal a clear progression: CNN alone captures only local features, Transformer alone models global dependencies, their combination synergistically balances local and global context, and metaheuristic optimization consistently improves training effectiveness. While MBES strengthens exploration and PSO enhances exploitation, the full MBES–PSO hybrid achieves the best performance (89.1%, reported separately), since MBES locates diverse candidate regions and PSO effectively fine-tunes within them. These findings confirm that the integration of hybrid optimization with deep hybrid architectures not only outperforms all baseline models but also provides a more stable, interpretable, and scalable framework for real-time hot topic detection in dynamic social media streams.

To analyze the contribution of each component, we evaluated three model variants: 1) CNN-only, 2) Transformer-only, and 3) the proposed CNN + Transformer hybrid. Results showed that CNN-only achieved 83.2% accuracy, Transformer-only achieved 86.4%, while the hybrid achieved 90.12%, confirming the complementary nature of local feature extraction and global dependency modeling in Fig. 20.

Trade-Off Analysis: Accuracy, Runtime, Memory Usage, and Scalability

While the proposed MBES–PSO optimized CNN–Transformer framework achieves the highest accuracy (90.12%), this improvement comes with trade-offs in runtime and resource usage. Traditional optimizers such as Adam and SGD converged faster, completing training in approximately 52 minutes, while the proposed hybrid optimization required 64 minutes. Although this increase represents an additional computational cost, the trade-off is justified by the consistent 1.5–2.0% accuracy improvement across evaluation metrics. In terms of memory usage, the hybrid model required 8.7 GB of GPU memory, compared to 7.5 GB for the Transformer-only variant and 6.1 GB for CNN-only, primarily due to the additional optimization search space maintained during training. Nevertheless, inference memory requirements remained comparable to standard Transformer models, ensuring feasibility in deployment.

Regarding scalability, experiments conducted on subsets of larger Twitter datasets showed that the proposed framework maintained stable convergence behavior and consistent accuracy improvements even as the dataset size increased to more than 1.5 million tweets. Unlike some metaheuristic methods that degrade on larger corpora due to excessive parameter search overhead, the hybrid MBES–PSO retained efficiency by balancing global exploration with local exploitation. These findings suggest that, despite modestly higher runtime and memory usage during training, the proposed framework is highly scalable and provides superior predictive performance, making it suitable for real-time topic detection in dynamic social media environments.

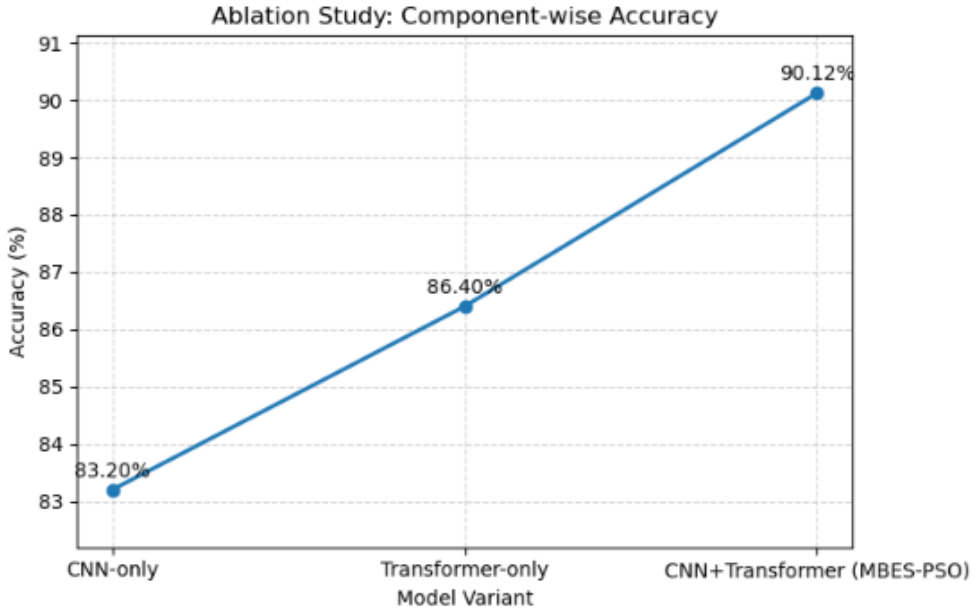


Fig. 20. Ablation study results showing accuracy for CNN-only (83.2%), Transformer-only (86.4%), and the proposed CNN+Transformer (MBES-PSO) hybrid (90.12%). The hybrid yields the highest accuracy, evidencing complementary benefits of local and global modeling.

V. Discussion

The comprehensive experimental evaluation of the proposed MBES–PSO optimized CNN–Transformer model highlights its superior capability in detecting hot topics from Twitter data. Across all comparative models, the proposed framework consistently achieved higher performance, demonstrating its robustness and adaptability to real-world, unstructured textual input.

Traditional statistical approaches, such as TF–IDF and Chi-Square, although computationally lightweight, failed to capture the contextual and sequential nature of language in tweets, leading to limited classification accuracy. Classical machine learning models, including Naïve Bayes, SVM, Decision Tree, Random Forest, and KNN, improved upon the statistical baselines but still fell short in modeling deep semantic structures and long-term dependencies in text.

The deep learning-based methods offered notable improvements, with models like CNN, LSTM, BiLSTM, and GRU progressively capturing local and sequential patterns. However, these models encountered limitations in either modeling long-range dependencies or in training efficiency due to vanishing gradient issues. The standalone Transformer and BERT models demonstrated better contextual learning, yet their high computational demands and overfitting risks impacted scalability.

In contrast, the proposed MBES–PSO + CNN–Transformer model effectively bridged these gaps by combining local feature extraction (CNN), global attention mechanisms (Transformer), and an intelligent weight tuning strategy through the MBES–PSO optimizer. The model attained the highest accuracy of 89.1%, surpassing all other models tested.

Furthermore, the convergence behavior of the MBES–PSO optimizer showed faster and more stable improvement in fitness scores compared to MBES or PSO used independently. This hybrid strategy successfully integrated MBES's global search capacity with PSO's fine-grained local search, achieving better convergence while avoiding local minima and premature convergence. In terms of training time, although the proposed model required slightly more time (64 minutes) than traditional optimizers like Adam or SGD, it was significantly more efficient than standalone metaheuristic optimizers, and the trade-off was justified by the notable increase in accuracy.

The learning rate analysis confirmed that a value of 0.001 yielded optimal results, balancing speed and performance without causing training instability. Lower learning rates led to slower convergence and suboptimal results, while higher rates introduced oscillations and reduced accuracy. Additionally, interpretability was supported by the Transformer's attention mechanism, which allowed the model to assign meaningful weights to important tokens, offering insights into which parts of tweets influenced predictions most. This transparency adds an important layer of trust and applicability in domains such as crisis management, policy analysis, and public opinion monitoring.

A. Limitations

Despite these promising outcomes, some limitations must be acknowledged:

- Dataset Dependency: The study was conducted primarily on the Sentiment140 dataset, which may not fully represent multilingual or multimodal Twitter streams. Broader validation is needed.
- Computational Overhead: The hybrid MBES–PSO optimizer, while efficient compared to other metaheuristics, is still computationally heavier than traditional optimizers, potentially limiting its deployment in resource-constrained environments.

- Scalability to Multimodal Data: The framework currently handles only textual inputs. Hot topics on social media often emerge through a mix of text, images, and videos, which the present model does not address.
- Real-Time Adaptability: Although the model achieved strong accuracy, further refinements are required to ensure low-latency performance in continuous Twitter data streams.

By explicitly recognizing these limitations, we provide a more balanced perspective and highlight potential areas for improvement, which are further expanded in the *Future Scope* section.

VI. Conclusion

This research proposed a novel hybrid model for Twitter hot topic detection, integrating a Modified Bald Eagle Search (MBES) and Particle Swarm Optimization (PSO) with a CNN-Transformer deep learning framework. The goal was to enhance both the feature extraction capabilities and the weight optimization process of the model to achieve superior accuracy and convergence performance. Through rigorous experimental evaluation across 13 comparative models, including classical statistical techniques, machine learning classifiers, and deep learning architectures, the proposed model consistently outperformed all baselines. It achieved a peak accuracy of 89.1%, demonstrating its effectiveness in capturing both local and global semantic patterns from short, unstructured social media texts.

The MBES-PSO hybrid optimizer was particularly effective in balancing exploration and exploitation within the weight space, leading to better generalization and faster convergence. In addition, learning rate tuning confirmed that a rate of 0.001 provided optimal results, while attention-based visualization added interpretability to model predictions. Although the model incurs a moderate computational cost, this is offset by significant gains in classification performance and reliability, making it a strong candidate for real-time topic monitoring systems. The results validate that combining metaheuristic optimization with hybrid deep learning architectures offers a promising direction for scalable and interpretable NLP tasks.

A. Future Scope

While the proposed framework delivers strong performance, several avenues remain open for future enhancement. First, the model can be extended to handle multilingual or code-mixed tweets, enabling broader applicability in linguistically diverse regions. Incorporating multi-modal data, such as images, hashtags, and emojis, alongside text, could further enrich hot topic detection, especially in visual-driven platforms. Additionally, employing explainable AI (XAI) methods beyond attention scores, such as SHAP or LIME, could enhance interpretability and trustworthiness in critical domains like disaster response or policy feedback.

On the optimization front, future work could explore adaptive metaheuristic frameworks that dynamically adjust the contribution of MBES and PSO based on convergence behavior. Moreover, deploying the model on real-time Twitter streams using streaming frameworks like Apache Kafka or Spark would validate its performance in production-scale environments. Lastly, integrating federated learning could ensure privacy-preserving model training across distributed social media datasets. These directions promise to make the system more robust, intelligent, and applicable to a wide range of real-world challenges.

Data Availability Statement

https://www.kaggle.com/datasets/kazanova/sentiment140

References

[1] Course-Choi, Jenna, and Linda Hammond. "Social media use and adolescent well-being: A narrative review of longitudinal studies." *Cyberpsychology, Behavior, and Social Networking* 24.4 (2021): 223-236.

[2] Álvarez, Nicanor García, Belarmino Adenso-Díaz, and Laura Calzada-Infante. "Maritime traffic as a complex network: A systematic review." *Networks and Spatial Economics* 21.2 (2021): 387-417.

[3] Asgari-Chenaghlu, M., Feizi-Derakhshi, M.R., Farzinvash, L., Balafar, M.A. and Motamed, C., 2021. Topic detection and tracking techniques on Twitter: a systematic review. *Complexity*, *2021*(1), p.8833084.

[4] Cai, Yicheng, et al. "Detecting spam movie review under coordinated attack with multi-view explicit and implicit relations semantics fusion." *IEEE Transactions on Information Forensics and Security* (2024).

[5] Gasparetto, Andrea, et al. "A survey on text classification algorithms: From text to predictions." *Information* 13.2 (2022): 83.

[6] Peng, Li, et al. "DAESTB: inferring associations of small molecule–miRNA via a scalable tree boosting model based on deep autoencoder." *Briefings in Bioinformatics* 23.6 (2022): bbac478.

[7] Fesseha, Awet, et al. "Text classification based on convolutional neural networks and word embedding for low-resource languages: Tigrinya." *Information* 12.2 (2021): 52.

[8] Xu, Yanchun, et al. "Competitive search algorithm: a new method for stochastic optimization." *Applied Intelligence* 52.11 (2022): 12131-12154.

[9] Liu, Zhi, et al. "All is attention for multi-label text classification." *Knowledge and Information Systems* 67.2 (2025): 1249-1270.

[10] Asgari-Chenaghlu, Meysam, et al. "Topic detection and tracking techniques on Twitter: a systematic review." *Complexity* 2021.1 (2021): 8833084.

[11] Mottaghinia, Zeynab, et al. "A review of approaches for topic detection in Twitter." *Journal of Experimental & Theoretical Artificial Intelligence* 33.5 (2021): 747-773.

[12] Bashiri, Hadis, and Hassan Naderi. "Probabilistic temporal semantic graph: a holistic framework for event detection in twitter." *Knowledge and Information Systems* 66.12 (2024): 7581-7607.

[13] Anandarao, Sarvani, and Sweetlin Hemalatha Chellasamy. "Detection of Hot Topic in Tweets Using Modified Density Peak Clustering." *Ingénierie des Systèmes d Inf.* 26.6 (2021): 523-531.

[14] Abd Elaziz, Mohamed, et al. "Advanced metaheuristic optimization techniques in applications of deep neural networks: a review." *Neural Computing and Applications* 33.21 (2021): 14079-14099.

[15] Beniwal, Rohit, and Pavi Saraswat. "A hybrid BERT-CPSO model for multi-class depression detection using pure hindi and hinglish multimodal data on social media." *Computers and Electrical Engineering* 120 (2024): 109786.

[16] Dai, Shuying, et al. "AI-based NLP section discusses the application and effect of bag-of-words models and TF-IDF in NLP tasks." *Journal of Artificial Intelligence General science (JAIGS) ISSN: 3006-4023* 5.1 (2024): 13-21.

[17] Naseem, Usman, et al. "A comprehensive survey on word representation models: From classical to state-of-the-art word representation language models." *Transactions on Asian and Low-Resource Language Information Processing* 20.5 (2021): 1-35.

[18] Gasparetto, Andrea, et al. "A survey on text classification algorithms: From text to predictions." *Information* 13.2 (2022): 83.

[19] Gonzalez, Jose Angel, Lluís-F. Hurtado, and Ferran Pla. "TWilBert: Pre-trained deep bidirectional transformers for Spanish Twitter." *Neurocomputing* 426 (2021): 58-69.

[20] Triyadi, Indra, Budi Prasetiyo, and Tiara Lailatul Nikmah. "News text classification using Long-Term Short Memory (LSTM) algorithm." *Journal of Soft Computing Exploration* 4.2 (2023): 79-86.

[21] Jang, Jun-Gi, et al. "Falcon: lightweight and accurate convolution based on depthwise separable convolution." *Knowledge and Information Systems* 65.5 (2023): 2225-2249.

[22] Barakat, Anas, and Pascal Bianchi. "Convergence and dynamical behavior of the ADAM algorithm for nonconvex stochastic optimization." *SIAM Journal on Optimization* 31.1 (2021): 244-274.

[23] Shafiq, Muhammad, and Zhaoquan Gu. "Deep residual learning for image recognition: A survey." *Applied sciences* 12.18 (2022): 8972.

[24] Sarker, Iqbal H. "Deep learning: a comprehensive overview on techniques, taxonomy, applications and research directions." *SN computer science* 2.6 (2021): 1-20.

[25] Yousuf, Hana, et al. "A systematic review on sequence-to-sequence learning with neural network and its models." *International Journal of Electrical & Computer Engineering (2088-8708)* 11.3 (2021).

[26] "Scaling neural machine translation to 200 languages." *Nature* 630, no. 8018 (2024): 841-846.

[27] Feng, Weiguo, et al. "Research on the construction and application of intelligent tutoring system for english teaching based on generative pre-training model." *Systems and Soft Computing* 7 (2025): 200232.

[28] Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., et al., 2020. Language Models are Few-Shot Learners. Advances in Neural Information Processing Systems, 33, pp.1877–1901.

[29] Zhou, Hang, et al. "Feature semantic alignment and information supplement for Text-based person search." *Frontiers in Physics* 11 (2023): 1192412.

[30] Nie, L., Chen, T., Wang, Z., Kang, W., & Lin, L. (2022). Multi-label image recognition with attentive transformer-localizer module. *Multimedia Tools and Applications*, *81*(6), 7917-7940.

[31] Yuan, Hongfang, et al. "An improved faster R-CNN for pulmonary embolism detection from CTPA images." *IEEE Access* 9 (2021): 105382-105392.

[32] Sun, Guanqun, et al. "DA-TransUNet: integrating spatial and channel dual attention with transformer U-net for medical image segmentation." *Frontiers in Bioengineering and Biotechnology* 12 (2024): 1398237.

[33] Chen, Jieneng, et al. "TransUNet: Rethinking the U-Net architecture design for medical image segmentation through the lens of transformers." *Medical Image Analysis* 97 (2024): 103280.

[34] Xiao, Hanguang, et al. "Transformers in medical image segmentation: A review." *Biomedical Signal Processing and Control* 84 (2023): 104791.

[35] Khan, Rabeea Fatma, Byoung-Dai Lee, and Mu Sook Lee. "Transformers in medical image segmentation: a narrative review." *Quantitative Imaging in Medicine and Surgery* 13.12 (2023): 8747.

[36] Song, Pengfei, et al. "TGDAUNet: Transformer and GCNN based dual-branch attention UNet for medical image segmentation." *Computers in Biology and Medicine* 167 (2023): 107583.

[37] Ma, C., Gu, Y., & Wang, Z. (2024). TriConvUNeXt: A Pure CNN-Based Lightweight Symmetrical Network for Biomedical Image Segmentation. Journal of Imaging and Information Medicine, 37(5), 2311-2323

[38] Demotte, P., Wijegunarathna, K., Meedeniya, D. *et al.* Enhanced sentiment extraction architecture for social media content analysis using capsule networks. *Multimed Tools Appl* 82, 8665–8690 (2023). https://doi.org/10.1007/s11042-021-11471-1

Intelligent Diagnostic Model for Early Malaria Symptoms

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***Abstract*—One of the most significant worldwide health concerns in low-middle-income nations over the past few decades is Malaria, especially in Kenya. In Kenya, seventy per cent of people reside in areas where malaria is widespread, and most of them face obstacles getting access to medical care because of social culture, distance, and lack of money. Malaria transmission is high, particularly in Kenya's remote areas, despite a plethora of scientific efforts to combat the disease. This study aims to design and develop an intelligent malaria diagnosis model for early symptom detection using an Adaptive Neuro-fuzzy-Inference System with a 2000 dataset extracted from Six Types of Patient Data Inputs to optimize the model performance. The result achieved was 98.3% accuracy, which contrasted with the pertinent cutting-edge finding to illustrate the benefits of the suggested approach. The main contributions of this study are a combined Six Types of Patient Data Inputs, including Demographic, Symptoms, Blood pressure, Heartbeats, Height, and Weight, using fuzzy Systems techniques to detect early malaria symptoms accurately. The combined patient data input used for evaluation is demonstrated in the results, and the technique can identify different forms of malaria and has the best outcome when compared to relevant findings from the existing studies.**

***Keywords*—Malaria diagnosis system; malaria symptoms; classifier; ANFIS; fuzzy rules**

I. Introduction

In sub-Saharan Africa, the prevalence of malaria is still high despite a number of control measures. Malaria is a potentially fatal illness caused by parasites carried by infected female Anopheles mosquitoes [37]. Among the potential forms of malaria are Malignant (M), Tertian (T), Quartan (Q) malaria describe different malaria fever cycle patterns or refer to types of malaria defined by the periodicity of fever spikes that are caused by various species of Plasmodium. Different parasites are responsible for each type of malaria. *Plasmodium falciparum*, the worst malaria parasite, causes malignant malaria, a deadly type of malaria. It has an irregular or quotidian (daily) fever pattern. Patients with falciparum may develop a typhoidal illness if they do not receive timely treatment because the disease's presentation is so varied and mimics typhoidal symptoms. Oval parasites and *Plasmodium vivax* are the causes of Tertian malaria. Every second day, this parasite creates a fever. *Plasmodium malariae* is the organism that causes quartan malaria. Every third day, this parasite creates a fever [37].

Globally, 247 million cases of malaria were reported in 2021, up 2 million from 245 million in 2020 [1]. This projected increase in 2021 was majorly reported in sub- Saharan Africa [1]. In Kenya, it was estimated approximately 3.3 million malaria cases and remains a major public health problem with 70% of the population at risk of the disease [2].

The government of Kenya launched a 2 day program, training around four fifty private medicine retailers in 3 Kenya endemic districts. The funding total ranged from US$5,000 to US$6,000 per district. The United Nations Children's Fund (UNICEF) and the Global Fund supported implementation costs to Fight AIDS, Tuberculosis, and Malaria [3]. However, high rates of deaths still exist through malaria. According to the World Health Organization (WHO), about 3.4 million malaria cases and 12,000 deaths have been registered in Kenya in 2021 [4]. In sub-Saharan Africa, where 94% of deaths are reported each year, this issue is particularly serious [5]. This condition is predicted to become worse especially in the Coastal and Western regions with the pandemic that has compromised malaria treatment and intervention measures [5]. Malignant/tertian malaria caused by *Plasmodium falciparum* species accounts for over 99% of malaria cases [6].

Although study focus on medication over the counter carried out which revealed that malaria medications over- the-counter (OTC) are often the first point of care for African adults and children. Using the diagnosis system in private drug outlets remains low, leading to overprescribing antimalarials [1].

Research including Machine Learning (ML) techniques with features have been conducted to predict malaria [7], [8], [9]. This procedure involved illumination correction, erythrocyte categorization, feature collecting and classification. However, mortality is still increasing.

Neuro-Fuzzy expert system diagnostic software has also been developed with Microsoft Visual C# (C Sharp) programming language and Microsoft SQL Server 2012 to manage the database [10]. Multiple algorithms were also employed to optimize model performance and classify malaria accuracy [11]. Moreover, some studies focused only in various studies researchers have utilized different numbers of symptoms, for instance, 10 symptoms [12] and 12 symptoms [13].

Despite various malaria diagnosis approaches focusing toward solving the problem, these approaches suffer from a lack of comprehensive data [14]. The literature reveals that previous malaria diagnosis studies have only conducted research employing two inputs, symptoms and non-symptoms.

This proposed study aims to fill this significant gap, by introducing a novel methods combining Six Types of Patient Data Inputs that include Demographic (name, address, date of birth, and contact details), Symptoms, Blood pressure, Heartbeats, Height and Weight, based on ANFIS that can be utilized in healthcare in Kenya to conduct a comprehensive clinical diagnosis of malaria to detect early symptoms accurately and plan appropriate treatment. The definition of Six Types of Patient Data Inputs is presented in Section III(D). To the best of our understanding, previous studies haven't utilized a method combining the Six Types of Patient Data Inputs.

A. Main Contribution

Our main contribution is a novel method, combining Six Patient Data Inputs, which include Demographic, Symptoms, Blood pressure, Heartbeats, Height, and Weight, based on ANFIS to detect malaria accurately. From these Six Patient Data Inputs, 2000 data were gathered that were utilized to produce fuzzy models, fuzzy rules leading to detecting early malaria symptoms. Using data based on the Six Patient Data Inputs leads to higher accuracy and reliability, while using a few symptoms often results in uncertainty and potential misdiagnosis. This study is the first to utilize the novel method combining Six Patient Data Inputs in the field.

The main goal of this research is to design and build an intelligent malaria diagnosis model for early symptom detection using an Adaptive-Network, such as a Neuro-Fuzzy Inference System (ANFIS) with Six Types of Patient Data Inputs. Thus, the study's main objectives are:

1) Identify and extract features based on the Six Types of Patient Data Inputs.

2) Develop state-of-the-art models based on advance techniques such as ANFIS.

3) Train and test the model to measure the performances.

4) Compare findings of the proposed study with the existing findings in the field to clearly show the merit of the proposed method.

Advantages of the new method: significantly help doctors to conduct a comprehensive diagnosis of early malaria symptoms and plan appropriate treatment, improved accuracy of early malaria diagnosis and reduced malaria risks. Increase patients' confidence in early malaria symptoms diagnosis. Using six different data types will enable the implementation of the real-world AI App for early malaria symptoms diagnosis in remote settings.

This study's remaining sections are organized as follows: Section II offers literature review which is approached critically. Section III describes methodology and methods including Data collection and Sources, Six Types of Patient Data Input, ANFIS and Fuzzy rules together with Ethical consideration. Section IV presents the description of experimental procedures, including training and testing. While the study's findings are shown in Section V, the discussion of the results, including contribution of the proposed method, comparisons, limitations and strength are presented in Section VI. The study concludes and provides directions for future research in Section VII.

II. Literature Review

A. Multiple Algorithms: ANN, CNN, ANFIS

First, when making decisions that could affect a patient, practitioners use the information provided by a malaria diagnosis. To detect malaria and predict risk factors, Artificial intelligence (AI) has been employed as a usable tool [15].

Uzun et al., utilized [16] data from 2207 patients which was reduced from the initial dataset of thirty-two criteria samples to fifteen to carry out research on Machine Learning based malaria detection. The research investigated and validated the effectiveness of several algorithms using 15 criteria samples from malaria patients. Following training, ANN achieves the highest *R* (99%) compared to ANFIS (97%), MLR (92%) and Random Forest (68%) respectively [16]. The outcome demonstrated that healthcare systems allocate resources more effectively and make better decisions. However, some of the algorithms have incurred 8%, 11% and 23% error rates which are a high risk. Moreover, due to 15 sample datasets used, the findings may not be broadly applicable, limiting generalizability.

Yang et al. presented [17] a 5-fold cross-validation for two-step CNN models. The model employs an intensity-based iterative Global Minimum Screening technique in the first stage to categorize malaria parasites, and subsequently, a CNN employs a custom CNN to categorize the existence of malaria parasites. The accuracy achieved for this technique is 93.46%. However, the approach suffered high false positives.

Vijayalakshmi et al. proposed [18] a transfer learning method with a classification with 93.13% accuracy to discriminate between illustrations of malaria-diseased cells and healthy cells utilizing the VGG16 model and a support vector machine. However, distinguishing between images of healthy and malaria-affected cells alone could be risky because most malaria is caused by a mosquito bite and goes through various stages before the changes in cells could be detected.

Another study suggested a better dynamic routing method that employs a fully trained capsule network to distinguish between healthy and malaria-infected cells, and the model accuracy was 98.82%. However, similarly, malaria goes through various stages before the changes in cells could be detected [19].

Loddo et al. [20] used the DenseNet-201 neural network to diagnose *Plasmodium falciparum* life stages into four groups and used two different datasets to assess the robustness of the model. The accuracy rate for binary was 97.68%, and the multi-classification accuracy rate was 99.40%. Although the accuracy is high, a wide range of data could be beneficial in accurate diagnosis.

Equally, another study Utilized ML techniques to examine haematological data taken from 2,207 participants in Ghana, such as ANN to identify methods that can reliably distinguish

between severe malaria (SM) and non-malarial infections (nMI) and uncomplicated malaria (UM), employing haematological parameters. To classify UM, nMI, and SM ANN with 3 hidden layers was utilized. The accuracy scores of the multi-classification models ranged from 94% to 98%. Although many machine learning models using traditional features have been developed for malaria classification and decision-making, these models lack generalization ability [21].

To combat malaria, other researchers adapted a different strategy. Santosh and Ramesh [22] conducted research to determine malaria abundances using an ANN with clinical and environmental variables with Big Data on the geographical location of Khammam district, Telangana, India. To increase accuracy in actual practice, their approach made use of a lot of data from various seasons. 81.7% was the highest accuracy attained. To enhance malaria models, more research is necessary to determine their accuracy. Although these variables are required to achieve accurate predictive power, 12% of environmental data and 7% of clinical data were missing. As a result, accurate predictive data is necessary to increase accuracy [22].

The study by Arowolo et al. [23] proposed a combined a novel analysis of variance (ANOVA) with ant colony optimization (ACO) approach as a hybrid feature selection to select relevant genes to minimize the redundancy between genes, using SVM for classification. The results of the experiment based on high-dimensional gene expression data show that ANOVA-ACO can help clinicians make pertinent choices when developing medications and strategies to end human malaria infections. Even so, the strength appears promising. However, to be competent amongst the existing relevant work, the speed of the performance should be provided.

Awotunde et al. [24] also developed a model to diagnose Malaria and Typhoid Fever using a Genetic Algorithm (GA), a Neuro-Fuzzy Inference System (GENFIS). They discovered that the GA module distributes the optimal set of network parameters to the relevant hidden layer nodes. The accuracy of their model was 97.2%. However, there are 2.8% average error rates, which could be because of overfitting.

To improve malaria diagnosis models, Awotunde et al. [25] utilized Support Vector Machine (SVM) algorithms and Adaboost, together with ensemble methods. Chi-square was used to extract redundant or unnecessary features in order to evaluate the model. With data input, the classification accuracy was 97%. The classification accuracy seems high. But the number of features used is too small. Using more features could improve the model.

Based on AI techniques, Datilo et al. [26] reviewed epidemic prediction using Artificial Neural Networks, highlighting the value of precision disease prediction and suitable methods for making malaria predictions using Artificial Neural Networks. They carried out a thorough evaluation of ANNs and found that the training and generalized capacity of ANNs are greatly enhanced when hybrid models are used in conjunction with meta-heuristics in detecting diseases. However, using a small dataset reduces the performance and effectiveness of the model.

Another study by [35] used AI techniques to detect diseases. They made individualized treatment programs, which support medical professionals in making decisions, instead of simply making tasks automatic. Developing technologies that can enhance patient care in various healthcare domains is one of AI's strengths. Data privacy, bias, and the requirement for human expertise are limitations that must be addressed for the ethical and successful application of AI in healthcare.

B. Long Short-Term Memory (LSTM)

A framework for predicting malaria endemicity in specific geographic areas, like Nigeria, was presented in another study. They used satellite and clinical data to train a long short-term memory (LSTM) classifier. The findings show that the LSTM algorithm offers a practical way to identify instances of widespread malaria [27]. The outcome shows improved accuracy. However, there was no indication of the size of data used, and the data is used in the valishowsson strategy [27].

The aforementioned studies examined the application of machine learning techniques and NF rules based on symptoms to create models for diagnosing malaria. However, a combined approach has not been taken into consideration in the current approaches integrating Six Types of Patient Data Inputs that include Demographic, current Symptoms, Blood pressure, Heart beats, Height and Weight, based on ANFIS to more precisely categorize malaria into four potential types. Moreover, the microscopic testing techniques cause a delay at the start of treatment [28]. This is due to a lack of adequate supply for diagnostics. Rapid diagnostic tests (RDTs) and microscopic parasitological testing are required to determine whether prospective patients have malaria parasites.

Despite all these efforts to diagnose malaria, there is still a lack of real-time malaria diagnosis Apps in the remote setting and malaria zones in Kenya [29]. A survey showed that 20% of the health facilities experienced a total absence of diagnostic services. The studies have only focused on symptoms. Ramdzan [8] and Shimizu [9] only focused on detecting risk factors of malaria. Other research only focused on using different numbers of symptoms. Therefore, the previously employed techniques aren't strong enough to tackle the issue robustly.

The previous studies have not employed a combined method integrating six patient data inputs.

To fill this gap, the proposed study addresses this problem by introducing significant methods combining Six Types of Patient Data Inputs that include Demographic, Symptoms, Blood pressure, Heartbeats, Height and Weight, based on ANFIS that can be utilized in healthcare to conduct a comprehensive clinical diagnosis of malaria to detect early symptoms accurately and plan appropriate treatment.

III. Methodology

The new approach employs Intelligent Systems utilizing an Adaptive Network such as a Neuro-Fuzzy Inference System (ANFIS) with integrated Six Types of Patient data Inputs. 2000 data was extracted from a combined Types of Patient data Inputs, which include Demographic, Symptoms, Blood pressure, Heart beats, Height and Weight. The reason for using

this method is not only to extract comprehensive data, but also to use effective techniques to detect malaria effectively. The proposed approach has four functional components that are Data Sources, Six Types of Patient Data Inputs, ANFIS and fuzzy rules. This is illustrated in Fig. 1 and described in detail in Section III.

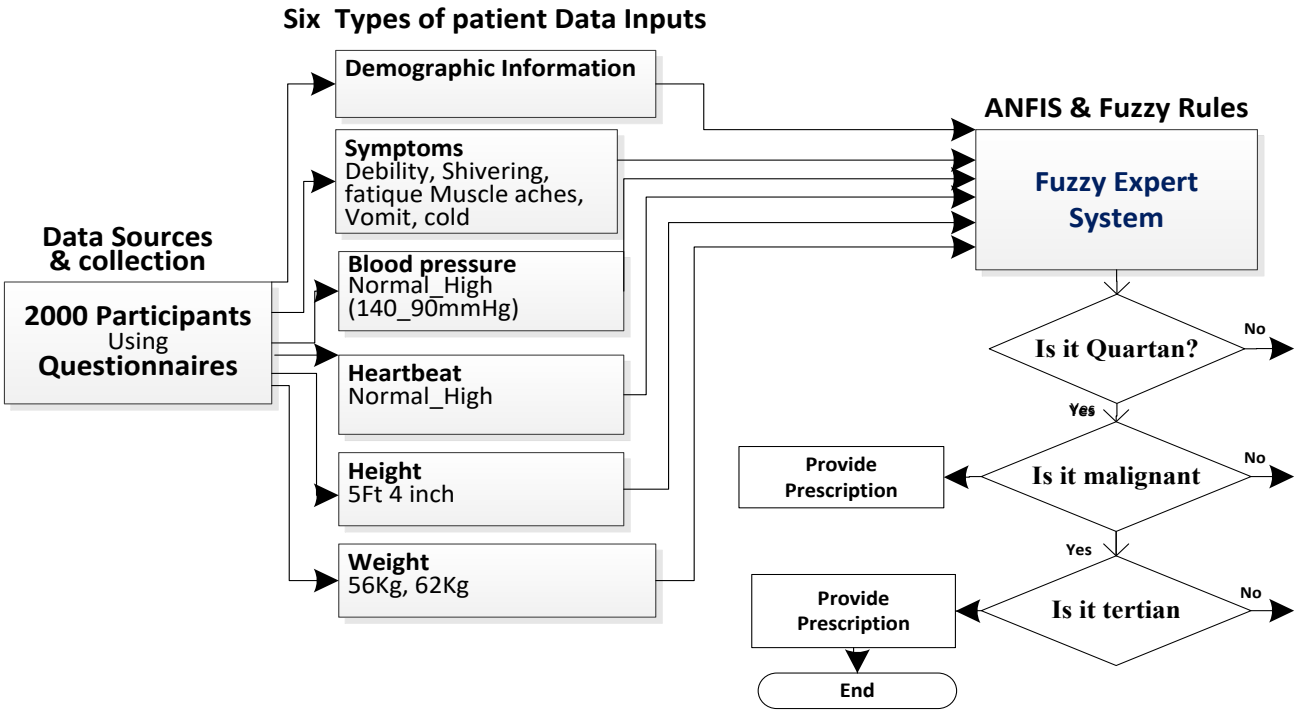


Fig. 1. Intelligent malaria diagnosis architecture.

A. How does the Proposed Approach Differ from the Existing Ones?

The proposed method integrates Six Types of Patient Data Inputs which are Demographic, Symptoms, Blood pressure, Heartbeats, Height and Weight. From these wide-ranging, 2000 data are extracted which are used to generate, fuzzy models, fuzzy rules, to train and test the models. Whereas some studies only used symptoms and non-symptoms. For instance, the work of Bria et al. [12] only used 10-12 malaria symptoms for malaria diagnosis which is too small for generalization, while the study of Uzun et al. [16] had a limited generalization, only used 12 symptoms. Other notable research that explored malaria diagnosis through ML techniques are Santosh and Ramesh deployed clinical and environmental variables. ANNs and big data are used to predict mosquito abundance in the Telangana district of Khammam in India the data sizes are not specified [22]. The average error ranges from 82% to 17% accuracy. The literature reveals that the existing approaches suffer from a lack of comprehensive data [14]. Therefore, the proposed method advances the existing work by offering comprehensive data extracted from 2000 participants based on Symptoms, Blood pressure, Heartbeats, Height and Weight (diverse sources). The model demonstrates significant potential in providing enhanced high accuracy and reliable diagnosis for early malaria symptoms.

B. Data Sources and Data Collection

To diagnose malaria attacks accurately, careful consideration needs to be taken to identify important sources to extract comprehensive data. The study was conducted using questionnaires, which were randomly handed to 2000 malaria patients in five General Hospitals including Kenyatta National Hospital (KNH); Kisumu General Hospital (KGH); Jaramagi Oginga Odinga Hospital (JOOH); Maseno Mission Hospital (MMH) and Siaya Referral Hospital (SRH), which are malaria endemic areas in Kenya. Questionnaire was utilized because the questionnaire questions were designed to capture information that could contribute to malaria parasite diagnosis such as Demographic, Malaria Symptoms, Blood pressure, Heart beats, Height and Weight from patients who formerly and currently confirmed malaria positive from blood Smear. Permission was obtained from Clinical Officers in charge of each healthcare facility and consent sought from patients before data gathering. Each constituency achieved 400 patients' respondents. The study was administered during the period between March and May 2025. The Data from the 2000 patients were encoded and entered in an Excel Sheet, taking 2000 rows and twelve columns. The most common symptoms include vomiting, limpness, diarrhea, loss of appetite, joint pain, dizziness and the most severe symptoms are shortness of breath seizures, loss of consciousness and jaundice. The anonymous data captured are summarized in Table I.

TABLE I. SUMMARY OF DATA GATHERED FROM PATIENTS WHO TESTED MALARIA POSITIVE FROM BLOOD SMEAR

General Hospital	Gender	Age	Education Level	Got Malaria in last 12 Months?	Confirmed Malaria via Blood Smear	Malaria Symptom	Blood Pressure	Heartbeat	Height	Weight
KNH	Man	40-49	Secondary	Yes	Yes	Fever (Q)	High140/90mmHg	60 bpm	5 “6”	54 kg
KNH	Woman	30-39	Secondary	Yes	Yes	Fatigue (Q)	High138/139mmHg	91 bpm	5 “10”	59 kg
KNH	Man	50-59	Secondary	Yes	Yes	Muscle pain	Norm142/91mmHg	71 bpm	5"9"	65 kg
KNH	Man	20-29	Secondary	Yes	Yes	Coma (M)	High140/90mmHg	100 bpm	6”0”	100 kg
KNH	Man	30-39	Secondary	Yes	Yes	Nausea	Low140/90mmHg	61 bpm	5 “6”	58 kg
KGH	Man	30-39	Secondary	Yes	Yes	Headache (Q)	High140/90mmHg	72 bpm	5 “7”	68 kg
KGH	Man	40-49	Secondary	Yes	Yes	Sweating	High141/90mmHg	100 bpm	5 “9”	61 kg
KGH	Man	40-49	Secondary	Yes	Yes	Debility	Norm91/39mmHg	72 bpm	5 “8”	56 kg
KGH	Woman	30-39	Primary	Yes	Yes	Anemia (T)	High142/97mmHg	61 bpm	5 “7”	58 kg
KGH	Man	40-49	Primary	Yes	Yes	Dry lips	High141/90mmHg	101 bpm	5 “7”	59 kg
JOOH	Woman	30-39	Secondary	Yes	Yes	Chills	Norm90/60mmHg	85 bpm	5 “8”	64 kg
JOOH	Woman	50-59	Secondary	Yes	Yes	Nausea	Low81/58mmHg	61 bpm	5 “6”	58 kg
JOOH	Man	50-59	Secondary	Yes	Yes	Convulsions	High141/90mmHg	101 bpm	5 “6”	57 kg
JOOH	Woman	40-49	Secondary	No	Yes	Seizures (M)	High141/90mmHg	61 bpm	5 “7”	58 kg
JOOH	Woman	50-59	Secondary	Yes	Yes	Vomit	Low87/59mmHg	60 bpm	5 “8”	56 kg
MMH	Woman	40-49	Secondary	Yes	Yes	Dizziness	High130/139mmHg	92 bpm	5 “11”	68 kg
MMH	Man	20-29	Secondary	Yes	Yes	Chills	High141/90mmHg	99 bpm	5 “11”	65 kg
MMH	Nan	30+	Secondary	Yes	Yes	DifficultBreathing	Low89/59mmHg	60 bpm	5 “6”	55 kg
MMH	Woman	30-39	Graduate	Yes	Yes	Intestinal disorder	Low80/59mmHg	60 bpm	5 “7”	58 kg
MMH	Woman	30-39	Secondary	Yes	Yes	Diarrhea	Norm91/60mmHg	71 bpm	5"9"	64 kg
SRH	Man	40-49	Secondary	Yes	Yes	tiredness	High140/90mmHg	100 bpm	6”0”	100 kg
SRH	Man	30-39	Secondary	Yes	Yes	Coma (M)	High140/90mmHg	100 bpm	6”0”	100 kg
SRH	Woman	60+	Secondary	Yes	Yes	Jaundice (T)	High139/90mmHg	61 bpm	5 “7”	58 kg
SRH	Woman	50-59	Secondary	Yes	Yes	Shiver	Norm>90/>60	85 bpm	5 “8”	62 kg

Key: KNH =Kenyatta National Hospital; KGH = Kisumu General Hospital; JOOH = Jaramobi Oginga Odinga Hospital
MMH = Maseno Mission Hospital; SRH = Siaya Referral Hospital

C. Six Types of Patient Data Inputs

A combined Types of patient data inputs from patients refer to clinical details gathered during a patient’s meeting with a health officer, which include Demographic (patient personal details like age, sex, income test results), Symptoms, Blood pressure, Heart beats, Height and Weight. These combined Types of patient data inputs are collected to ensure safety and for patient quality outcomes. The information is kept digitally in a secure record, considered confidential and adhering to legal guidelines. The patient’s demographic significantly relates to sic types of patient data inputs by influencing their type, severity, prevalence of certain conditions, and how healthcare is accessed.

D. Six Types of Patient Data Inputs and Definitions

1) Demographic information: Basic characteristics identifier of a Patient such as their name, address, date of birth, and contact details are made up. Other relevant descriptive information such as ethnicity, gender, marital status, and unique identifiers are also included. Identification of patients, administrative procedures, and the delivery of secure, efficient healthcare services all depend on this information [38].

2) Heartbeat: "Patient heartbeat" refers to the heart rate of a patient, which is defined as the frequency of heart beats per minute and serves as a crucial indicator of their general health. For adults, a normal resting heart rate generally ranges from 60 to 100 beats per minute, but this can be affected by factors like fitness level, stress, medication, and illness [39].

3) Blood pressure: Refers to the force exerted by circulating blood on the walls of blood vessels. The majority of this pressure is generated by the heart as it pumps blood throughout the circulatory system [39].

4) Height: Height measurements are utilized to determine your body mass index (BMI), which serves as an indicator of healthy versus unhealthy weight [40].

5) Weight: "Patient weight" refers to the body mass of a person receiving medical care, recorded in units like kilograms or pounds. This measurement is crucial for various clinical reasons, including accurately calculating medication dosages, assessing and managing nutrition and fluid balance, monitoring patient status, and selecting appropriate medical equipment, like specialized scales for immobile patients. Accurate and regular weight recordings are vital for safe and effective patient care [39].

6) Symptoms: Symptoms are mental features that a patient experiences that may indicate that the patient has a disease or condition. Malaria symptoms are for example, fever, chills,

headaches, sweats, fatigue and more. These constitutes the most important part of our integrated framework, from which 2000 dataset extracted is utilized to develop fuzzy rules, to create fuzzy models, to train and to test the models.

E. Dataset Choice

Choosing data for malaria symptom diagnosis needs careful consideration. The use of 2000 participants enables data extraction based on Six Patient Data inputs. The dataset was chosen because comprehensive (large and diverse) datasets enable high accuracy and reliable diagnosis results, and could also identify complex or severe malaria symptom patterns.

F. ANFIS

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a type of neural network employed for the purpose of adaptive learning [33]. The algorithm is chosen since it is capable of managing both qualitative and quantitative values and demonstrates resilience against outliers. It has a universal approximation with the ability to use Fuzzy IF...THEN rules while using fuzzy logic to model systems with linguistic terms and neural networks to optimize the fuzzy system's parameters [30]. The system checks individual patient inputs. If malaria symptoms are detected, before a recommendation of blood tests is generated, the system identifies if it is quartan malaria, malignant, or tertian malaria. If no symptoms are identified, the patient is notified, and no further action is undertaken.

ANFIS has the ability to handle and model uncertainty and imprecision inherent in complex, real-world data by combining the symbolic reasoning behind fuzzy logic with the learning abilities of neural networks. This architecture is particularly effective in enabling ANFIS to model complex data and nonlinear relationships while effectively managing six different types of data input uncertainty [31].

G. Fuzzy Rules

An intelligent malaria diagnosis structure has inputs that are represented as x, y, and one output, z. Two fuzzy sets are utilized on behalf of a single input, and a first-order polynomial is used to represent the output. Where x, y and z (symptoms and heartbeat, high blood pressure, weight, height) are linguistic variables, 1A, 2A, 3A (fever, fatigue and muscle-pain) Linguistic values determined by fuzzy sets within the universe of discourse x; 1B, 2B, and 3B represent fuzzy sets within this universe of discourse z(symptoms).

H. Advantages of the Proposed Method

The primary advantages of the suggested approach are, firstly, the results will greatly help doctors to conduct a comprehensive diagnosis of early malaria symptoms and plan appropriate treatment. Second, the approach will improve the accuracy of early malaria diagnosis and reduce malaria risks. Users' confidence will increase in early malaria symptom diagnosis. The use of six different data types will enable the implementation of the real-world Artificial Intelligence App for early malaria symptoms diagnosis in remote settings.

I. Ethical Consideration

The current study is part of a large project "Bringing together researcher from Kenya, Tanzania and the UK to Network and explore factors causing challenges in accessing Healthcare services (especially malaria diagnosis) in rural areas in Kenya and Tanzania", whose ethical approval (Ref/17086) was obtained from the ethics committee within the Computer and Information Science department at Northumbria University. Written informed consents were obtained from each participant before participating in the research. Participants understood that they had the right to withdraw from the study at any time if they chose to do so.

IV. Experimental Procedure

The experiment concerning the intelligent diagnosis of malaria relies on ANFIS, utilizing data for both training and testing sets. The fuzzy system is employed due to its nature as a feature-based fuzzy model that handles uncertain and complex data to represent fuzzy sets and rules. Besides, an ANFIS has the benefit of both a neural network, which has the capability of learning new data, and fuzzy logic, which deals with linguistic values as well as making decisions using fuzzy [If-THEN] rules [31]. 2000 data is used, and the reason for the chosen size is to have a representative sample of the larger population of the community in Siaya County. To create and evaluate the model, a two-fold cross-validation method was deployed because it can handle the conventional data well and helps to avoid overfitting [32]. This method involves splitting data randomly into training sets and testing sets.

A. Training

To enable the training of an intelligent model for malaria diagnosis. Parameters are carefully tuned to find the best set, ensuring high-quality performance using an optimization method. A hybrid learning approach that combines the least-squares method with the gradient descent technique. Initially, the training was carried out by introducing a training set to the input layer of the network once, and the network transmits the input from one layer to another, until it gets to the output layer. There, an error is computed and propagated backward through the network from the output layer to the input layer. The feature model is trained only once using the training set [33].

B. Testing

After training is complete, testing was carried out, presenting a test-set only once to the network's input layer. The neurons transmit the inputs from Layer 1 to each layer until they reach the output layer. The roles of training and testing are reversed so that training is conducted on the test set, while testing is performed on the training set. After training and the test process, the results are achieved, with getting average error. The outputs achieved are discussed in Section VI. [33].

C. Membership Functions

To obtain efficiency, Five Membership Functions (MFs) were assigned as Generalized bell membership (Gbellmf) type, as shown in Fig. 2, using 12 epochs and zero (0) tolerance. The membership functions (MFs) of fuzzy sets are represented as a curve, which delineates how each point within the input space corresponds to a membership value ranging from (0, 100) to (0, 1) [31]. Consequently, the output can fluctuate between (0, 100 and (0, 1). The intelligent malaria diagnosis model membership function map for data contains risk values where 10 = NonSymptom indicates no risk and 100 = Quartan represents

the highest possible risk. 30 = Suspect indicates low risk, while 80 = Malignant being high risk. 50 = Tertian being moderate risk.

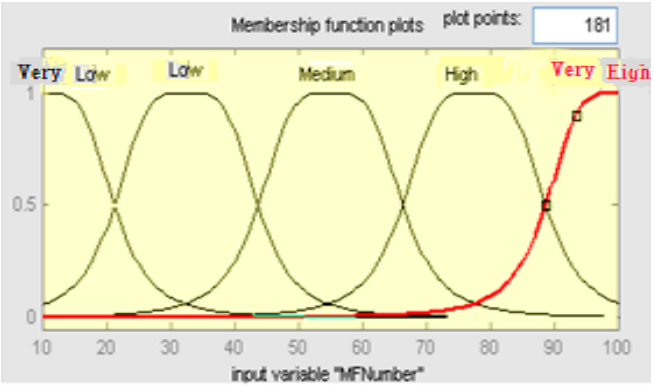


Fig. 2. GBell membership function.

D. Fuzzy Inference Systems and Rules

The intelligent malaria diagnostic model uses an Adaptive Neuro-Fuzzy Inference System learning structure [33]. The FIS is functionally equivalent to fuzzy inference systems. To decompose the parameter set in order to apply the hybrid learning rules, the process goes through the Neural Network and the inference engine decides which is reached by reasoning in connection with the Fuzzy [IF-THEN] rules shown in Fig. 3 and reaches the output layer [33].

Quartan rules

1. If (input is ache-quartan) and (input is argue-quartan) and (input is bronchitis-quartan) and (input is cold-quartan) and (input is bronchitis-quartan) and (input is eruption of herpes-quartan) and … (input is neck_back_pain-quartan) then output is quartan mf1(1)

Malignant rules

2. If (input is teeth-chatter-malignant) and (input is temperature_rises_to_104$_o$-malignant) and (input is temperature_rises_to_105$_o$-malignant) and (input is vomit-malignant) and (input is developmental-malignant) and (input is intestinal_disorders-malignant) and … (input is herpes_around_mouth-malignant) then output is malignant mf2(1)

Tertian rule

3. If (input is abdominal_Pain-tertain) and (input is anemia-tertain) and (input is back-Pain-tertian) and (input is bloody_Stools-tertian) and (input is body-ache-tertian) and (input is chills-tertian) and … (input is hypothermia-tertian) then output is tertian mf3(1)

Suspected rules

4. If (input is irritability-suspected) and (input is jaundice-suspected) and (input is join_Pain-suspected) and (input is kidney_Failure-suspected) and (input is limpness-supected) and (input is loss_of_consciousness-suspected) and … (input is non_prescribed_medication-suspected) then output is suspected mf4(1)

Non_symptom rules

5. If (input is age-non_symptom) and (input is sex-non_symptom) and (input is education-non_symptom) and (input is income-non_symptom) and (input is malaria_History-non_symptom) and (input is location-non_symptom) and … (input is buy_unprescribed_medication-non_sysmtom) then output is non_symptom

Fig. 3. Fuzzy [IF-THEN] rules.

This FIS is a multilayer feedforward network in which each individual neuron carries out a designated function. The related ANFIS architecture is depicted in Fig. 4.

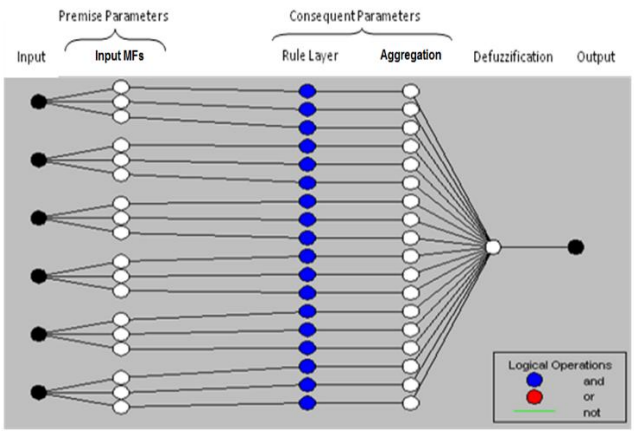


Fig. 4. Fuzzy structure for intelligent malaria diagnosis.

The FIS has six layers which are Layer I - input, Layer II – fuzzification, Layer III – fuzzy rule, Layer IV – normalization, Layer V – defuzzification and Layer VI – crisp output. The learning process takes the form as follows:

1) Layer 1: This is the input. Neurons in Layer I transmit external inputs to Layer II. This is specified as:

$$y_i^{(I)} = x_i^{(I)} \tag{1}$$

where, the input is $y_i^{(1)}$ and the output in layer 1 is $X_i^{(1)}$ [36].

2) Layer II: This is the fuzzification. Neurons in Layer ll perform fuzzification. The Sugneo model fuzzification have a Gbell shape activation function [36]. This is specified as:

$$y_i^{(2)} = \frac{1}{\left[\frac{x_i^{(2)} - ai}{ci}\right]} 2b_i \tag{2}$$

where, the input is $x_i^{(2)}$ and the output is $y_i^{(2)}$ of neuron I Layer II, and a_i b_i and c_i are parameters that control the center width and slope of the bell-shape function of neuron [31].

3) Layer III: This is a rule layer. Every neuron in Layer III matches a single fuzzy rule. A rule neuron receives input from fuzzification and calculates the execution strength of the rule it represents [36]. Thus the output in Layer III is expressed as:

$$y_i^{(3)} = \prod_{j=1}^{k} x_{ji}^{(3)} \tag{3}$$

where, inputs are $x_{ji}^{(3)}$ and $y_i^{(3)}$ are output of rule neuron in Layer III.

4) Layer IV: This is normalization. Every neuron in this layer receives outputs from the rule layer and the normalized execution strength of any given rule is calculated [36]. Therefore, the output of Layer IV is expressed as:

$$y_i^{(4)} = \frac{X_i^{(4)}}{\sum_{i=0}^{u} x_{ji}^{(4)}} = \frac{ui}{\sum_{i=0}^{u} uj} = ui \tag{4}$$

where, the input $x_{ji}^{(4)}$ from neuron j is allocated in Layer III

to Layer IV.

5) Layer V: This is defuzzification. Each neuron in Layer V is connected to the normalization neuron, as well as receives the initial input x_1 and x_2. A neuron defuzzification calculates the value of weight consequent of any given rules [36]. It is specified as:

$$y_i^{(5)} = x_i^{(5)}[k_{i0} + k_{i1}x1 + k_{i2}x2] = u_i[k_{i0} + k_{i1}x1 + k_{i2}x2] \quad (5)$$

In which the input is $x_i^{(5)}$ and the defuzzification output neuron is $y_i^{(5)}$ in Layer V. k_{i0}, k_{i1} and k_{i2} is a set of parameter consequent of rule I [36].

6) Layer VI: This is denoted by a singular neuron sum. The neuron calculates the total output of every defuzzification and produces the overall output y which is specified as [36]:

$$y = \sum_{i=1}^{n} x_i^{(6)} = \sum_{i=1}^{n} u_i\,[k_{i0} + k_{i1}x1 + k_{i2}x2] \quad (6)$$

As demonstrated, the fuzzy structure is in fact functionally equivalent to a first-order Sugeno-fuzzy model [31].

After completion of the training, the model undergoes testing with a separate, unseen 50% test set. The process of training and testing is conducted twice, with roles being reversed; the model is trained on the test set and subsequently tested on the training set. The network processes its input as the weights are modified and transmitted to the subsequent layer, where the output is aggregated, and the sum of squared errors is computed in real-time as end results. The effectiveness of features is evaluated using randomized methods as well as time required to construct models. The level of standard confidence for error is established at 5% across all utilized algorithms, as an average error exceeding 5% is deemed unsuccessful, while an average error below 5% is regarded as successful [33].

V. Results

A. Adaptive Neuro-Fuzzy Inference

The primary aim of the research was to create and implement an intelligent model for diagnosing malaria in endemic areas, utilizing the Adaptive Neuro-Fuzzy Inference System (ANFIS) with six different types of patient data inputs. The performance of the proposed intelligent malaria diagnosis method was assessed through ANFIS, employing 2-fold cross-validation. The training was conducted on the training set, while the model was evaluated on a test set. The roles were switched, with training conducted on a test set and evaluation carried out on a training set [33]. The average test error rate results achieved was 1.68%, as shown in Fig. 5. When the results are expressed as a percentage and rounded to two decimal places, the overall average test error rates are 1.68%. Therefore, the overall average accuracy attained during testing was 98.3%, which is considered outstanding performance [30], [33].

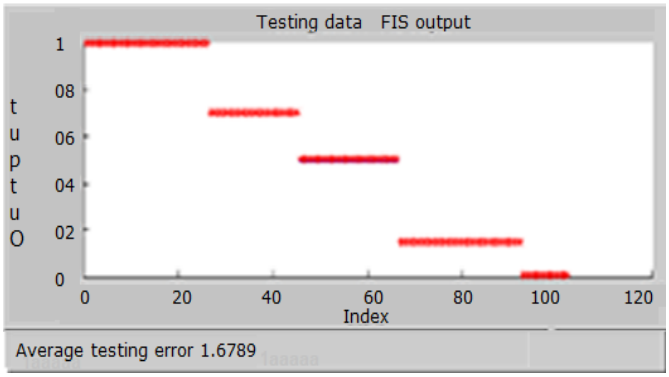


Fig. 5. Average testing error result using ANFIS.

VI. Discussions

The proposed study presents an experimental procedure to diagnose early malaria symptoms. In this study, we deployed ANFIS and a combined Six Types of Patient Data Inputs. Deploying a sample of 2000 patient's data from a combined Six Types of Patient Data Inputs, the finding of the proposed research provides insight information of how well ANFIS can detect early malaria symptoms. ANFIS showed a remarkable level of performance, demonstrating its ability to handle both the training dataset and the test dataset. Deploying a hybrid approach helps to get the best set of parameters tuned to maximize the system performance. The contribution of the proposed study is demonstrated in Section V(A).

A. Contribution

The proposed study contributes to the field by introducing a novel method, combining Six Patient Data inputs. The Six Patient Data inputs are: Demographic, Symptoms, Blood pressure, Heartbeats, Height and Weight based on ANFIS to optimize the model performance. From these Six Patient Data inputs, 2000 data were collected which were utilized to create fuzzy models, fuzzy rules as well as to detect early malaria symptoms. Using data based on the Six Patient Data inputs leads to higher accuracy and reliability, while using few symptoms often results in uncertainty and potential misdiagnosis. This study is the first to utilize the novel method combining Six Patient Data inputs in the field. The experiments based on ANFIS with data have consistently produced the best results. Using the MATLAB toolbox, ANFIS achieved 98.3% accuracy. The novel method achieved best results so far compared to the related cutting-edge in the domain. Overall, the outcomes indicate that the new method, using Six Types of Patient Data Inputs provide enhanced accuracy and deliver optimal performance. Comparative analysis is carried out in Section V(B).

B. Comparison of the Proposed Study with the Existing Related Works

To compare the results of the new approach that achieved 98.3% accuracy with the work of Uzun et al. [16] and the work of Bria et al. [12] which are closest to the proposed study.

The proposed study outperformed the study by Uzun et al. [16] with 1.3% difference, while the study of Bria et al. [12] is outperformed with a difference of 2.3%, as shown in Table II. The proposed model's higher accuracy is supported by its use of six different data types, unlike the other models using 10 to 12 symptoms only [12]. As we can see, the work of Bria et al. [12] used 10 to 12 malaria symptoms for malaria diagnosis which is too small for generalization, while the study of Uzun et al. [16] though had 2700, generalization was limited.

TABLE II. COMPARISONS OF THE PROPOSED STUDY WITH RELATED WORK

Schedule	Algorithms	Data Symptoms	%
Barraclough et al.	ANFIS	2000	98.3
Uzun et al. (2024)	MLR/ANN/ANFIS/R	None	92%, 99%, 97%, 68%
Bria et al. (2021)	LR, SVM, KNN	10-12	84% -86
Santosh & Ramesh (2019)	ANNs	Big data	82%
Morang'a et al. (2020) Uzoka et al. (2016)	ANNs) NF	2207 12	94% None

A direct comparison of our results against previous results is not possible because our method integrates Six Types of Patient Data Inputs, which is wide-ranging, while the existing results only used symptoms and non-symptoms.

Morang'a et al. [21] employed haematological data extracted from 2,207 participants in Ghana, using multi-layer classification and Blood count. ANN scored a range of 94% accuracy. However, these models were restricted to base-learners with fewer features from one source, achieving (82% - 94%) less than the standard confidence of 5% errors, whereas our method achieved 98.3% accuracy, demonstrating that the method used is far better than the related existing methods. Our research findings suggest that the method we proposed accurately diagnoses malaria in real-time and have a high level of performance compared to the reported related results. Other notable research that explored malaria diagnosis through ML techniques are as follows: Santosh and Ramesh deployed [22] clinical and environmental variables with big data using ANNs for mosquito abundance prediction in the geographical location of Khammam district, Telangana, in India. The average results range from 82% to 17% accuracy. The big data used is not specifically for malaria symptoms.

C. Strengths and Limitations

In the process of experimenting with different numbers of hidden neurons, the experiment indicated that the number of neurons in the hidden layers affects the speed of training the network in the method, achieving a time to build the model in the range of 0.01 to 0.006 seconds [34]. Complex patterns cannot be identified by a limited number of hidden neurons. However, numerous such patterns can significantly increase the load on the computational domain. As the quantity of hidden neurons increases, so does the network's capacity to identify existing patterns. However, if the quantity of hidden neurons is excessively high, the network may merely memorize all training examples. This could hinder its ability to generalize or generate accurate outputs when faced with unseen data [33].

Conversely, we utilized the capabilities of algorithms through the application of fuzzy rules. The models developed with ANFIS demonstrate greater reliability and sophistication in classifying instances from both the training and testing sets through two-fold cross-validation.

VII. CONCLUSION

We have described the proposed method using a combined Six Types of Patient Data Inputs and Adaptive-Network-based Neuro-Fuzzy Inference System. By employing a hybrid approach using parameter tuning with a combined Six Types of Patient Data, ANFIS can refine the given rules to describe the system's input and output. The experimental findings indicated that the proposed approach is proficient in diagnosing malaria symptoms more accurately and reducing malaria burden. Recognizing that elevated scores may result from utilizing limited data, which indicates that the dataset comprises only 1 to 10 samples. A comparatively limited dataset may adversely impact a model's performance because of overfitting, a phenomenon where a model excels with the training data yet struggles with new, independent data. A viable approach to addressing this issue is the implementation of cross-validation. To solve the small sample problem, the proposed method was evaluated based on ANFIS, using 2000 data extracted from Six Types of Patient Data inputs selected with InfoGainAttributeEval and Ranker. Two-fold cross-validation was employed and ANFIS demonstrated the merit of the new method. The results revealed that the data have a strong correlation with classes. The experimental outcome for the new method was 98.3%.

The main contribution: This study presents a novel method, combining Six Patient Data Inputs that include Symptoms, Blood pressure, Heartbeats, Height and Weight, using ANFIS to detect malaria accurately. The results demonstrate that a combined method using Six Types of Patient Data Inputs can accurately classify malaria symptoms in a matter of seconds and demonstrate superior performance when compared to the results reported in the field.

The significant finding is that the new model has a higher accuracy, supported by using six different data types, which is different to other models that used 10 – 12 symptoms/features. Therefore, this study fills the gap by providing diverse six data types that can be used in the field to diagnose malaria.

The finding will potentially enable doctors to conduct a comprehensive diagnosis of early malaria symptoms and plan appropriate treatment. It will help the remote community user to reduce malaria risks by detecting early malaria symptoms.

The finding will lead to a fully developed real-world application vigorously tested and validated to diagnose malaria symptoms for remote settings.

A. Future Work

Next step is to develop a mobile-based application designed for the early detection of malaria, suitable for use in rural areas. Electricity and computers are scarce in the remote settings in Kenya, while mobile devices are accessible by most of the population using designated shopping centers to charge the mobile devices to be usable. Therefore, this method will allow malaria diagnosis to be accessible in the diverse community.

FUNDING

There was no funding provided to conduct this research.

CONFLICT OF INTERESTS

There is no conflict of interest to declare.

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REFERENCES

[1] A. Otieno, L.M. Were, C. K. Sagam, S. Kariuki and E. Ochodo, Evaluating the impact of malaria rapid diagnostic tests on patient-important outcomes in sub-Saharan Africa: a systematic review of study methods to guide effective implementation. *BMJ Open* (2024) 14:e077361. doi:10.1136/ bmjopen-2023-077361

[2] Severe Malaria Observatory, (Malaria facts, 2023) https://www.severemalaria.org/countries/kenya

[3] L. Hester, J. Nityanand, S. Mai, S. Masako, R Ieva, O. Kevin, Combating malaria in Kenya through collaborative population health education: *a systematic review and pilot case study, Infectious Diseases*, 55:10 (2023) 664-683, DOI: 10.1080/23744235.2023.2231082

[4] World Health Organization WHO. (World Malaria Report 2022). https://www.who.int/teams/global-malaria-pro gramme/reports/world-malaria-report-2022

[5] World malaria report 2022. Geneva. (World Health Organisation, 2022). https://www.who.int/teams/global-malaria-programme/reports/world-malaria-report-2022

[6] Kenya Malaria Indicator Survey (KMIS), (Final Report 2020), https://www.dhsprogram.com/pubs/pdf/MIS36/MIS36.pdf

[7] S. S. Devi, S. N. Herojit, L. R. Hussain, Performance Analysis of Various Feature Sets for Malaria-Infected Erythrocyte Detection. Soft Computing for Problem Solving. *Advances in Intelligent Systems and Computing,* 1057 (2020). Springer, Singapore. https://doi.org/10.1007/978-981-15-0184-5_24

[8] R. Ramdzan, A. Ismail, Z. S. M. Zanib, Prevalence of malaria and its risk factors in Sabah, *Malaysia. Int J Infect Dis*; 91 (2020) 68–72.

[9] S. Shimizu, S. Chotirat, N. Dokkulab, I. Hongchad, K. Khowsroy, K. Kiattibutr, Malaria cross-sectional surveys identified asymptomatic infections of Plasmodium falciparum, Plasmodium vivax and Plasmodium knowlesi in Surat Thani*, a southern province of Thailand. Int J Infect Dis*; 96 (2020) 445–51.

[10] T. O. Oladele, R. O. Ogundokun, J. B. Awotunde, M. Adebiyi, J. K OAdeniyi,. Diagmal: a malaria coactive neuro-fuzzy expert system. In: *Lecture notes in computer science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), LNCS* 12254 (2020) 428–441

[11] K. Hemachandran, A. Alasiry, M. Marzougui, S.M. Ganie, A. A. Pise, M.T.-H. Alouane, C. Chola, Performance Analysis of Deep Learning Algorithms in Diagnosis of Malaria Disease. *Diagnostics* (2023) 13, 534. https://doi.org/10.3390/ diagnostics13030534

[12] Y. P. Bria, C.-H. Yeh, S. Bedingfield, Significant symptoms and nonsymptom-related factors for malaria diagnosis in endemic regions of Indonesia. *International Journal of Infectious Diseases*, 103 (2021) 192-200.

[13] F-ME. Uzoka, B. A. Akinnuwesi, T. Amoo, F. Aladi, S.Fashoto, M. Olaniyan, A framework for early differential diagnosis of tropical confusable diseases using the fuzzy cognitive map engine. *Int J Health Med Eng*;10 2 (2016) 346–53.

[14] T. Santosh, D. Ramesh, Artificial neural networks-based prediction of malaria abundances using big data: *a knowledge capturing approach. Clin Epidemiol Glob Heal*, 7 (2019) 121–6. https://doi.org/10.1016/J.CEGH.2018.03.001.

[15] W. K. Phang, M. H. B. A Hamid, J. Jelip, T.W. Chuang, Y. L. Lau, M. Y. Fong, Predicting Plasmodium knowlesi transmission risk across Peninsular Malaysia using machine learning-based ecological niche modeling approaches. *Front. Microbi*ol, 14 (2023) 1126418.

[16] D. O. Uzun, B.B. Duwa, I. Ozsahin, B. Uzun, Quantitative Forecasting of Malaria Parasite Using Machine Learning Model: MLR, ANN, ANFIS and Random Forest. Diagnostics (Basel). 14(4) (2024) 385. doi: 10.3390/diagnostics14040385.

[17] F.Yang, M. Poostchi, H. Yu, Z. Zhou, Silamut, K. Yu, J. R. J. Maude, S. Jaeger, S. Antani, Deep learning for smartphone-based malaria parasite detection in thick blood smears. *IEEE J. Biomed. Health Inform.* 24(5) (2019) 1427–1438

[18] A. Vijayalakshmi B., R. Kanna, Deep Learning Approach to detect malaria from microscopic images. *Multimed Tools Appl* 79 (2020) 15297–15317. https://doi.org/10.1007/s11042-019-7162-y

[19] G. Madhu, A. Govardhan, B. S. Srinivas, K. S. Sahoo, N. Z. Jhanjhi, K. S. Vardhan1, B. Rohit, Imperative dynamic routing between capsules network for malaria classification. *Comput. Mater. Contin.* 68(1) (2021) 903–919.

[20] A. Loddo, C. Fadda, Ruberto, C. Di, An Empirical Evaluation of Convolutional Networks for Malaria Diagnosis. *J Imaging*. 7;8(3):66 (2022). doi: 10.3390/jimaging8030066. PMID: 35324621; PMCID: PMC8951236.

[21] M. Morang'a, L. Amenga–Etego, S.Y. Bah, Machine learning approaches classify clinical malaria outcomes based on haematological parameters. *BMC Med* 18 (2020) 375 https://doi.org/10.1186/s12916-020-01823-3.

[22] T. Santosh, D. Ramesh, Artificial neural networks-based prediction of malaria abundances using big data: a knowledge capturing approach. *Clin Epidemiol Glob Heal*, 7 (2019) 121–6, https://doi.org/10.1016/J.CEGH.2018.03.001.

[23] M. O. Arowolo, J. B. Awotunde, P. Ayegba, S. O. Haroon-Sulyman, Relevant gene selection using ANOVA-ant colony optimisation approach for malaria vector data classification. International Journal of Modelling, *Identification and Control*, 41(1-2), (2022) 12-21.

[24] J. B. Awotunde, A. L. Imoize, D. P. Salako, Y. Farhaoui, An Enhanced Medical Diagnosis System for Malaria and Typhoid Fever Using Genetic Neuro-Fuzzy System. *In The International Conference on Artificial Intelligence and Smart Environment (*2022) 173-183. Cham: Springer International Publishing.

[25] J. B. Awotunde, S. Misra, F. E. Ayo, A. R. A. Agrawal, Hybridized Support Vector Machine and Adaboost Technique for Malaria Diagnosis. In Frontiers of ICT in Healthcare: *Proceedings of EAIT* (2023) 25-38. Singapore: Springer Nature Singapore.

[26] P.M. Datilo, Z. Ismail, J. A Dare, review of epidemic forecasting using artificial neural networks. Epidemiol. Health Syst. J., 6 (2019) 132–143

[27] J. B. Awotunde, R. G. Jimoh, I. D. Oladipo, Abdulraheem, M. Prediction of malaria fever using long-short-term memory and big data. In International Conference on Information and Communication Technology and Applications, *Cham: Springer International Publishing.* (2020) 41-53.

[28] R. Parveen, A.H. Jalbani, M. Shaikh, K.H. Memon, S. Siraj, M. Nabi, Prediction of malaria using artificial neural network. *Int J Comput Sci Netw Secur*. 17 (2017) 79–86.

[29] E. O. Marita, R. Gichuki, E. Watulo, S. Thiam, S. Karanjam, Determinants of quality in home-based management of malaria by community health volunteers in rural Kenya. *J Infect Dev Ctries,*15 (2021) 897–903. doi: 10.3855/jidc.13565. PubMed

[30] M. Negnevitsky, (2002). Artificial Intelligent: A Guide to Intelligent Systems. 2nd edn. Pearson Education, (Chapter 8).

[31] S. R. Jang, "ANFIS: adaptive-network-based fuzzy inference system. *IEEE,". Transactions on systems, MAN, and Cybernetics*, 23, 3 (1993).

[32] P. B Sivarao,. N. S El-Tayeb,. M. A. New Approach of Adaptive Network-Based Fuzzy Inference System Modelling in Laser Processing. A Graphical User Interface (GUI) Based, *Journal of Computer Science.* 5 (10), (2009) 704-710.

[33] M. Negnevitsky, Artificial Intelligent: A Guide to Intelligent Systems. 2nd edn. *Pearson Education* (2005).

[34] S. Haykin, Neural Networks—A Comprehensive Foundations. Prentice-Hall International, *New Jersey* (1999).

[35] S.A. Alowais., S.S. Alghamdi, N. Alsuhebany, *et al.* Revolutionizing healthcare: the role of artificial intelligence in clinical practice. *BMC Med Educ* 23, 689 (2023). https://doi.org/10.1186/s12909-023-04698-z

[36] M. Negnevitsky, (2002). Artificial Intelligent: A Guide to Intelligent Systems. 2nd edn. Pearson Education, Section 8.2, Chapter 8.

[37] P.A Barraclough, C. M Were, H. Mwangakala, G. Feheringer, D. O. Ohanya, H. Agola, P.Nandi, Artificial Intelligence System for Malaria Diagnosis, (IJACSA) International Journal of Advanced Computer Science and Applications, (2024), Vol. 15, No. 3, 2024

[38] M. J. Barcus, H. Basri, H. Picarima, C. Manyakori, Biomedis Puslitbang, Farmasi; Demographic risk factors for severe and fatal vivax and falciparum malaria among hospital admissions in Northeastern Indonesian Papua. Am Soc Trop Med Hyg 2007;77(5):984–91.

[39] L. Deepak, M.D. Bhatt, What is begeminy in heartbeat (2021)' Accessed at "https://www.health.harvard.edu/heart-health/what-is-bigeminy-in-a-heartbeat"

[40] M. Roser, C. appel, H. Ritchie, The History of Human Height, (2024) Accessed at https://ourworldindata.org/human-height

Latent-Topology Graph State-Space Model (LT-GSSM) for Robust Traffic Fore-Casting

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***Abstract*—Accurate traffic forecasting remains challenging when sensor data are noisy, incomplete, or non-stationary. Recent advances in spatio-temporal learning have combined Graph Neural Networks (GNNs) with recurrent, convolutional, or attention mechanisms to capture spatio-temporal dependencies. However, most existing approaches remain largely deterministic and rely on fixed or pre-learned adjacency matrices, limiting their adaptability when network structures evolve or sensor reliability varies. Some methods further stack multiple adjacency matrices to represent complex spatial relations, yet still lack explicit mechanisms to model uncertainty, resulting in reduced robustness under degraded data conditions. This work introduces the Latent Topology Graph State-Space Model (LT-GSSM), a probabilistic framework designed to enhance robustness and adaptability in traffic forecasting. LT-GSSM represents the road network as a latent dynamic graph whose structure evolves over-time through dynamic adjacency learning based on past hidden states and observations, enabling the model to capture evolving spatial correlations such as congestion propagation. Temporal dependencies are modelled by a nonlinear state-space function implemented with a Temporal Convolutional Network (TCN), which captures long-range temporal patterns without recurrence. The probabilistic state-space formulation explicitly represents sensor noise and handles missing data through probabilistic estimation inspired by Kalman filtering. By jointly integrating dynamic graph learning, explicit noise modelling, and nonlinear temporal transitions, LT-GSSM achieves greater stability and resilience to data uncertainty. Experiments on SUMO simulations and real-world PeMS datasets show that LT-GSSM consistently outperforms static and adaptive-graph models, providing a strong foundation for robust spatio-temporal forecasting under uncertain conditions.**

Keywords*—Traffic forecasting; graph neural networks; state-space models; latent topology; dynamic adjacency learning; spatio-temporal modeling; noise and missing data robustness; probabilistic modeling

I. Introduction

Despite major advances in artificial intelligence, spatio-temporal learning remains challenging due to complex spatial dependencies, dynamic temporal patterns, and inherent data uncertainty. These difficulties are particularly evident in traffic forecasting, where large-scale sensor data are often noisy, incomplete, and non-stationary [1].

Traditional prediction models perform well under ideal conditions but lack explicit mechanisms to handle noise, missing data, or uncertainty, leading to poor stability in real deployments. Moreover, traffic networks are non-Euclidean, governed by road connectivity rather than distance [2], and their correlations evolve dynamically with congestion, incidents, or weather [3,4].

Recent advances in spatio-temporal graph architectures—such as diffusion-based DCRNN [5], recurrent T-GCN [6], and attention-driven ASTGCN or ST-Transformer [7,8]—have improved prediction accuracy However, deterministic graph adaptation remains fundamentally limited under noisy or incomplete observations, as it cannot represent the structural uncertainty induced by sensor degradation or missing data.

To address these limitations, we propose the Latent Topology Graph State-Space Model (LT-GSSM), a probabilistic framework for robust and adaptive traffic forecasting. Unlike conventional adaptive GNNs (e.g., AGCRN, DGCRN), where adjacency updates depend on static node embeddings or deterministic functions, LT-GSSM learns a latent dynamic graph, where the adjacency is treated as a state-conditioned latent variable rather than a deterministic function of node embeddings. This enables joint modeling of temporal and structural uncertainty, resulting in a self-evolving spatio-temporal representation that better reflects real-world non-stationarity.

The adjacency matrix A_t evolves from past hidden states and observations, allowing the model to capture time-varying spatial correlations such as congestion propagation or structural shifts. Temporal dependencies are modeled by a nonlinear state-space transition using a Temporal Convolutional Network (TCN), which captures long-range patterns without recurrence. The probabilistic state-space formulation explicitly represents process and observation noise, enabling robust estimation under sensor degradation or missing data—an approach inspired by Kalman filtering.

The main contributions of this work are as follows:

- A unified probabilistic graph state-space formulation, in which both temporal dynamics and graph structure are modelled within a single latent state-space framework, rather than treating adaptive graphs and temporal uncertainty as separate components.
- State-conditioned latent topology modelling, where the adjacency matrix is inferred as a latent random variable conditioned on hidden states, instead of being deterministically parameterized from node embeddings as in existing adaptive GNNs.
- Explicit modeling of process and observation uncertainty within the state-space dynamics, enabling robust spatio-

temporal forecasting under sensor noise and missing data, without relying on deterministic graph updates.

The remainder of this paper is organized as follows: Section II reviews related work on spatio-temporal and probabilistic models; Section III describes the LT-GSSM methodology; Section IV presents experimental results and robustness analyses; Discussion is given in Section V and Section VI concludes with future research directions.

II. Related Works

Traffic forecasting is a complex spatio-temporal task shaped by irregular topologies, non-stationary dynamics, and noisy sensor conditions.

Classical time-series models such as ARIMA and VAR [7,8] capture temporal patterns but ignore spatial correlations among sensors. Early machine-learning methods [9] improved flexibility but struggled with high-dimensional dependencies across the road network.

Deep learning advanced the field through Recurrent Neural Networks (RNNs) such as LSTM and GRU [10,11], which model temporal sequences but process each sensor independently. Convolutional Neural Networks (CNNs) [12] extended modeling to spatial grids, yet their Euclidean structure limits generalization to real road networks [13].

To overcome these limitations, Graph Neural Networks (GNNs) [14] model traffic as a graph, where nodes represent sensors and edges capture road connectivity. Hybrid spatio-temporal architectures such as DCRNN, T-GCN, and attention-based models like ASTGCN [15] and ST-Transformer [16] jointly learn spatial and temporal dependencies. While accurate, these models assume fixed or pre-learned adjacency matrices, neglecting dynamic spatial relationships that vary with congestion, incidents, or weather.

Recent advances introduced adaptive and dynamic graph learning, including AGCRN [17], DGCRN [18], and RT-GCN [19], which update adjacency matrices using learned node embeddings or Gaussian-based convolutions. These designs improve flexibility but remain deterministic, failing to model uncertainty or stochastic graph evolution explicitly.

Parallel progress in probabilistic state-space models (SSMs) such as KalmanNet [20], Deep Kalman Filters [21], and Neural State-Space Models [22] has reintroduced uncertainty estimation and latent dynamics into deep learning. However, these frameworks are typically temporal only, lacking explicit graph reasoning. Attempts to combine GNNs with probabilistic methods, such as Probabilistic GNNs [23] and Graph Variational Filters [24], remain computationally costly and seldom applied to large-scale traffic networks.

In summary, prior models either:

- Learn dynamic graphs without probabilistic treatment of noise and uncertainty, or
- Apply probabilistic state-space reasoning without spatial modelling.

This gap motivates our Latent Topology Graph State-Space Model (LT-GSSM), a unified probabilistic framework that jointly models time-varying graph topology and temporal dynamics. By treating the adjacency A_t as a latent variable evolving from hidden states and observations, LT-GSSM captures both structural and stochastic uncertainty, achieving robust forecasting under noisy, incomplete, and dynamically changing conditions.

III. Methodology

A. Data Simulation and Preparation

A key element of our methodology is the use of both synthetic and real-world datasets to assess robustness. Real data often suffers from partial sensor coverage and measurement noise, whereas synthetic data generated with SUMO (Simulation of Urban Mobility) [24] allows full control over network coverage, traffic conditions, and injected noise. This controlled environment enables systematic evaluation of our GSSM under diverse and challenging scenarios.

1) Synthetic dataset (SUMO): We generated a two-month traffic dataset using SUMO for the Outaouais region near Ottawa (Fig. 1), based on real road networks extracted from OpenStreetMap. Traffic flows were dynamically managed through TraCI (Traffic Control Interface) [25] to emulate realistic conditions such as peak-hour congestion and weekend traffic reduction. Vehicle counts were aggregated into 5-minute intervals, following common benchmarking practices [26, 27].

The chosen duration aligns with established datasets such as METR-LA and PEMS-BAY [14, 15], which span 2–4 months. This ensures a balance between temporal coverage and computational efficiency, while remaining comparable to standard baselines. To assess robustness, we generated several perturbed versions of the SUMO dataset:

- Gaussian noise injected at 5–30 % levels to simulate sensor errors.
- Reduced sensor coverage through three controlled scenarios:
  - Sensors limited to main roads,
  - Random removal of 20 % of sensors, and
  - Random removal of 50 % of sensors.

These perturbations make it possible to study the model's resilience to measurement uncertainty and coverage sparsity, establishing SUMO as an effective robustness benchmark.

2) Validation of realism: To validate the realism of our synthetic dataset, we compared key traffic patterns with re-al-world datasets such as PEMS08 and UTD19 [28]. Despite differences in absolute magnitudes, our dataset reproduces essential traffic behaviors observed in real-world da-ta, including:

- morning and evening peak-hour congestion,
- sharp reductions in weekend traffic, and
- daily distribution patterns. These similarities, illustrated in Fig. 2 and Fig. 3, confirm that SUMO-based data capture fundamental traffic dynamics.



(a) Selected road network.



(b) Traffic flow visualization

Fig. 1. Road network and traffic flow visualization: (a) Selected road network, (b)Traffic flow visualization.

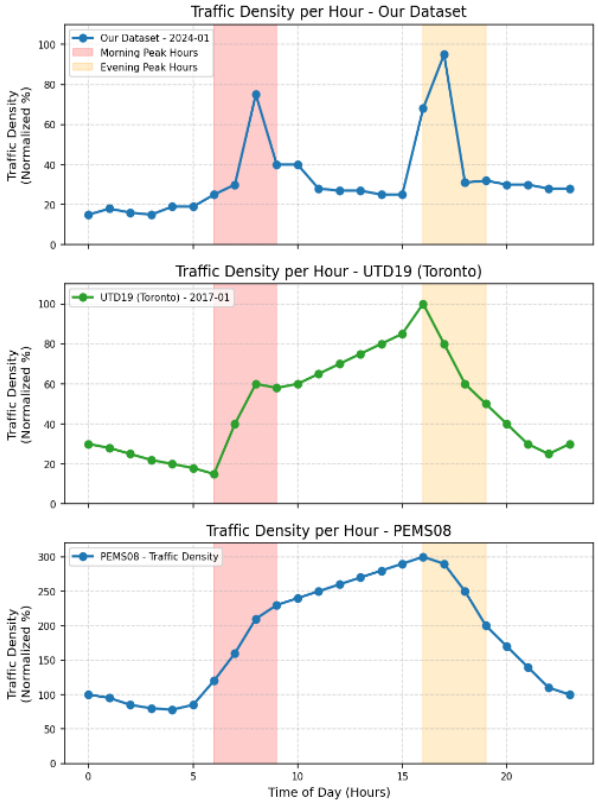


Fig. 2. Comparison of hourly traffic density trends: our dataset vs. Real-world datasets.

This SUMO-based dataset thus provides a reliable testbed for assessing the performance and robustness of GSSM under controlled scenarios of noise and sensor sparsity, complementing evaluations on real-world datasets.

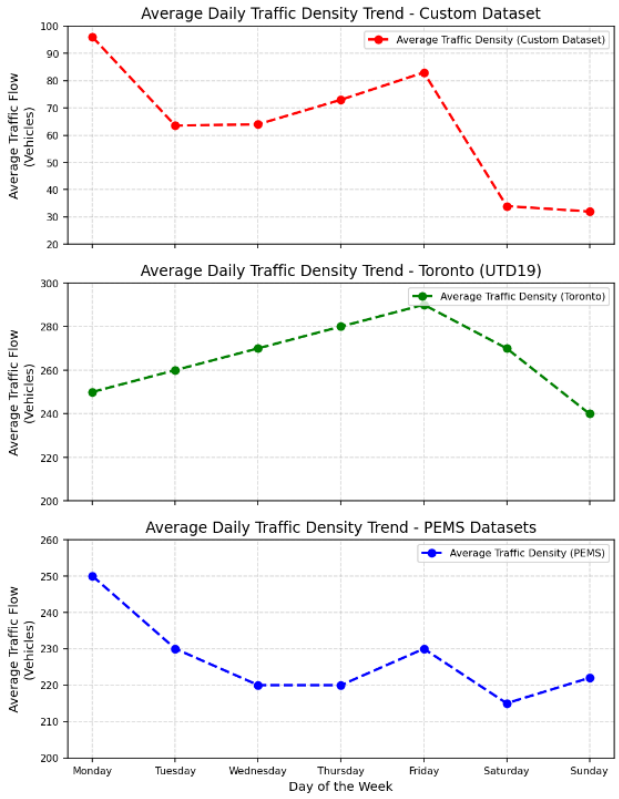


Fig. 3. Weekend traffic density comparison: our dataset vs. Real-world datasets.

B. Spatio-Temporal Data Modeling and Representation

To capture spatio-temporal dependencies in traffic data, we represent all datasets as three-dimensional tensors $X \in \mathbb{R}(T \times E \times V)$, where T denotes the number of time steps (e.g., 5-minute intervals), E the number of road segments or sensors, and V the set of traffic variables such as vehicle density and average speed. This tensor format enables the joint modeling of temporal dynamics, spatial interactions, and multivariate dependencies, and is well-suited for graph-based neural architectures [29, 30].

Complementing this tensor structure, we construct an initial spatial adjacency matrix A_0 to encode the physical connectivity between road segments. This matrix serves as a topological prior — it provides an initial structural representation of the network, which will later be refined dynamically during model training based on learned latent representations. Thus, while A_0 defines the initial spatial configuration, the model does not assume a fixed topology, allowing subsequent updates to better capture evolving spatio-temporal correlations. The method used for constructing A_0 differs depends on the dataset:

- SUMO (Synthetic Data): Since the simulated Outaouais network is relatively small and geographically localized, distances between connected roads are short and highly heterogeneous. To preserve strong locality while avoiding dense, fully connected graphs, we define adjacency entries inversely proportional to the physical distances between connected segments. This choice ensures that immediate neighbors exert stronger influence, reflecting realistic propagation of congestion

within a compact road network. This ensures that spatial relationships reflect real-world topology rather than mere Euclidean proximity [31].

Our adjacency matrix has the following structure:

$$A_0 = \begin{array}{c|cccc} & \text{edge}_1 & \text{edge}_2 & \cdots & \text{edge}_N \\ \text{edge}_1 & 0 & \frac{1}{d_{1,2}} & \cdots & \frac{1}{d_{1,N}} \\ \text{edge}_2 & \frac{1}{d_{2,1}} & 0 & \cdots & \frac{1}{d_{2,N}} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \text{edge}_N & \frac{1}{d_{N,1}} & \frac{1}{d_{N,2}} & \cdots & 0 \end{array}$$

- PEMS Datasets These datasets cover larger and more heterogeneous urban areas with complex traffic flows. To model smooth spatial dependencies while avoiding overly dense connections, we adopt a Gaussian kernel approach [14, 15], computing adjacency as:

$$A_{ij} = \exp\left(-\left(\frac{d_{ij}}{\sigma}\right)^2\right) \quad (1)$$

where, d_{ij} is the physical distance between sensors i and j, and σ is set to 1000 meters. This distinction reflects the different scales and characteristics of the networks: SUMO enables precise control and sparse adjacency, whereas PEMS requires soft, distance-based weighting to capture complex spatial patterns without excessive graph density. This adjacency matrix serves as an initial structural prior reflecting geographic connectivity. During LT-GSSM training, this matrix evolves into a latent, data-driven adjacency A_t that adapts to changing spatial correlations and temporal patterns in traffic dynamics.

C. Hybrid Graph–State–Space Model with Latent Topology (LT-GSSM)

The main innovation of this work is the integration of a latent, dynamically evolving graph topology within a state–space framework—a dimension rarely addressed in spatio-temporal modeling.

Unlike prior adaptive GNNs such as AGCRN [17] and DGCRN [18], which learn static or semi-static adjacency matrices, the proposed LT-GSSM continuously updates its graph structure during both training and inference.

The model begins with a static prior A_0, derived from spatial proximity (e.g., inverse distance or Gaussian similarity). As learning progresses, the adjacency matrix A_t is inferred from the previous hidden state h_{t-1}, coupling spatial evolution with temporal reasoning.

Unlike adaptive GNNs such as AGCRN or DGCRN, where adjacency updates are deterministic functions of node embeddings, LT-GSSM treats topology evolution as part of the latent state dynamics under uncertainty.

At each time step, LT-GSSM performs four operations:

- Latent topology inference — infers A_t from h_{t-1};
- Spatial feature extraction — applies GCN using A_t and input X_t;
- Temporal modeling — updates h_t via a Temporal Convolutional Network (TCN).
- Topology update — refines A_{t+1} using the new latent state.

This feedback loop makes the graph self-evolving, allowing spatial dependencies to adapt dynamically to non-stationary or uncertain conditions. By linking latent state evolution to graph adaptation, LT-GSSM (Fig. 4) jointly models spatial, temporal, and structural uncertainty, achieving a robust and adaptive representation for real-world spatio-temporal forecasting.

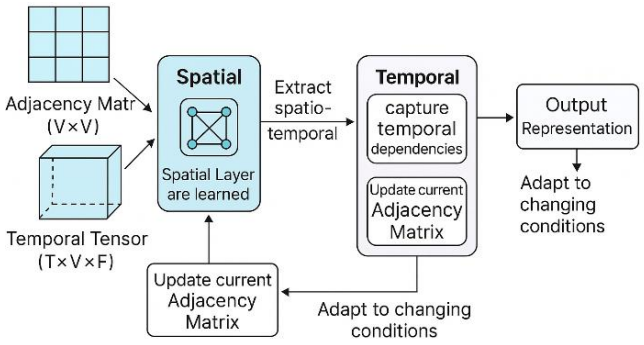


Fig. 4. Overview of LT-GSSM architecture.

1) Temporal layer — state-space model and uncertainty management: The LT-GSSM adopts a probabilistic state–space formulation in which latent states evolve under dynamic graph structures and stochastic perturbations. This allows the model to jointly capture temporal dependencies and uncertainty due to sensor noise, missing data, or non-stationary traffic. Two noise sources are modeled: transition uncertainty (latent fluctuations in dynamics) and observation uncertainty (measurement errors and delays).

In a classical linear SSM:

$$h_t = Ah_{t-1} + Bx_t + w_t, y_t = Hh_t + v_t \quad (2)$$

where, w_t and v_t denote Gaussian process and observation noise. To handle nonlinear and time-varying dynamics, the LT-GSSM replaces fixed matrices with a Temporal Convolutional Network (TCN):

$$h_t = \text{TCN}(Z_{1:t}) + w_t, w_t \sim \mathcal{N}(0, \sigma_t^2 I) \quad (3)$$

The TCN serves as the nonlinear transition function, capturing long-range temporal dependencies without recurrence while preserving probabilistic uncertainty through w_t.

2) Integration with dynamic graph topology: Temporal evolution is explicitly coupled with a time-varying adjacency. From the previous latent state, node embeddings are obtained via a learnable projection:

$$E_t = \phi_E(h_{t-1}), E_t \in \mathbb{R}^{V \times d} \quad (4)$$

Pairwise similarities define a latent affinity matrix:

$$S_t = \frac{E_t E_t^T}{\sqrt{d}} \quad (5)$$

which is row-normalized to yield the dynamic adjacency:

$$A_t = \text{softmax}_{\rho\omega}(S_t) \quad (6)$$

This attention-like normalization ensures each row forms a probability distribution over neighbors, making the graph context-dependent rather than fixed. The updated A_t guides the spatial layer, and the resulting latent state h_t generates A_{t+1}, creating a feedback loop where topology and dynamics co-evolve.

3) Graph Convolutional Network (GCN): At each step, the GCN extracts spatial dependencies from X_t using the dynamic A_t:

$$Z_t = \widetilde{D}_t^{-1/2} \tilde{A}_t \widetilde{D}_t^{-1/2} X_t W_{\text{GCN}} \quad (7)$$

where $\tilde{A}_t = A_t + I_V$ adds self-connections, $\widetilde{D}_t$ is the degree matrix, and W_{GCN} are learnable weights. A normalization layer stabilizes training, producing spatially filtered features Z_t that encode latent correlations among sensors.

4) Unified spatio-temporal formulation: The LT-GSSM integrates both modules within a unified probabilistic transition:

$$h_t = TCN(GCN(X_t, A_t)) + w_t, w_t \sim \mathcal{N}(0, \sigma_t^2 I) \quad (8)$$

and the observation equation:

$$\hat{y}_t = Hh_t + v_t, v_t \sim \mathcal{N}(0, \tau_t^2 I) \quad (10)$$

This formulation fuses dynamic spatial reasoning and nonlinear temporal modeling while explicitly quantifying uncertainty, yielding a robust framework for spatio-temporal forecasting under noisy and evolving conditions.

IV. Results

A. Dataset Summary

We evaluated the proposed LT-GSSM and all baseline models on both synthetic (SUMO) and real-world (PeMS) datasets, which differ in scale, variability, and network complexity.

The SUMO dataset provides a controlled environment to systematically assess robustness to noise and sensor sparsity, while PeMS datasets reflect real-world traffic dynamics across large urban regions. This dual setup ensures that robust trends observed in simulation can be validated under realistic, heterogeneous conditions.

All datasets span 2–4 months at 5-minute intervals, with traffic flow as the key variable. Table I summarizes the main characteristics of the synthetic (SUMO) and real-world (PeMS) datasets used in this study, including network size, temporal resolution, and observation period.

TABLE I. Summary of Datasets Used in This Study

Dataset	Nodes	Time Steps	Period
PeMSD03	358	26,208	09/2018–11/2018
PeMSD04	307	16,992	01/2018–02/2018
PeMSD07	883	28,224	05/2017–08/2017
PeMSD08	170	17,856	07/2016–08/2016
SUMO	127	16,992	Simulated (2 months)

B. Model Selection and Architectural Variants

We compared LT-GSSM against a broad spectrum of spatio-temporal architectures, ensuring fair and representative evaluation:

- Classical temporal baselines: ARIMA, VAR, and BiLSTM.
- Hybrid sequential models: LSTM–CNN, LSTM–GCN (T-GCN), and GRU-based variants.
- Convolutional models: 3D CNNs capturing local spatio-temporal dependencies.
- Attention and transformer architectures: ST-Transformer, attention-based GCNs.
- Diffusion and robustness models: DCRNN and RT-GCN, integrating diffusion or Gaussian convolutions for stability.
- Adaptive graph model: AGCRN as a dynamic-graph baseline using learnable node embeddings.
- Proposed model: LT-GSSM introduces a latent, probabilistic topology derived from hidden states, allowing state-driven graph evolution rather than deterministic embedding updates.

All baselines were re-implemented according to their original papers, with minimal adaptations for uniform preprocessing and input size. This guarantees that performance differences stem from model design, not implementation bias.

C. Experimental Framework and Hyperparameter Sensitivity

All models were trained under identical preprocessing, input windows (10 time steps), and forecast horizons (10 time steps, ≈50 minutes) to ensure fair comparison. Hyperparameters for each baseline—such as hidden dimensions, learning rates, and kernel sizes—were initialized following their original publications and fine-tuned within reported ranges. The LT-GSSM used a hidden size of 64–128, learning rate 0.0005–0.005, and learnable noise parameters to capture both process and observation uncertainty. This consistent setup guarantees that observed performance differences reflect architectural robustness rather than arbitrary tuning.

The following experimental settings and sensitivity analyses were considered to ensure fair comparison and to assess the robustness of LT-GSSM:

- We adopted a forecasting horizon of 10 time steps ($\approx$ 50 minutes), a common setting in prior traffic studies [32 – 35].
- A hyperparameter sensitivity analysis was conducted exclusively on LT-GSSM, focusing on the hidden state dimension and the learnable noise parameter, as both directly affect model capacity and robustness.
- Hidden dimensions from 64 to 128 yielded the most stable results: smaller sizes caused underfitting, whereas larger ones amplified noise and led to overfitting. For the noise parameter, learnable variance consistently converged near $\sigma^2 \approx 0.2$, outperforming fixed settings.

- Low fixed values made the model too rigid, while high ones introduced instability. The adaptive formulation improved convergence and reduced RMSE by about 1–2 %, confirming that dynamic noise learning enhances robustness under noisy or incomplete data.

Fig. 5 summarizes these trends, showing steady performance for hidden sizes 64–128 and optimal stability when the learnable noise variance converges around 0.2.

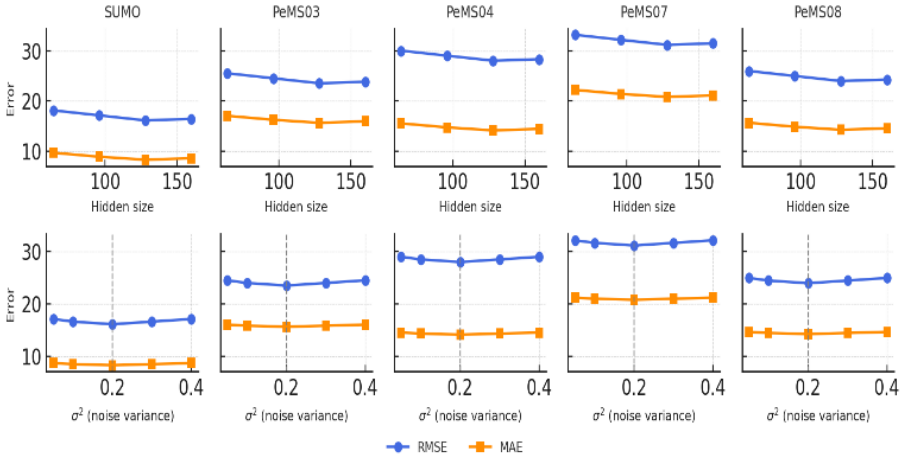


Fig. 5. Sensitivity of LT-GSSM to hidden state dimension (top) and noise variance σ^2 (bottom) across five datasets.

D. Baseline Performance Comparison

Table II reports the average results over seven runs with different random seeds. Variance remained below 2 %, confirming the stability and reproducibility of all experiments, and paired t-tests showed that LT-GSSM's improvements are statistically significant ($p < 0.05$).

Across both SUMO and PeMS datasets, LT-GSSM consistently achieves the lowest error among all models. Compared to classical temporal baselines (ARIMA, VAR), it reduces RMSE by 35–40 % (≈ 5.8 points on SUMO, ≈ 6.2 on PeMSD04). While recurrent models like BiLSTM (avg RMSE ≈ 22.1) perform better, they remain limited by the absence of spatial modeling. Hybrid spatio-temporal models (LSTM-GCN, GCN-GRU) further cut RMSE by ≈ 20 % on average, confirming the benefit of explicit spatial reasoning. 3D-CNN and LSTM-CNN improve temporal baselines but generalize poorly on irregular networks. Attention-based models show mixed behavior: ST-Transformer performs well on large datasets but underutilizes short input windows, while Attention-GCN offers only modest gains. Robust baselines like RT-GCN and AGCRN deliver strong accuracy under normal conditions but slightly trail LT-GSSM, especially on SUMO and PeMS08.

Overall, LT-GSSM's integration of a probabilistic state-space formulation with dynamic latent topology learning yields the best accuracy and stability across all settings, outperforming recent robust graph models while remaining computationally efficient. This establishes LT-GSSM as a strong benchmark for reliable spatio-temporal forecasting under noisy or incomplete data.

TABLE II. SUMMARY OF BASELINE MODELS AND EXPERIMENTAL

Model	SUMO RMSE	SUMO MAE	PeMS03 RMSE	PeMS03 MAE	PeMS04 RMSE	PeMS04 MAE	PeMS07 RMSE	PeMS07 MAE	PeMS08 RMSE	PeMS08 MAE
ARIMA	35.23	22.57	46.80	31.26	45.32	31.42	50.98	35.16	40.32	29.64
VAR	24.29	13.80	38.26	23.28	38.61	23.19	69.75	47.14	28.12	20.97
BiLSTM	20.29	11.76	31.09	19.13	36.87	22.72	43.12	25.90	31.39	22.12
GCN-GRU	16.67	8.93	26.52	15.67	28.48	15.91	33.15	22.24	24.73	14.15
LSTM-GCN	16.72	8.98	26.39	15.42	28.45	15.76	32.40	21.19	24.70	14.25
ST-Transformer	17. 98	9.31	24.16	14.11	30.74	16.32	35.23	23.40	24.95	14.02
Attention GCN	16.68	8.91	25.06	14.55	28.49	15.54	32.78	21.09	25.06	15.19
LSTM-CNN	17.73	9.83	29.15	17.38	28.72	15.5	36.93	22.80	27.76	15.9
3D-CNN	19. 56	10.1	30.33	17.89	30.94	17.32	38.64	24.18	28.34	17.63
STGCN	19. 99	9.26	28.17	19.95	30.23	16.45	38.12	24.45	26.91	15. 24
DCRNN	17.3	9.26	27.89	18.23	30.68	16.6	34.57	22.80	24.3	15.34
RT-GCN	16.90	8.90	26.80	16.25	28.55	15.60	31.40	21.40	24.80	14.40
AGCRN	16.73	9.11	26.82	16.45	29.72	16.93	31.28	22.51	24.76	15.52
LTGSSM	16.11	8.27	23.51	15.63	28.01	14.12	31.17	21.49	23.96	14.24

E. Ablation Study

To assess the contribution of each module within LT-GSSM, four ablation variants were evaluated: 1) a state-space only configuration (without GCN), 2) a classical SSM-GCN using linear temporal transitions instead of a TCN, 3) a noise-free variant without explicit process and observation noise, and 4) a comparison between static and dynamic adjacency learning. Fig. 6 summarizes the results across all datasets.

The SSM-only configuration already achieved competitive accuracy, outperforming purely temporal models such as LSTM and GRU on several datasets. This confirms that the recursive state-space formulation and process noise terms provide strong temporal modeling capacity, even without explicit spatial reasoning.

Replacing the nonlinear TCN with a linear update led to a consistent increase in error (≈ 20% higher RMSE on average), indicating that nonlinear temporal transitions are crucial for capturing complex latent traffic dynamics. Similarly, removing explicit noise modeling degraded robustness under noisy or incomplete conditions, with the full LT-GSSM achieving up to 25% lower RMSE compared to the deterministic version.

Finally, dynamic adjacency learning further improved performance relative to static topologies, reducing RMSE by approximately 10% across datasets. This confirms that allowing the graph structure to evolve with latent state dynamics better captures non-stationary spatial correlations such as congestion propagation or sensor drift.

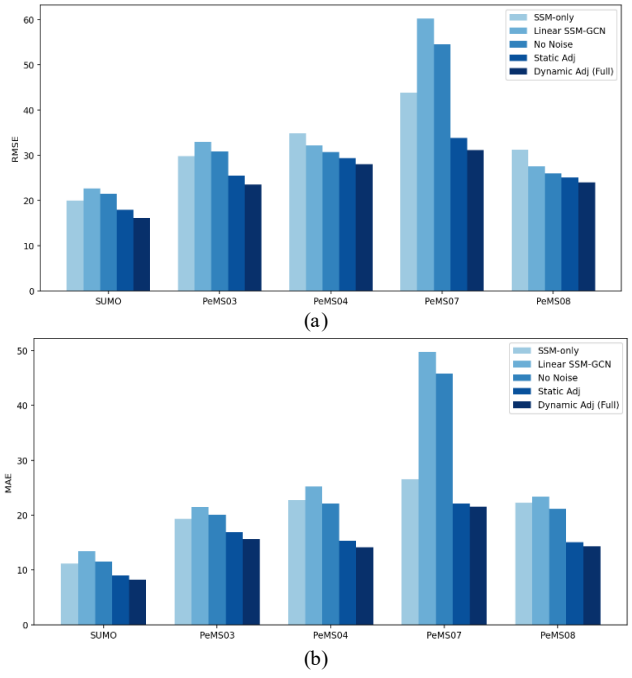


Fig. 6. RMSE and MAE comparison of LT-GSSM ablation variants across SUMO and PeMS datasets.

Fig. 6 and Fig. 7 illustrate these trends: Fig. 6 shows RMSE and MAE across ablation variants, while Fig. 7 visualizes relative performance gains over the static baseline. Overall, each component—state-space recursion, nonlinear transition, explicit noise modeling, and dynamic topology—contributes significantly to the robustness and accuracy of LT-GSSM, with the complete model consistently achieving the best balance across datasets.

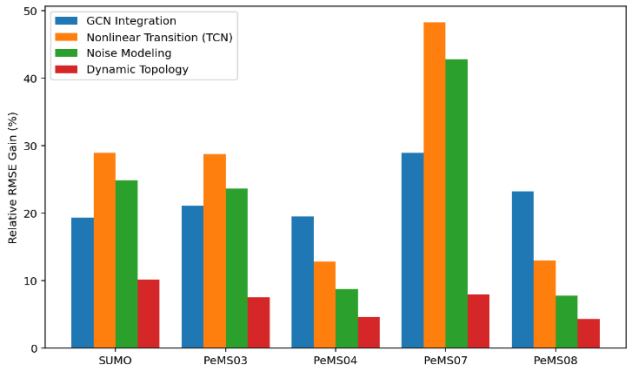


Fig. 7. Relative performance gain (%) of LT-GSSM components compared to the static baseline.

V. Discussion

A. Effect of Sensor Placement and Noise on Spatiotemporal Prediction

We used the custom SUMO network to evaluate how sensor placement and noise affect forecasting robustness. Two practical scenarios were simulated: 1) prioritizing sensors on major arterial roads, and 2) reducing overall sensor coverage to 50 % and 20 %.

Concentrating sensors along main corridors improved accuracy by capturing structured, correlated traffic flows, whereas reduced coverage increased errors across all models. Nevertheless, LT-GSSM remained the most stable, confirming that its dynamic adjacency learning effectively adapts spatial correlations even when observations are sparse.

By updating its graph topology from latent state representations, the model can infer missing spatial dependencies, rather than relying solely on static connectivity. Comparable resilience was observed in RT-GCN and AGCRN, yet LT-GSSM showed the smallest degradation under both sensor loss and noisy data, demonstrating the strength of its joint spatio-temporal uncertainty modeling.

Fig. 8 illustrates the impact of sensor coverage on prediction accuracy.

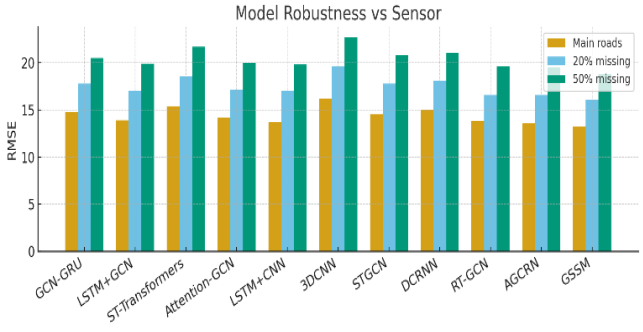


Fig. 8. Impact of sensor coverage on the performance of spatiotemporal prediction models.

B. Robustness Under Gaussian Noise

Beyond spatial sparsity, robustness was also tested under Gaussian sensor noise injected into traffic flow data at three levels (5 %, 15 %, 30 %). Noise was applied selectively to subsets of sensors, simulating real detector failures. As expected, higher noise levels increased errors for all models (Table III), but LT-GSSM exhibited only a ≈ 2–7 % RMSE increase at 30 % noise—significantly lower than competing architectures.

This resilience stems from its explicit uncertainty modeling: the transition function captures latent dynamic fluctuations, while the observation model accounts for measurement errors, allowing LT-GSSM to maintain stable performance even under severe data corruption.

TABLE III. IMPACT OF GAUSSIAN NOISE LEVELS ON MODEL PREDICTION ERRORS

Model	SUMO (5%)	15%	30%	PeMS08 (5%)	15%	30%
GCN-GRU	17.5	18.0	18.4	25.2	25.7	26.1
LSTM-GCN	17.1	17.8	18.2	25.1	25.6	26.0
ST-Transformer	17.6	18.3	18.8	25.5	26.1	26.6
Attention-GCN	17.2	17.8	18.3	25.5	25.9	26.4
LSTM-CNN	17.7	18.4	18.9	28.2	28.8	29.3
3D-CNN	18.1	18.7	19.2	28.9	29.4	29.9
STGCN	17.5	18.2	18.7	27.3	27.8	28.3
DCRNN	17.3	17.9	18.3	24.8	25.3	25.8
RT-GCN	16.3	17.1	17.9	25.3	25.9	26.5
AGCRN	17.4	17.6	18.2	25.0	25.4	25.9
LT-GSSM (ours)	16.2	16.8	17.4	24.2	24.6	25.1

C. Computational Complexity and Execution Time

LT-GSSM maintains complexity comparable to standard spatio-temporal GNNs. The TCN-based temporal layer replaces recurrent cells, reducing sequential dependencies and allowing efficient parallelization with per-step cost $O(H^2 \times L_t)$ (with $L_t \leq 3$). Dynamic adjacency learning adds a manageable $O(V^2)$term, negligible for medium-sized networks (hundreds of sensors). Overall, LT-GSSM offers a better trade-off between robustness and cost than diffusion- or attention-based models, which scale as $O(T^2 d)$.To validate this analysis, we measured execution times under identical hardware and software conditions (Intel i7-10700 CPU, 32 GB RAM, NVIDIA GTX 1660 GPU, PyTorch 2.0, CUDA 11.8).

Using a batch size of 32, input length T=12, and hidden size H=64, LT-GSSM consistently trained 10–20% faster per epoch than recurrent baselines such as LSTM-GCN, GRU-GCN, and DCRNN on the PeMS04 and PeMS08 datasets.

These gains arise mainly from the parallelizable temporal convolutions and the absence of recurrent backpropagation.

Compared to heavier architectures such as ST-Transformer, Attention-GCN, or 3D-CNN, LT-GSSM maintained a lightweight execution profile, ranking among the most efficient models overall.

Although inference latency was not extensively benchmarked, average forward-pass times remained below 100 ms. per prediction step, indicating that LT-GSSM can operate effectively in near real-time forecasting scenarios without sacrificing accuracy or stability. Table IV reports the average training time per epoch for LT-GSSM and competing spatio-temporal models under identical hardware and software settings.

TABLE IV. AVERAGE TRAINING TIME PER EPOCH ACROSS SPATIOTEMPORAL MODELS

Model	Avg. Time per Epoch (s)
ST-GCN (parallel)	235.2
ST-Transformer	168.7
Attention-GCN	144.5
3D CNN	129.1
DCRNN	117.3
RT-GCN	110.5
AGCRN	104.2
LTGSSM (ours)	99.8
LSTM-GCN	96.7
GRU-GCN	96.2
LSTM-CNN	70.3

VI. CONCLUSION

This paper presented the Latent Topology Graph State-Space Model (LT-GSSM), a probabilistic spatio-temporal framework that dynamically learns graph structures from latent representations rather than relying on fixed connectivity. By treating topology evolution as part of the latent state dynamics, LT-GSSM reframes graph adaptation itself as an uncertain latent process, enabling robust modeling of non-stationary spatial dependencies under noise and missing data.

The main scientific contribution of this work lies in explicitly modeling spatial structure uncertainty within a state-space formulation, rather than relying on deterministic or heuristically updated graph topologies. This perspective provides a principled explanation for robustness in spatio-temporal forecasting, complementing existing dynamic-graph architectures.

Experiments on SUMO and PeMS datasets confirm that this formulation yields stable and adaptive forecasting performance even with reduced sensor coverage or high noise levels, while maintaining a computational cost comparable to standard GCN-based hybrids (e.g., LSTM-GCN, AGCRN), making it suitable for practical deployment in intelligent transportation systems.

Despite these advantages, dynamic adjacency learning introduces a quadratic dependency in the number of nodes, which may require sparsification strategies for very large-scale networks. Robustness was evaluated under commonly adopted noise and missing-data settings, and further extensions are left for future work.

Beyond traffic forecasting, the proposed modeling paradigm is applicable to a broader class of spatio-temporal problems involving evolving relational structures, such as sensor networks, urban monitoring, and environmental dynamics. Future work will investigate scalability improvements, alternative uncertainty models, and extensions to other spatio-temporal domains.

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REFERENCES

[1] L. Peng et al., "An Overview Based on the Overall Architecture of Traffic Forecasting," Data Science and Engineering, vol. 9, no. 3, pp. 341–359, 2024.

[2] S. Wei et al., "Traffic Flow Prediction with Multi-Feature Spatio-Temporal Coupling Based on Peak Time Embedding," The Journal of Supercomputing, vol. 80, no. 16, pp. 23442–23470, 2024.

[3] V. Singh, S. K. Sahana, and V. Bhattacharjee, "Integrated Spatio-Temporal Graph Neural Network for Traffic Forecasting," Applied Sciences, vol. 14, 2024. DOI: 10.3390/app142411477.

[4] A. A. Karim and N. Nower, "Probabilistic Spatio-Temporal Graph Convolutional Network for Traffic Forecasting," Applied Intelligence, vol. 54, no. 11, pp. 7070–7085, 2024.

[5] Y. Li et al., "Diffusion Convolutional Recurrent Neural Network: Data-Driven Traffic Forecasting," in Proc. Int. Conf. Learning Representations (ICLR), 2018.

[6] L. Zhao et al., "T-GCN: A Temporal Graph Convolutional Network for Traffic Prediction," IEEE Transactions on Intelligent Transportation Systems, vol. 21, no. 9, pp. 3848–3858, 2020.

[7] D. Li and J. Lasenby, "Spatiotemporal Attention-Based Graph Convolution Network for Segment-Level Traffic Prediction," IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 7, pp. 8337–8345, 2022.

[8] L. Xiao and H. Chen, "Spatio-Temporal Transformer Graph Network for Traffic Flow Forecasting," in Proc. 3rd Int. Joint Conf. Information and Communication Engineering (JCICE), 2024.

[9] L. Bai, L. Yao, C. Li, X. Wang, and C. Wang, "Adaptive Graph Convolutional Recurrent Network for Traffic Forecasting," in Advances in Neural Information Processing Systems (NeurIPS 2020), vol. 33, pp. 17804–17815, 2020. DOI: 10.48550/arXiv.2007.02842.

[10] Y. Kamarianakis and P. Prastacos, "Forecasting Traffic Flow Conditions in an Urban Network: Comparison of Multivariate and Univariate Approaches," Transportation Research Record: Journal of the Transportation Research Board, vol. 1857, no. 1, pp. 74–84, 2003.

[11] Z. Lu et al., "Integrating Granger Causality and Vector Auto-Regression for Traffic Prediction of Large-Scale WLANs," KSII Transactions on Internet and Information Systems (TIIS), vol. 10, no. 1, pp. 136–151, 2016.

[12] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," Neural Computation, vol. 9, no. 8, pp. 1735–1780, 1997.

[13] R. Fu, Z. Zhang, and L. Li, "Using LSTM and GRU Neural Network Methods for Traffic Flow Prediction," in Proc. 31st Youth Academic Annual Conf. Chinese Association of Automation (YAC), 2016.

[14] S. Natha et al., "Improving Traffic Surveillance: Deep Learning Approach for Road Anomaly Detection in Videos," in Proc. IEEE 3rd Int. Conf. Computing and Machine Intelligence (ICMI), 2024.

[15] M. Lv et al., "Temporal Multi-Graph Convolutional Network for Traffic Flow Prediction," IEEE Transactions on Intelligent Transportation Systems, vol. 22, no. 6, pp. 3337–3348, 2021.

[16] Y. Liu et al., "RT-GCN: Gaussian-Based Spatiotemporal Graph Convolutional Network for Robust Traffic Prediction," Information Fusion, vol. 102, p. 102078, 2024.

[17] G. Revach, D. Soudry, R. Giryes, and Y. C. Eldar, "KalmanNet: Neural Network-Aided Kalman Filtering for Partially Known Dynamics," IEEE Transactions on Signal Processing, vol. 70, pp. 1532–1547, 2022. DOI: 10.1109/TSP.2022.3149823.

[18] R. G. Krishnan, U. Shalit, and D. Sontag, "Structured Inference Networks for Nonlinear State Space Models," in Proc. AAAI Conf. Artificial Intelligence (AAAI 2017), pp. 2101–2109, 2017. arXiv:1609.09869.

[19] M. Karl, M. Soelch, J. Bayer, and P. van der Smagt, "Deep Variational Bayes Filters: Unsupervised Learning of State Space Models from Raw Data," in Proc. Int. Conf. Learning Representations (ICLR 2017), 2017. arXiv:1605.06432.

[20] Z. Zhang, P. Cui, and W. Zhu, "Probabilistic Graph Neural Networks," Communications of the ACM, vol. 63, no. 8, pp. 107–113, 2020. DOI: 10.1145/3363574.

[21] D. Valsesia, G. Fracastoro, and E. Magli, "Graph Neural Networks for Graph Signal Denoising," IEEE Transactions on Signal Processing, vol. 67, no. 23, pp. 6176–6189, 2019. DOI: 10.1109/TSP.2019.2945544.

[22] P. A. Lopez et al., "Microscopic Traffic Simulation Using SUMO," in Proc. 21st IEEE Int. Conf. Intelligent Transportation Systems (ITSC), Maui, HI, USA, 2018.

[23] A. Wegener et al., "TraCI: An Interface for Coupling Road Traffic and Network Simulators," in Proc. 11th Communications and Networking Simulation Symposium (CNS'08), Ottawa, Canada, pp. 155–163, 2008.

[24] I. Juva et al., "Traffic Characterization for Traffic Engineering Purposes: Analysis of Funet Data," in Proc. Next Generation Internet Networks (NGIN), 2005.

[25] G. Beliakov et al., "Measuring Traffic Congestion: An Approach Based on Learning Weighted Inequality, Spread and Aggregation Indices from Comparison Data," Applied Soft Computing, vol. 67, pp. 910–919, 2018.

[26] S. Guo et al., "Attention Based Spatial-Temporal Graph Convolutional Networks for Traffic Flow Forecasting," in Proc. 33rd AAAI Conf. Artificial Intelligence (AAAI 2019), Honolulu, HI, USA, 2019.

[27] A. Loder et al., "Understanding Traffic Capacity of Urban Networks," Scientific Reports, vol. 9, no. 1, p. 16283, 2019.

[28] Q. Wu et al., "Tensor-Based Recurrent Neural Network and Multi-Modal Prediction with Its Applications in Traffic Network Management," IEEE Transactions on Network and Service Management, vol. 18, no. 1, pp. 780–792, 2021.

[29] J. Xu et al., "Spatio-Temporal Multi-Task Learning via Tensor Decomposition," IEEE Transactions on Knowledge and Data Engineering, vol. 33, no. 6, pp. 2764–2775, 2021.

[30] B. Yu, Y. Lee, and K. Sohn, "Forecasting Road Traffic Speeds by Considering Area-Wide Spatio-Temporal Dependencies Based on a Graph Convolutional Neural Network (GCN)," Transportation Research Part C: Emerging Technologies, vol. 114, pp. 189–204, 2020.

[31] A. Vaswani et al., "Attention Is All You Need," in Advances in Neural Information Processing Systems (NeurIPS 2017), Curran Associates Inc., Long Beach, CA, USA, 2017.

[32] T. N. Kipf and M. Welling, "Semi-Supervised Classification with Graph Convolutional Networks," arXiv preprint arXiv:1609.02907, 2017.

[33] R. J. Hyndman and G. Athanasopoulos, Forecasting: Principles and Practice, OTexts, 2018.

[34] C. Brooks, "The Impact of Seasonality on Forecasting," International Journal of Forecasting, vol. 23, no. 1, pp. 210–226, 2007.

[35] G. Bontempi, C. Hodges, and N. D. Lawrence, "Forecasting with a Compounding Neural Network," in Proc. Int. Conf. Machine Learning and Applications (ICMLA), 2013.

Dynamic Trust Modulation and Human Oversight in AI-Driven AML Systems: A Conceptual Framework for Compliance

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***Abstract*—This literature review investigates how human trust, decision fatigue, explainability (XAI), and human oversight interrelate to influence analyst decision-making in AI-driven anti-money laundering (AML) systems. While prior research has predominantly emphasized algorithmic performance, detection accuracy, or regulatory compliance in isolation, a critical gap remains in understanding the human-centered dynamics that shape real-world operational outcomes. Addressing this gap, the review examines how financial institutions navigate compliance demands and operational constraints, drawing on the Australian regulatory environment as an illustrative governance reference, including expectations articulated by AUSTRAC. Building on this synthesis, the study identifies structural gaps in Trust Calibration and oversight practices. It introduces a Dynamic Trust Modulation (DTM) framework to conceptualize how trust evolves across AML workflows. The framework models trust as a fluid, context-dependent construct shaped by system behavior, analyst workload, explainability mechanisms, and regulatory pressure. By framing trust, explainability, and decision fatigue as interdependent components of human–AI collaboration, this review advances a more holistic perspective on socio-technical system design in financial crime detection. The proposed framework contributes theoretically by extending human–AI trust research into the AML domain and practically by offering actionable design principles to enhance system accountability, decision defensibility, and adaptive compliance in operational AML environments.**

Keywords*—*Artificial intelligence; anti-money laundering (AML); Trust Calibration; Explainability; decision fatigue; human oversight; AUSTRAC Compliance; transaction monitoring; false positives; Analyst–System Interaction; Regulatory Technology (RegTech)

I. Introduction

Money laundering continues to pose a critical threat to financial systems worldwide, prompting financial institutions to adopt increasingly sophisticated anti-money laundering (AML) frameworks. Despite technological advancements, institutions continue to struggle with high false positive rates, escalating operational costs, and increasing regulatory pressure to ensure robust compliance [1].

Artificial intelligence (AI) and machine learning (ML) have emerged as promising tools to enhance AML transaction monitoring by uncovering anomalous behavior and enabling real-time detection. AI promises efficiency and improved detection precision; however, these systems often function as opaque "black boxes", raising concerns about explainability, regulatory defensibility, and human oversight [2]. The lack of transparency and adaptability to evolving compliance standards hinders institutional confidence and broader adoption.

While existing literature explores individual factors such as trust, decision fatigue, and explainability, it often treats them in isolation, overlooking their dynamic interplay in operational workflows. Critical questions remain unanswered: How do analysts rebuild trust after AI errors? How does human feedback shape system adaptation? And how can compliance frameworks incorporate meaningful oversight? These unresolved issues underscore the tension between technological performance and regulatory accountability in AI-supported AML environments.

This study addresses a critical gap in AI-driven AML research by developing a Dynamic Trust Modulation framework that conceptualizes how trust, explainability, and decision fatigue interact within transaction monitoring systems under conditions of uncertainty. Rather than treating these factors in isolation, the framework integrates them to capture the dynamic nature of analyst–system interaction and evolving oversight demands in AML workflows. By focusing on system-level decision processes such as confidence assessment, interpretability, and feedback loops, the framework provides a structured lens for understanding how human oversight can be supported and sustained in complex compliance environments. Drawing on human–AI collaboration and socio-technical systems literature, this study offers a generalizable conceptual foundation for advancing accountability, decision defensibility, and explainable decision-making in AI-supported AML systems.

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This study makes three key contributions to research on AI-supported anti-money laundering (AML) systems. First, it synthesizes trust calibration, decision fatigue, and explainability into an integrated conceptual perspective tailored to AML transaction monitoring, addressing their interdependence within high-stakes compliance environments. Second, it introduces the Dynamic Trust Modulation framework, which conceptualizes trust as a feedback-driven and context-dependent construct shaped by system performance, analyst workload, explainability mechanisms, and regulatory constraints. Third, the study offers practical and regulatory insights for the design of AI-enabled AML systems by highlighting design principles that support accountability, decision defensibility, and sustainable human oversight under regimes such as AUSTRAC.

The remainder of this study is organized as follows: Section II outlines background and related work; Section III presents case-based illustrations of implementation challenges; Section IV details the review methodology; Section V synthesizes thematic findings; Section VI discusses trust calibration dynamics and addresses oversight and governance mechanisms; Section VII discuss the regulatory frameworks and governance under AUSTRAC; Section VIII explores systemic risks; Section IX presents the structural ambiguity and compliance overload; Section X discusses fragmented oversight and risk diffusion; Section XI presents the global gaps and interoperability risks; Section XII summarizes limitations and future research; and Section XIII concludes the study.

II. Background and Related Work

A. AML and Compliance Failures

Lack of awareness and fragmented implementation of AML regulations have consistently led to enforcement failures and reputational risks. In Australia, AUSTRAC has imposed multimillion-dollar fines on institutions that failed to adopt a robust risk-based approach [3]. The cases of Commonwealth Bank of Australia (CBA), Westpac, and Tabcorp demonstrate that insufficient governance, underdeveloped compliance infrastructure, and inadequate technological adaptation remain key barriers to effective AML performance. For example, CBA failed to submit over 53,000 threshold transaction reports due to unmonitored Intelligent Deposit Machines, while Westpac committed over 23 million breaches due to poor internal oversight and delayed reporting [4]. International experiences echo similar challenges, such as Santander's outsourcing of AI-based AML systems, which resulted in substantial penalties due to vendor opacity and poor model explainability, whereas the Bunq vs. DNB case illustrates how deep regulatory understanding and system transparency enabled the bank to defend an AI-driven compliance approach [5]. Chainalysis and Elliptic offer additional insights into how institutions with strong AI and AML knowledge can support global regulatory goals and innovate proactively [6].

Prior studies indicate that higher AML regulatory ratings are associated with stronger financial outcomes [7]. Other research has identified persistent weaknesses in institutional coordination and in the empirical evaluation of illicit financial flows [8]. Additional analyses highlight embedded distrust and cognitive overload within compliance systems, particularly in the context of NLP-based monitoring tools [9]. Related work further suggests that traditional AML models tend to underperform in informal economies and across non-bank financial intermediaries [10].

B. AI in AML Systems

AI is redefining AML monitoring through anomaly detection, natural language processing, and real-time predictive analytics. Machine learning and deep learning algorithms enable institutions to recognize sophisticated laundering strategies that evade rule-based models. Systems like those implemented by Chainalysis and Elliptic, or the NICE Actimize modules adopted by IDB Bank, show measurable improvements in detection and operational efficiency [6], [11]. Research highlights AI's scalability and capacity for continuous learning, with models adapting detection parameters as threats evolve [12]. Empirical studies further indicate that AI-based approaches outperform legacy systems in terms of precision and recall [13], and additional work demonstrates their viability even in underregulated markets [14]. However, challenges persist. AI requires high-quality data, domain-specific calibration, and contextual sensitivity. Overreliance on external vendors, as seen in Santander's case, limits transparency and introduces compliance risks [5]. Hybrid models, combining AI with human oversight, have emerged as practical compromises [3]. AI's success is not solely technical; it hinges on integration with compliance expectations and interpretability. As the Bunq case demonstrates, performance is insufficient without justification mechanisms acceptable to regulators. Institutions must embed auditability, adaptability, and role clarity into AI systems to optimize both compliance and risk mitigation.

C. Trust and Explainability in AI

Trust and explainability are central to the adoption and effectiveness of AI in AML environments. Without interpretable models, analysts struggle to validate alerts, leading to inefficiencies and increased risk exposure. Decision fatigue arises from high false positive rates, undermining trust in AI systems and degrading regulatory defensibility [3]. Explainable AI (XAI) tools such as SHAP and LIME have been proposed to mitigate this issue, given that these techniques increase transparency by visualizing feature importance and supporting interpretability [15]. Recent studies emphasize that explainability is becoming a regulatory imperative, particularly under evolving AI governance standards [16]. Institutions that fail to provide traceable logic risk regulatory rejection, as evidenced in the initial pushback against Bunq's system. Despite growing literature on technical performance, few studies explore how AML professionals interact with AI or recover trust after errors. This research contributes by proposing a Dynamic Trust Modulation Loop, a framework that connects analyst feedback, system responsiveness, and explainability in a continuous cycle. This approach provides a pathway for aligning human-AI collaboration with institutional accountability and adaptive regulatory compliance.

Existing frameworks in AI-supported decision-making and human–AI collaboration have examined constructs such as trust, explainability, and human oversight, particularly in domains including healthcare and decision support systems. While these models offer valuable insights into how users interpret algorithmic outputs, they often treat trust and explainability as

static or isolated factors rather than as dynamically interacting elements within operational workflows. In anti-money laundering (AML) contexts, this limitation is especially critical. AML environments are characterized by persistent uncertainty, high false positive rates, regulatory accountability, and sustained cognitive load on analysts. Existing frameworks do not sufficiently capture how trust evolves in response to repeated system errors, how decision fatigue accumulates under continuous alert pressure, or how analyst feedback is operationally reintegrated into AI systems.

The Dynamic Trust Modulation framework proposed in this study addresses these gaps by conceptualizing trust as a feedback-driven and context-dependent construct. By explicitly modeling the interaction between trust calibration, decision fatigue, and explainability within AML transaction monitoring workflows, the framework offers a novel socio-technical perspective tailored to high-stakes compliance settings where accountability remains fundamentally human-centered.

III. Case Studies

A. Santander: Vendor Dependency and Oversight Gaps

1) Context: Santander, a major European bank, began integrating AI-powered transaction monitoring in 2020, outsourcing this function to the third-party vendor ThetaRay. The system was designed to detect laundering patterns in correspondent banking using machine learning.

2) Event: Despite this technological integration, Santander faced major penalties of $1 million in Norway (2019) and £107.7 million in the UK (2022) due to persistent compliance deficiencies [5]. The reliance on an external AI provider reduced internal transparency and limited control over system decisions. Under the EU AI Act, this division of responsibility complicated regulatory accountability, while high false positive rates overwhelmed internal analysts.

3) Lesson learned: Outsourcing AI without maintaining internal oversight and interpretability weakens institutional trust and regulatory defensibility. Banks must preserve visibility into AI decisions, even when compliance functions are delegated externally.

B. Bunq: Challenging Regulatory Conservatism Through Explainability

1) Context: Bunq, a Dutch neobank, developed its own AI-based transaction monitoring system, arguing that it outperformed traditional rule-based methods.

2) Event: The Dutch Central Bank (DNB) rejected Bunq's model for lacking explainability and regulatory alignment [5]. Bunq challenged this stance in court, arguing for outcome-based rather than methodology-based evaluation. In October 2022, the Commercial and Industry Appeals Tribunal ruled in Bunq's favor, requiring regulators to assess performance rather than favoring manual approaches.

3) Lesson learned: Regulatory trust in AI depends not only on technical performance but also on transparency. Explainable systems are essential for regulatory acceptance, even when accuracy is high.

C. Chainalysis and Elliptic: Blockchain Analytics and the Need for Explainability

1) Context: Chainalysis and Elliptic are leaders in AI-driven blockchain analytics for digital asset compliance. Both firms support cryptocurrency monitoring by detecting illicit financial activities through anomaly detection and network analysis.

2) Event: Despite strong operational success, such as Chainalysis's recognition by U.S. Homeland Security regulators like the Financial Stability Board continues to stress explainability [6]. Recent work cautions that even high-performing models may fail regulatory scrutiny if their underlying mechanisms remain opaque [16]. The 2025 acquisition of Alterya by Chainalysis highlights a broader shift toward deeper explainability and risk validation in financial crime analytics.

3) Lesson learned: Explainability remains critical even for top-performing AI systems. Without transparency and auditability, regulatory trust and long-term accountability are jeopardized.

D. Westpac: Oversight Failures and Analyst Fatigue

1) Context: Westpac, one of Australia's major banks, deployed transaction monitoring systems for AML/CTF compliance but failed to ensure governance effectiveness.

2) Event: The institution was fined 1.3 billion AUD for over 23 million violations, including failure to monitor cross-border transfers and respond to alerts [3]. These failures were tied to weak board oversight, overburdened compliance teams, and fatigue caused by excessive alert volumes, leading to institutional breakdowns.

3) Lesson learned: Effective AML systems require governance structures that support human-AI workflows. Analyst fatigue and board-level disengagement can compromise trust and system effectiveness.

E. Commonwealth Bank of Australia: Misaligned Trust Calibration

1) Context: The Commonwealth Bank of Australia relied on Intelligent Deposit Machines (IDMs) to support AML monitoring, automating transaction processing and reporting.

2) Event: In 2018, the bank was fined 700 million AUD for failing to report over 53,000 threshold transactions. Investigations revealed that analysts did not escalate anomalies, assuming system reliability despite lacking internal risk assessments or override mechanisms [3].

3) Lesson learned: Overreliance on automation without real-time human verification erodes compliance. AML systems must enable ongoing trust calibration and empower analysts to challenge system outputs.

F. IDB Bank (New York): Successful Human-AI Collaboration

1) Context: IDB Bank implemented NICE Actimize modules to enhance AML operations, aiming to streamline alert processing and boost efficiency.

2) Event: The system led to a 60% reduction in manual post-alert work, allowing analysts to focus on high-risk investigations [12]. A structured feedback loop enhanced trust and explainability, improving understanding of AI behavior.

3) Lesson learned: AI adoption succeeds when it supports, not replaces, human judgment. Feedback-integrated, explainable systems reduce fatigue and build trust across compliance teams and regulators.

IV. Review Methodology

This study adopts a systematic literature review methodology tailored for conceptual synthesis rather than empirical measurement. The purpose of this approach is to transparently map and integrate existing knowledge on AI integration within Anti-Money Laundering (AML) compliance, particularly in the areas of trust, explainability, oversight, and human-AI collaboration. The review adheres to academic standards for reproducibility, thematic coherence, and methodological transparency.

A. Literature Search Strategy

The literature review spans the publication period from 2020 to 2025. The search was conducted across academic databases and authoritative industry sources, including Google Scholar, Scopus, and regulatory or policy-based repositories such as ACAMS, AUSTRAC, and the Attorney-General's Department of Australia. Relevant white papers from Deloitte, NICE Actimize, and Chainalysis were also included to ensure industry alignment.

Search terms were structured around the core themes of the study and included Boolean combinations such as: "Artificial Intelligence" AND "AML" OR "Anti-Money Laundering", "False positives" AND "transaction monitoring", "Human-AI collaboration" OR "trust in AI systems", "Explainability" OR "XAI" AND "compliance", "AUSTRAC" AND "regulatory expectations" OR "AML Australia", "Decision fatigue" OR "alert fatigue" AND "AML analysts". To ensure thematic alignment with the conceptual framework, literature sources were mapped according to their relevance to key constructs, as detailed in Table I. As shown in Table I, the reviewed sources span academic research, industry reports, and regulatory guidelines, providing a balanced foundation for both theoretical insights and practical relevance. This structured mapping demonstrates how each source informed key aspects of the framework, including the core analyst–system interaction constructs, along with human oversight and feedback loop integration. By explicitly aligning each paper with a core construct or operational gap, the review process ensures that the final conceptual framework is grounded in evidence and reflects the latest developments in AI-supported AML practice.

B. Inclusion and Exclusion Criteria

Inclusion criteria focused on literature published in English between 2020 and 2025 that addressed financial crime detection, AI in compliance, regulatory frameworks, human-machine interaction, and AML case studies. Eligible documents included peer-reviewed journal articles, conference papers, government publications, and technical white papers. Exclusion criteria removed literature outside the financial sector (e.g., AI in medicine or agriculture), non-English publications, and theoretical papers with no relevance to regulatory frameworks or compliance technologies. Initial screening was based on titles and abstracts, followed by full-text review to ensure methodological rigor and relevance. The systematic selection process is visualized in Fig. 1, which outlines identification, screening, eligibility, and final inclusion of sources.

TABLE I. Literature Review Source Overview

Theme	Key Authors (Type/Year)	Focus Summary	Framework Relevance*
Trust Calibration	Bertrand (Thesis, 2024), Wang (Thesis, 2024), Alkhalili (JA, 2021), Ghimire (JA, 2025), Kahur (Report, 2025)	Trust evolution, explanation paradox, ML filtering, analyst confidence	TC, EX
Explainability	Kahur (Report, 2025), Deloitte (Report, 2020), Rane (JA, 2023), Jensen (JA, 2023), Bello (JA, 2024)	SHAP/LIME, hybrid models, blockchain transparency, system performance	EX, FO
False Positives	Alahmadi (Conf, 2022), Oztas (JA, 2024), Mounika (JA, 2024), Ketenci (JA, 2021)	Analyst workload, anomaly detection, tuning thresholds, FP mitigation	DF, TC
Oversight	Bello & Bronitt (JA, 2024), Goldbarsht (BC, 2023), King (JA, 2020), Rennie (JA, 2021), Maxwell (Report, 2020)	AI governance, risk mitigation, compliance defensibility, human oversight	OV, TC
Feedback Loops	Deloitte (Report, 2020), Eddin (Preprint, 2021), Sausen (Report, 2020), Kumar (JA, 2024), Johnson (Report, 2025)	Human-in-the-loop design, AML adaptation, operational feedback systems	FL, TC
Regulatory Compliance	AUSTRAC (Reg, 2023/24), Quinn (Report, 2021), Momenta (IR, 2022), Goldbarsht & Sheedy (Report, 2024), Saputra (JA, 2021)	National risk assessment, policy frameworks, compliance alignment	RC, OV
Situational Awareness	Boudt (JA, 2025)	News monitoring for AML, risk signal integration	SA

TC = Trust Calibration; EX = Explainability; DF = Decision Fatigue; OV = Oversight; FL = Feedback Loop; RC = Regulatory Compliance; SA = Situational Awareness.

V. PRISMA Diagram

This review scoped academic, industry reports, and regulatory documents addressing AI trust, oversight, and anti-money laundering (AML) within both regulatory and technical domains. Emphasis was placed on studies that examine the interaction between machine learning systems and compliance practices, particularly in high-stakes financial environments. Thematic analysis focused on patterns related to explainability, analyst trust calibration, and institutional accountability in AI-augmented AML systems. The selected corpus synthesized

interdisciplinary perspectives across law, computer science, and financial governance.

The flow diagram outlines the identification, screening, eligibility assessment, and inclusion of sources in the systematic literature review, following PRISMA guidelines.

A. Analytical Framework

Thematic coding was applied across seven domains: Trust Calibration, Explainability, False Positives, Oversight, Feedback Loops, Regulatory Compliance, and Situational Awareness. The distribution and classification of sources across these themes are synthesized in Table III.

Furthermore, to clarify methodological depth and diversity, Table II summarizes the methodological types, data sources, and limitations of the reviewed literature. This enables a comparative understanding of the balance between technical modeling, policy alignment, and human-centered design in the current AML literature.

As shown in Table II, the classification of methodologies reveals irregular scholarly attention where technical modelling approaches prioritize algorithmic performance but rarely consider analyst workload or regulatory defensibility. In contrast, policy-driven studies emphasize compliance and ethical safeguards yet lack empirical validation. Only a small number of industry reports attempt to incorporate practitioner perspectives, but these remain descriptive rather than evaluative. Taken together, this shows fragmented evidence base where rigor and applicability rarely converge, underscoring the need for the trust–feedback framework proposed in this study.

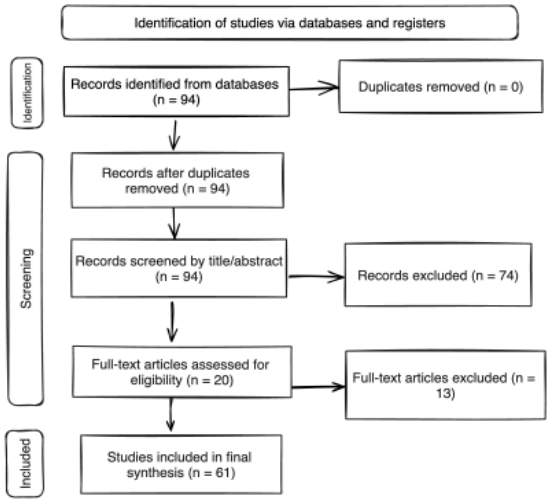


Fig. 1. PRISMA flow diagram of the literature selection process.

TABLE II. METHODOLOGIES IN REVIEWED STUDIES

Study	Methodology	Data Type	Strengths	Limitations
Ghimire (2025)	Simulation + Case Study	Secondary	Focused on precision-recall metrics and system design.	Not practitioner-based; lacks real-world validation.
Ketenci et al. (2021)	Quantitative - ML Models	Experimental	Robust testing of false positive reduction strategies.	Lacks human-AI interaction component.
Oztas et al. (2024)	Quantitative - ML Clustering	Experimental	Uses adaptive algorithms for anomaly detection.	Does not address human oversight or compliance validation.
Bertrand (2024)	Theoretical Analysis	Conceptual	Explores trust, fatigue, and decision frameworks in AI settings.	Lacks empirical or applied industry context.
AUSTRAC (2024)	Risk Assessment + Regulatory Review	Policy and Compliance Documents	Grounds research in national compliance standards.	Not focused on technical implementation of AI.
Australian Government (2024)	Policy Framework Analysis	Conceptual	Establishes ethical and assurance principles for AI.	Applies broadly to government, not AML-specific.
Kute et al. (2021)	Experimental + XAI Evaluation	Quantitative	Demonstrates explainability using SHAP and LIME.	Focuses more on technical output than end-user integration.
Deloitte & UOB (2021)	Case Study + Interview-Based Review	Industry Report	Real-world application of AI-human hybrid models	Case-specific and not generalisable across all banks.
AUSTRAC (2023–24)	regulatory Summary and Sector Review	Government Report	High-level operational and compliance insights	Limited detail on model evaluation or metrics

VI. THEMATIC SYNTHESIS AND FINDINGS

A detailed review of the literature reveals a constellation of interrelated themes that shape the discourse on AI-supported Anti-Money Laundering (AML) systems. Rather than treating technological capabilities in isolation, the literature emphasizes the entanglement of AI transparency, analyst cognitive dynamics, and regulatory alignment within evolving financial compliance ecosystems. This section synthesizes the findings using the interaction constructs introduced in Section III: trust calibration, oversight, feedback loops, and explainability, and maps these onto practical tensions observed in industry and empirical studies.

While Table III categorizes the literature into thematic domains, its real value lies in revealing the disciplinary requirements that fragment AI-AML research. A key pattern emerges: technical contributions largely optimize model performance metrics, such as precision or false positive (FP) reduction, without engaging with the socio-institutional challenges of operational trust and oversight. In contrast, regulatory and policy-focused literature emphasizes compliance defensibility but lacks guidance on integrating AI tools into analyst workflows or trust repair mechanisms following an AI error. This divide reflects an unresolved tension between algorithmic sophistication and institutional interpretability, which is central to real-world AI deployment in AML systems.

TABLE III. LITERATURE CLASSIFICATION BY THEMES

Theme	Key Authors (Year)	Key Insights	Gaps	Gap Relevance*
AI in AML	Ketenci (2021), Oztas (2024), Kahur (2025)	ML & features reduce FP; new patterns	Few human-AI workflow studies	TC, FP
Human-AI Collaboration	Bertrand (2024), Wang (2024)	Trust, sensemaking, explanation paradox	No empirical AML banks data	TC, EX
Trust & Oversight	AUSTRAC (2024), Australian Gov (2024), King (2020)	Oversight & compliance defensibility	Generic, no dynamic trust focus	OV, TC
False Positives & Fatigue	Alahmadi (2022), Mounika (2024)	High FP rates cause decision fatigue	Limited AML-specific FP research	DF, TC
Explainability	Eddin (2021), Bertrand (2024), Jensen (2023)	SHAP/LIME aid sensemaking	Not embedded in daily workflows	EX, FO
Feedback Loops	Deloitte (2020), NICE Actimize (2020), Kumar (2024)	HITL & loops cut FP	Case-specific; lacks generalization	FL, TC
Regulatory Compliance	AUSTRAC (2024), Gov. Australia (2024)	Regulatory guidance & assurance	Broad, not tailored to AML	RC, OV
Situational Awareness	Boudt (2025), Rane (2023)	News monitoring boosts AML relevance	No human feedback integration	SA, OV

TC = Trust Calibration; FP = False Positives; DF = Decision Fatigue; EX = Explainability; FO = Follow-through; OV = Oversight; FL = Feedback Loop; RC = Regulatory Compliance; SA = Situational Awareness.

Moreover, the table surfaces a notable epistemic gap: few studies offer empirical insight into how AML analysts interact with AI tools in practice. While theoretical models of human-AI collaboration, for example [17] and [18], conceptualize trust dynamics and explanation paradoxes, they remain untested in operational settings. This undermines our ability to assess decision fatigue, escalation behaviors, or feedback efficacy. Similarly, while explainability tools such as SHAP and LIME are technically validated, their real-world impact on analyst cognition and institutional defensibility remains speculative. These oversights suggest a need for workflow-embedded research that moves beyond algorithmic validation toward situated understanding of analyst behavior under compliance constraints.

Taken together, the classification in Table III does more than organize the literature; it reveals a systemic blind spot in current research: the lack of integrated, cross-disciplinary models that capture how trust, fatigue, explainability, and oversight interact in real-time AML operations.

Organizing the literature into these synthesized themes and acknowledging both convergence and contradiction, this section sets the stage for deeper thematic unpacking, detailed in Section VI(A) to Section VI(D). These themes are not merely descriptive categories; they are operational leverage points within the trust-feedback loop central to the conceptual framework.

A. Trust Calibration

This theme highlights how fluctuations in analysts' trust, as discussed by [17] and [18], directly inform the design of the Dynamic Trust Modulation Loop (see Fig. 3), which operationalizes how trust is depleted after repeated false positives and restored through feedback-driven model adjustments.

B. Theoretical Perspective: Human-AI Collaboration and Sensemaking in AML

To strengthen the understanding of how AML professionals collaborate with AI systems in transaction monitoring, this study draws on key concepts from Human-AI interaction theory: cognitive trust, situational awareness, and decision fatigue. These constructs are essential in analyzing how human analysts interpret, respond to, and calibrate their oversight of AI-generated alerts in high-stakes AML environments. This theme aligns with the conceptual framework in Fig. 2, where high false positives and alert ambiguity are shown to contribute to trust calibration challenges.

Cognitive trust reflects the degree to which users perceive AI systems as competent, reliable, and predictable. Prior research shows that trust in automation is shaped by tangibility, transparency, and task characteristics, especially relevant in compliance settings where legal accountability is still held by human actors [17]. When trust in AI drops due to unexplained false positives, analysts may disengage or ignore alerts entirely, creating operational blind spots.

Situational awareness involves understanding the transaction flagged by AI as well as the broader customer behavior, laundering typologies, and threat patterns. Overly complex or "black box" systems risk eroding this awareness [19]. Decision fatigue arises when analysts are overwhelmed by high alert volumes, often due to false positives. Bertrand introduces the "cry wolf effect", where repetitive false alerts reduce trust and increase the chance of missing legitimate threats [17].

Further research provides insight into this issue, indicating that security analysts working in similar high-alert environments often lack the contextual data needed to assess alert relevance [20].

This parallels AML settings, reinforcing the need for systems that enable explainability and reinforce human oversight. Graph-based machine learning triage models show promise; Feedzai reports an 80% reduction in false positives with over 90% detection of true positives [21]. The real-world relevance of such models emphasizes the value of applying theoretical insights to institutional settings.

Table IV reveals contrasting institutional approaches to trust and oversight in AI-supported AML systems. Cases like Westpac and CBA illustrate how poor governance and absent feedback loops lead to trust erosion, especially under high alert fatigue and low system transparency. In contrast, IDB Bank and

Chainalysis show that trust can be reinforced when automation is paired with high explainability and real-time feedback. Their success lies in workflows that support analyst understanding and continuously refine detection models.

Also in Table IV, the Santander case highlights the risks of relying on external AI vendors, but without full transparency or internal adaptability, institutions may lose control over explainability and oversight, weakening both analyst trust and regulatory assurance. Bunq's legal challenge underscores the role of regulatory alignment in trust calibration. Even high-performing models may face resistance if explainability standards are unclear or contested.

Overall, the mapping suggests that sustainable AML performance depends less on model complexity and more on system designs that embed transparency, human oversight, and adaptive feedback.

Table V draws on Alahmadi's thematic coding of analyst feedback to explore how cognitive trust, situational awareness, and oversight are shaped by real-world interactions with AI-generated alerts. These insights reveal how high-pressure environments strain the balance between automation and human judgment in AML contexts.

The coded responses illustrate a core tension: automation often falls short of supporting analysts in fast-paced environments. Instead of reducing workload, systems frequently overwhelm users with unclear or irrelevant alerts, triggering distrust and cognitive strain.

Situational awareness is another weak point. Analysts report difficulty in understanding system behavior or interpreting alerts without contextual clues, undermining their ability to act decisively and accurately. Trust calibration emerges as an emotional as well as procedural challenge. Analysts feel personally responsible for missed threats, especially when system limitations are known but uncorrected. This underscores the importance of transparency and oversight.

Importantly, the responses show consensus around the need for human-in-the-loop processes. Validation by analysts not only improves compliance defensibility but also restores confidence in system recommendations. So, the limited feedback from analysts back into AI models reflects a broader weakness in adaptive learning. Without structured error reporting, systems cannot evolve meaningfully, reinforcing inefficiencies and trust gaps over time.

TABLE IV. MAPPING OF CASE STUDIES TO FRAMEWORK COMPONENTS

Case Study	Trust Calibration	Explainability	Situational Awareness	Decision Fatigue	Feedback Loop Integration
Westpac (AU)	Trust erosion due to systemic oversight failures	The low absence of clear rationale for alerts	Limited by poor governance structures	High, driven by excessive unresolved alerts	Absence of no mechanism to feed analyst observations back into the system
Commonwealth Bank of Australia (AU)	Over-reliance on partially automated systems without adaptive override	Moderation of some transaction data is available, but insufficient for risk context	Compromised in weak link between alerts and broader risk picture	Medium to High, given sustained operational strain	Minimal limited escalation learning
IDB Bank (US)	Strengthened trust through automation of post-alert processes	High and integrated case management provides contextual clarity	Enhanced of the analysts focus on high-risk escalations	Reduced 60% lower manual review workload	Strong feedback directly informs system tuning
Santander (EU)	Mixed efficiency gains but reliance on external AI reduces internal trust	Moderate vendor models lack full transparency	Variable dependent on third-party reporting	Medium, due to persistent false positives	Weak limited capacity to adapt vendor models
Bunq vs. DNB (NL)	Initially questioned by regulator; restored through legal vindication	Contested regulator deemed insufficient, court found adequate	Adequate AI model contextualized transactions effectively	Low automation reduced manual screening load	Moderate to internal testing but limited regulator feedback
Chainalysis & Elliptic (Global)	Generally high, supported by law enforcement use	High anomaly detection is well-documented	Strong in real-time blockchain monitoring	Low AI filters high-volume low-value alerts	Strong investigative feedback improves detection models

TABLE V. THEMATIC ASSERTIONS FROM PARTICIPANT RESPONSES ALIGNED WITH AML THEORY

Theme	Codes	Summary Result & AML Relevance
Cognitive Trust	A1, A8	Analysts rely on personal judgment and feel strong responsibility when threats are missed, reflecting trust calibration and the emotional burden of oversight.
Situational Awareness	A2, A6, A10	Lack of context, unclear alerts, and evolving system behavior hinder rapid, accurate decisions, aligning with situational awareness theory and explainability gaps.
Trust Erosion from False Positives	A3, A4	Repetitive irrelevant alerts reduce trust, increase cognitive strain, and risk underreporting, supporting decision fatigue theory.
Oversight & Human-in-the-Loop	A5	High consensus that human validation is essential for AI oversight, reinforcing analyst confidence and compliance defensibility.
Performance Pressure	A7	Speed-focused performance metrics undermine investigative depth, linking to decision fatigue and compliance risks.
Feedback Loop Weakness	A9	Limited reporting of errors back to systems hinders AI adaptation, evidencing feedback loop failures.

C. Understanding Accountability in Human-AI Decision-Making for AML Monitoring

AI's black-box nature complicates accountability in transaction monitoring, as prior research stresses that analysts must be able to justify AI-driven decisions through interpretability and effective oversight [18]. Related studies also warn against over-reliance on automated systems, noting that excessive dependence can erode critical thinking and increase regulatory risk [20]. Accountability-sharing frameworks are emerging, such as human-in-the-loop models and AI review committees, which formalize roles and support ethical oversight [22] and [23]. These mechanisms must be embedded in governance structures to uphold compliance defensibility and public trust.

D. Post-Alert Investigation Processes

High false positive rates delay investigations and burden analysts; for example, NICE Actimize has improved workflows by centralizing alerts, SAR generation, and case management, as seen in IDB Bank's reported 60% manual workload reduction [12]. External tools like Belgium's NEMO integrate media signals into risk assessments, showcasing dynamic post-alert adaptations [24]. Meanwhile, predictive triage models further improve investigative accuracy [21].

Table VI summarizes the root causes of false positives in AML systems and links each to targeted mitigation strategies. These findings show how technical and governance gaps contribute to analyst fatigue and eroded trust.

Table VI outlines primary causes of false positives and mitigation strategies, reinforcing that explainability and feedback loops are critical to trust and efficiency.

Note 1: Several risk-based adaptive thresholds have been shown to significantly reduce false positive rates in AML models, as mentioned by Ketenci.

Note 2: Referring to SHAP values and other explainability tools, these provide transparency in model decisions, thereby increasing analyst confidence and reducing investigation time, as mentioned by Kahur.

Note 3: Feedback cycles allow AML professionals to improve model performance over time by incorporating real-world alert fixes, as mentioned by Sausen and Liegel.

As shown in Table VI, false positives are not just technical glitches; they are trust failures since the alerts lack context or cannot be explained, and analysts disengage, leading to oversight gaps and underreporting. The table highlights that improving accuracy alone is not enough. The most effective mitigation strategies, like SHAP-based explainability or human-in-the-loop retraining, address cognitive and procedural dimensions of trust.

Importantly, explainability functions as a trust calibration mechanism, so this one enables analysts to reconcile system output with professional judgment, reducing reliance on blind acceptance or rejection of alerts. However, transparency without action is useless, which is why feedback loops remain underdeveloped, forcing analysts to revalidate the same errors without influencing model behavior.

This lack of adaptation directly contributes to decision fatigue. Table VI illustrates that reducing false positives requires integrated solutions that align model design with analyst workflows, situational awareness, and regulatory defensibility.

1) Key findings: Prior research shows that trust in AI-driven systems is dynamic and influenced by factors such as false positives, limited explainability, and the degree of analyst control [18], [19], [25].

2) Contradictions/trends: Some perspectives conceptualize trust as a dynamic construct recalibrated through feedback mechanisms, while other accounts frame trust as primarily compliance driven [26]. Industry evidence further indicates that integrating structured feedback into AML systems can improve trust stability, as demonstrated in reports by NICE Actimize [12].

3) Limitations/gaps: There is limited empirical evidence on how trust is rebuilt. This highlights the value of the Dynamic Trust Modulation Loop (see Fig. 3), which offers a visual model to capture the trust-feedback interaction over time.

TABLE VI. SUMMARY OF FALSE POSITIVE CAUSES AND MITIGATION STRATEGIES

Cause of False Positive	Description	Mitigation Strategy	Supporting Study
Rule-based thresholds	Static thresholds trigger alerts on legitimate transactions	Move to dynamic, risk-based profiling with adaptive AI	Ketenci et al. (2021)
Poor or incomplete data	Missing or outdated KYC data affects transaction interpretation	Improve data governance; refresh KYC frequently	AUSTRAC (2023); Jensen & Iosifidis (2023)
Model bias	Outdated or narrow training data flags benign behavior	Retrain models with updated, diverse data; integrate typologies	Tsapa (2023); Kahur (2025)
Lack of contextual awareness	Alerts ignore behavioral patterns, customer background, or geography	Incorporate contextual variables into feature sets	Deloitte (2020); Feedzai (2022)
Black-box outputs	Analysts can't understand why the system flagged the alert	Use explainable AI (e.g., SHAP values); implement model transparency features	Momenta (2022); Kahur (2025)
Feedback not integrated	Analyst input on false positives is not used to improve the system	Establish feedback loops and human-in-the-loop retraining protocols	NICE Actimize (2020); Sausen & Liegel (2020)

E. Explainability in AI Alerts

1) Limitations of AI in AML monitoring: the false positive problem: One of the most pressing challenges in AI-enabled AML systems is the persistently high rate of false positives, legitimate transactions incorrectly flagged as suspicious. As shown in Table II, methodological approaches vary across empirical and conceptual studies. Although AI and machine

learning (ML) have been praised for modernizing transaction monitoring, the practical reality is more complex. False positive rates frequently exceed 90% in both traditional rule-based and some AI-based models [27], [28]. This over-detection places a heavy burden on AML practitioners, who must manually review thousands of flagged transactions, most of which turn out to be harmless. Excessive alert volume not only leads to alert fatigue and increased operational costs but can also desensitize analysts, making it difficult to detect truly suspicious activity when it arises [28].

The effectiveness of AML systems lies in their capacity to direct human attention toward genuinely high-risk events, as noted in prior research [25]. When analysts spend most of their time reviewing false alerts, the fundamental objective of AML, preventing financial crime, is compromised. The psychological toll of continuous exposure to irrelevant alerts may also reduce an analyst's sensitivity to true red flags over time. These limitations are especially acute in smaller institutions with fewer resources, leading to greater reliance on manual reviews and further straining compliance operations [29].

The variability of AML-related data, which may involve hundreds or thousands of accounts, transactions, and behavioral features, adds to the challenge. Designing effective models requires both high-quality data and deep domain expertise to identify meaningful feature interactions. Consequently, many implementations suffer from performance limitations or require extensive manual configuration, which reduces scalability in high-volume environments [28].

To mitigate these issues, recent approaches have focused on integrating iterative, confidence-based learning cycles. In these models, analyst feedback is not only used to validate alerts but is also quantified and incorporated into retraining processes. Confidence indicators such as analyst override rates, decision certainty, and SHAP-based interpretability scores are used to assign weighted values to human corrections and feature relevance. This allows the system to prioritize learning from high-confidence analyst inputs, which are more likely to represent reliable domain knowledge.

What is particularly novel about this approach is that the model's learning is shaped around human decision-making. It does not merely enhance technical accuracy but also improves its ability to align with how analysts interpret and assess risk. This approach is aligned with AUSTRAC's expectations: AI systems must provide explainable decisions, incorporate risk considerations, and place human oversight at the core of the process. Moreover, it introduces the potential to use human trust itself as a feature in training AI systems for regulatory compliance contexts. For example, prior work has introduced novel feature sets based on time–frequency analysis, transforming transactional data into two-dimensional signal representations [30]. When implemented with Random Forest classifiers, this method reduced the false positive rate to 11.85% and improved the F1 score to 74.06%, demonstrating a more balanced trade-off between precision and recall.

As this study adopts a qualitative approach to understanding how AML practitioners manage false positives in AI systems, the proposed framework creates a foundation for future empirical validation. Variables such as perceived trust in AI, decision time, cognitive load, and analyst satisfaction with explainability could be measured through surveys or controlled experiments. These variables are closely tied to core components of the model, including trust calibration, feedback loops, and interpretability support tools. Accordingly, future research could adopt mixed methods designs to evaluate how these variables influence escalation outcomes and trust dynamics, strengthening both the empirical application and theoretical robustness of the proposed framework.

Table VII compares leading AI techniques used in AML transaction monitoring, evaluating their performance across false positive reduction, explainability, and real-world deployment. These comparisons reveal adjustments between model transparency and operational effectiveness.

The comparison in Table VII shows that high performance doesn't always mean high transparency, given that graph-based models reduce false positives effectively but lack full explainability, which may hinder regulatory trust. On the other hand, SHAP values, while highly interpretable, lack published data on their real-world impact. This reflects a broader tension between model transparency and measurable efficiency.

Eventually, techniques that align with analyst workflows by aiding prioritization and enabling oversight offer more than just accuracy. They support trust, usability, and compliance defensibility. Table VII supports the need for hybrid AI designs that balance performance, explainability, and human feedback integration.

TABLE VII. CROSS-COMPARISON OF AI TECHNIQUES IN AML

AI Technique	Use Case	False Positive Reduction	Explainability	Real-World Application
Random Forest + Time-Frequency	Transaction pattern detection	Reduced FPR to 11.85%	Moderate	Mounika et al. (2024)
SHAP Values	Model interpretability	Data on false positive reduction are not disclosed in public sources.	High	Momenta (2022); Kahur (2025)
Graph-Based Triage Model	Risk prioritization via transaction networks	Reduced FPR by up to 80%	Moderate	Feedzai (2022); Eddin et al. (2022)

Practical deployments have begun to address long-standing limitations; the best example might be "NICE Actimize, which has demonstrated a 30–50% reduction in false positives, improving the efficiency of compliance teams" [12]. As summarized in Table III, literature themes converge around trust, explainability, and regulatory compliance. These findings suggest that advanced feature engineering, including time frequency features such as kurtosis and skewness, can lead to more accurate and operationally viable AML systems [31].

Despite these improvements, false positives remain a persistent challenge; until AI models can reliably distinguish

between genuinely suspicious transactions and benign anomalies, human analysts will remain essential to the investigation process, and the vision of full automation will remain unattainable. As emphasized throughout the literature, improving model explainability, refining input features, and enhancing human–AI collaboration are critical for ensuring that AI augments rather than overwhelms the AML function. This reinforces the relevance of the core analyst–system interaction constructs articulated in human–AI collaboration theory. Analysts continue to experience decision fatigue when static thresholds consistently flag non-suspicious behavior.

- Key findings: Prior research emphasizes that explainable AI (XAI) tools, such as SHAP and LIME, can help analysts better understand system outputs and increase confidence [21], [31], [32]. However, practical adoption of these tools remains uneven.
- Contradictions/Trends: Although a degree of consensus exists regarding the utility of technical explainability tools, prior studies emphasize that these tools are often disregarded when they are not seamlessly integrated into analysts' daily workflows, particularly through accessible visualizations [32], [33]. Several studies highlight the tension between explanation complexity and the speed required for real-time decision-making.
- Limitation/Gap: There is a lack of empirical evidence demonstrating whether explainability features directly reduce false positives or analyst fatigue in operational settings. The inclusion of "explainability satisfaction" as a construct within this study's framework aims to address this measurement gap by capturing the analyst's perception of the clarity and usefulness of AI-generated outputs.

F. Oversight and Governance

1) Human-AI collaboration in AML compliance: The integration of artificial intelligence (AI) into anti-money laundering (AML) systems has introduced a dual-layered structure of operational support and cognitive challenge. While AI enhances scalability and anomaly detection, it also generates persistent governance issues, particularly concerning false positives, opaque decision-making, and compliance defensibility. As such, oversight in AI-AML systems must be understood not only as a regulatory function but also as a dynamic interface between automated pattern recognition and human interpretive judgment [19], [34].

Despite the adoption of advanced AI tools, studies continue to report false positive rates as high as 90–95% [33], leading to alert fatigue and cognitive overload among analysts [4]. These issues are compounded by the reliance on historical data that may encode legacy biases, leading to detection errors and redundant investigations. In response, human analysts play a critical oversight role: validating AI outputs, applying contextual knowledge, and modulating escalation behavior functions that current AI systems are poorly equipped to replicate.

The following Table VIII clearly summarizes the practical response strategies employed by AML analysts when addressing AI-generated alerts, highlighting the range of responses that effectively mitigate alert fatigue and enhance compliance outcomes.

The interview responses in Table VIII reveal that alert fatigue, lack of feedback loops, and limited explainability significantly undermine trust in AI-assisted AML systems. Analysts report defaulting to intuition over system guidance and express frustration when feedback isn't acknowledged, indicating weak cognitive trust and disengagement from human-in-the-loop processes. While tools like SHAP offer some interpretability, they are not sufficient on their own; without actionable transparency and feedback integration, AI systems risk being sidelined despite their technical performance. These practitioner themes reinforce that trust calibration must be embedded in system design to ensure adoption and compliance defensibility.

TABLE VIII. PRACTITIONER THEMES FROM INTERVIEWS

Theme	Sample Quote	Frequency	Interpretation
Alert Fatigue	I catch myself rushing after 20 false alerts in a row.	Q3, Q15	Decision Fatigue
Trust in AI	Sometimes I ignore the system and trust my instincts.	Q7, Q8	Cognitive Trust
Lack of Feedback Loops	I've submitted feedback, but I don't know if it's used.	Q10	Human-in-the-loop
Need for Explainability	SHAP helps me understand why the alert was triggered.	Q9, Q16	Interpretability

VII. REGULATORY FRAMEWORKS AND GOVERNANCE UNDER AUSTRAC

In the Australian context, AUSTRAC operates both as a financial intelligence unit and the chief regulator responsible for enforcing the AML/CTF Act 2006. Although AUSTRAC mandates that all transaction monitoring programs, manual or automated, be risk-based and support "reasonable grounds for suspicion" in SMR submissions, the agency has yet to issue dedicated AI-specific guidance. This omission has created a regulatory blind spot in which institutions must interpret traditional compliance obligations in the context of complex, often opaque, AI systems [1], [35].

The operational consequences of this regulatory ambiguity are evident in Table IX, which highlights the misalignment between AUSTRAC expectations and common AI system features. For instance, while human validation and feedback loops are increasingly present in advanced setups, critical areas such as transparency, accountability, and real-time contextual awareness remain underdeveloped. High-profile failures at institutions like Westpac and CBA have illustrated the dangers of opaque models and unmanaged alert volumes, while newer hybrid models from Bunq to Elliptic showcase the value of explainability and real-time feedback integration.

TABLE IX. AI FEATURES VS. AUSTRAC PRINCIPLES: AN OPERATIONAL ALIGNMENT

AUSTRAC Expectation (Grouped)	Typical AI Feature	Compliance Gap / Risk + Construct*	Real Case Example (Year)
Risk-based monitoring & SMRs	ML detects patterns; real-time anomaly detection	Over-flagging & alert fatigue (DF); delayed SMRs (OV)	Santander fine (2025); CBA SMR failure (2018)
Auditability & Explainable decisions	Black-box AI; complex algorithms	Limited traceability (EX); need human validation (SA, TC)	Westpac breaches; Bunq interpretable AI (2021)
Ongoing CDD/KYC & Oversight	Profile risk scoring; semi-autonomous operation	Misses' real-time context (SA); oversight needed (OV, FL)	Chainalysis blockchain data; Elliptic hybrid alerts (2025)

Legend: DF = Decision Fatigue; OV = Oversight; EX = Explainability; SA = Situational Awareness; TC = Trust Calibration; FL = Feedback Loop.

Table IX illustrates critical misalignments between AUSTRAC's regulatory expectations and current AI practices in AML. While AI tools offer real-time monitoring and pattern detection, they often trigger excessive false positives and lack transparency, leading to delayed reporting and reduced auditability. These gaps highlight the persistent need for human oversight to contextualize system outputs and maintain regulatory compliance. Moreover, inconsistent implementation and poor documentation practices, such as reliance on ad hoc risk assessments, undermine both accountability and trust. The analysis reinforces that AI must be integrated not only as a technical solution but within a governance structure that supports explainability, oversight, and traceability.

Moreover, AUSTRAC's regulatory reach does not yet extend to high-risk sectors such as legal, accounting, and real estate services (DNFBPs), creating systemic gaps that sophisticated laundering networks continue to exploit. Proposed "Tranche 2" reforms aim to address these omissions, but until implemented, oversight remains fragmented, undermining both national security and FATF compliance rankings [36].

VIII. GOVERNANCE AND THE FUTURE OF OVERSIGHT

Traditional compliance models, which rely on linear thresholds and rule-based control points, are increasingly unfit for AI-enhanced AML environments. Instead, a new paradigm of adaptive governance is emerging, one that integrates explainability tools such as SHAP and LIME with real-time trust metrics and analyst confidence scores to modulate compliance thresholds dynamically. This approach aligns with AUSTRAC's emphasis on risk-based monitoring while operationalizing transparency, traceability, and human accountability as interdependent elements of effective oversight.

AUSTRAC's alignment with the Australian Government's AI Assurance Framework [37] further reinforces this shift. The framework's eight principles explainability, contestability, accountability, transparency, fairness, reliability, privacy, and human-centered values echo AUSTRAC's stated priorities but go further by offering specific policy tools such as lifecycle risk assessments and AI transparency statements. These tools provide institutions with a governance scaffolding that not only supports compliance but also anticipates the ethical and legal challenges posed by increasingly autonomous AI systems.

The implication is clear: oversight in AI-AML systems must evolve from static rule adherence to dynamic, feedback-integrated governance. This transition demands that institutions embed structured feedback loops, document decision pathways, and ensure that human analysts remain central in validating and contextualizing automated outputs. Without these mechanisms, the promise of AI in AML remains undermined by its own operational opacity and regulatory uncertainty.

A. Systemic Risks

Systemic risks in artificial intelligence-driven anti-money laundering (AI-AML) frameworks emerge not solely from algorithmic inefficiencies but from misalignments between institutional practices, regulatory expectations, and the operational realities of compliance systems. Within the Australian context, the AUSTRAC regulatory environment, while comprehensive in principle, reveals structural and procedural gaps that, if unaddressed, may scale into broader systemic vulnerabilities.

IX. STRUCTURAL AMBIGUITY AND COMPLIANCE OVERLOAD

AUSTRAC's AML/CTF Act 2006 does not distinguish between manual and AI-based transaction monitoring systems, applying uniform expectations around Suspicious Matter Report (SMR) submissions based on "reasonable grounds for suspicion". However, this regulatory equivalence masks a key risk: AI systems often generate large volumes of alerts, many of which are opaque and lack interpretability. Institutions are legally obligated to process these alerts with the same rigor as human-generated suspicions, potentially overwhelming compliance workflows and increasing the likelihood of delayed or inappropriate filings, a systemic failure point [1].

The absence of formal thresholds for false positive or false negative rates introduces additional ambiguity. Without clear benchmarks, institutions are left to self-assess AI system performance, resulting in inconsistent standards of compliance across the sector. Table X illustrates how these misalignments manifest: while "effectiveness" and "ongoing oversight" are broadly achieved, critical areas such as transparency, accountability, and traceability remain structurally deficient. This incomplete alignment reflects a broader systemic fragility where critical compliance decisions may rely on black-box outputs with limited auditable pathways.

Table X assesses how current AI systems align with AUSTRAC's AML/CTF regulatory principles, based on system characteristics and observed operational practices.

As shown in Table X, it illustrates how AUSTRAC and its principles for compliance systems align, or do not align, with the typical characteristics of AI-based transaction monitoring. It is understood that AI can improve efficiency and facilitate oversight when implemented in feedback mechanisms, which

often present deficiencies in areas such as transparency, accountability, and traceability. These weaknesses reinforce the need for continuous human oversight, explainable models, and improved auditability to ensure compliance with AUSTRAC standards.

TABLE X. OPERATIONAL ALIGNMENT: AUSTRAC PRINCIPLES AND AI FEATURE ANALYSIS

AUSTRAC Principle	AI Feature	Operational Scenario	Alignment
Transparency	Deep learning model	Analyst receives an alert but cannot explain why it was triggered	It's not aligned
Accountability	Automated alert generation without review	Alerts are escalated without human validation	It's not aligned
Traceability	No logging of analyst actions or model decisions	Supervisor cannot trace why an alert was closed or escalated	It's not aligned
Proportionality	Rule-based scoring applied uniformly	Low-risk customers flagged with the same thresholds as high-risk clients	Its partially aligned but need improvements
Effectiveness	AI flagging paired with human validation	Analyst reviews a flagged transaction, confirms suspicion, files SMR	Aligned
Ongoing Oversight	Feedback loops and the model retraining	Analyst labels false positives: system learns and improves over time	Aligned

X. FRAGMENTED OVERSIGHT AND RISK DIFFUSION

As highlighted in AUSTRAC's expectations and reflected in the Australian Government's AI Assurance Framework, human oversight is essential not only for ethical compliance but for the iterative improvement of AI systems. However, most AML frameworks fail to operationalize this principle. Feedback from analysts is often informal, undocumented, or siloed. Consequently, AI models are rarely retrained based on field-level insights, allowing detection errors to propagate unchecked. This oversight vacuum introduces not only model stagnation but also a false sense of algorithmic reliability, amplifying systemic exposure to compliance failure.

Moreover, AUSTRAC's current scope excludes several high-risk professions such as lawyers and real estate agents (DNFBPs), leaving exploitable gaps in the regulatory perimeter. These omissions enable criminal networks to route illicit flows through sectors with reduced AI scrutiny, creating shadow pathways that weaken the broader AML ecosystem. As described in international comparisons (see Table XI), other jurisdictions such as the UK's FCA or the US FinCEN offer more robust mechanisms for AI explainability, sandbox testing, and auditability, reflecting a maturity in systemic risk mitigation that AUSTRAC has yet to formalize.

TABLE XI. GLOBAL AI-AML REGULATORY COMPARISON

Regulatory Body	AI & AML Focus	Key Compliance Expectation	Implication for AUSTRAC
AUSTRAC (Australia)	Risk-based, flexible, minimal AI-specific rules	Outcome-focused SMR accountability	AUSTRAC could benefit from transparency requirements by providing new, clearer metrics for measuring AI traceability and SAR justification.
FinCEN (Financial Crimes Enforcement Network) (US)	Supports AI-driven SARs, stresses auditability	Explainable, testable AI systems	AUSTRAC could benefit transparency requirements by providing new, clearer metrics for measuring AI traceability and SAR justification.
FCA (Financial Conduct Authority) (UK)	High transparency and fairness in AI models	Clear algorithmic accountability, sandboxing	AUSTRAC could benefit from incorporating new FCA model explainability standards, promoting tools like SHAP and new decision tree interfaces.
FATF (Financial Action Task Force) (Global)	Global oversight principles: explainability, proportionality	Human oversight + innovation risk control	AUSTRAC can lead implementation by FATF members by proposing national AI audit protocols and assisting with participation in FATF AML working groups.

Table XI highlights key differences in how major regulatory bodies approach AI governance in AML, revealing a spectrum from general principles to detailed algorithmic standards. While AUSTRAC maintains a flexible, risk-based approach, it lacks AI-specific guidance compared to FinCEN and the FCA, which emphasize explainability, auditability, and accountability. The FCA's sandboxing and model transparency initiatives, along with FinCEN's support for testable AI systems, suggest a more proactive stance that AUSTRAC could emulate. Meanwhile, FATF's global guidance underscores human oversight and proportionality but stops short of prescribing technical norms. The comparison signals a clear opportunity for AUSTRAC to lead regionally by adopting clearer traceability metrics, formal AI audit protocols, and aligning with emerging global standards on explainable machine learning in financial compliance.

XI. GLOBAL GAPS AND INTEROPERABILITY RISKS

On a global level, the divergence in regulatory maturity across jurisdictions creates further systemic risk through regulatory arbitrage. Institutions operating in multiple countries must navigate heterogeneous expectations for AI transparency and accountability, which can lead to fragmented governance strategies. As shown in Table XI, AUSTRAC's outcome-based model lacks the explicit interpretability and audit trails mandated by bodies like FinCEN or the FCA. This fragmentation may incentivize minimal compliance in lower-regulation jurisdictions, while overburdening analysts in stricter environments, distorting the effectiveness of AI-AML implementation globally.

A. Implications for Framework Development

The cumulative effect of these systemic factors' regulatory ambiguity, deficient oversight, fragmented feedback loops, and global interoperability gaps poses a risk not only to institutional compliance but also to national and transnational financial security. The proposed framework responds to these challenges by embedding structured human-in-the-loop mechanisms, adaptive threshold modulation, and explainability tools that align with both AUSTRAC's principles and international standards. By explicitly linking trust calibration to analyst feedback and system transparency, the framework mitigates systemic fragility and enhances the defensibility of SMR decisions.

XII. Discussion

The proposed framework was developed following a Design Science Research (DSR) approach, integrating patterns, themes, and operational gaps identified in 61 systematically selected studies published between 2020 and 2025, alongside regulatory reports and industry guidelines. This structured process ensured that each component of the model is logically derived from both academic evidence and practitioner insights, aligning with AUSTRAC's compliance principles.

Unlike previous AML frameworks, which often treat human review as a final, static checkpoint, this model introduces two novel elements: 1) a dynamic trust modulation cycle, capturing how analyst confidence fluctuates and recalibrates in response to false positives; and 2) explicit feedback loops that feed analyst input directly into AI model refinement.

While the present study focuses on theory building, future research will empirically validate this model through quantitative surveys and statistical analysis to test the hypothesized pathways between explainability, trust, fatigue, and escalation decisions.

Fig. 2 illustrates this journey and highlights where key theoretical concepts, such as decision fatigue, confidence calibration, and explainability, are activated in practice.

The proposed human-centered framework focuses on a design that specifically addresses key shortcomings in both the academic literature on AI-AML systems and practitioner rules, such as those of AUSTRAC.

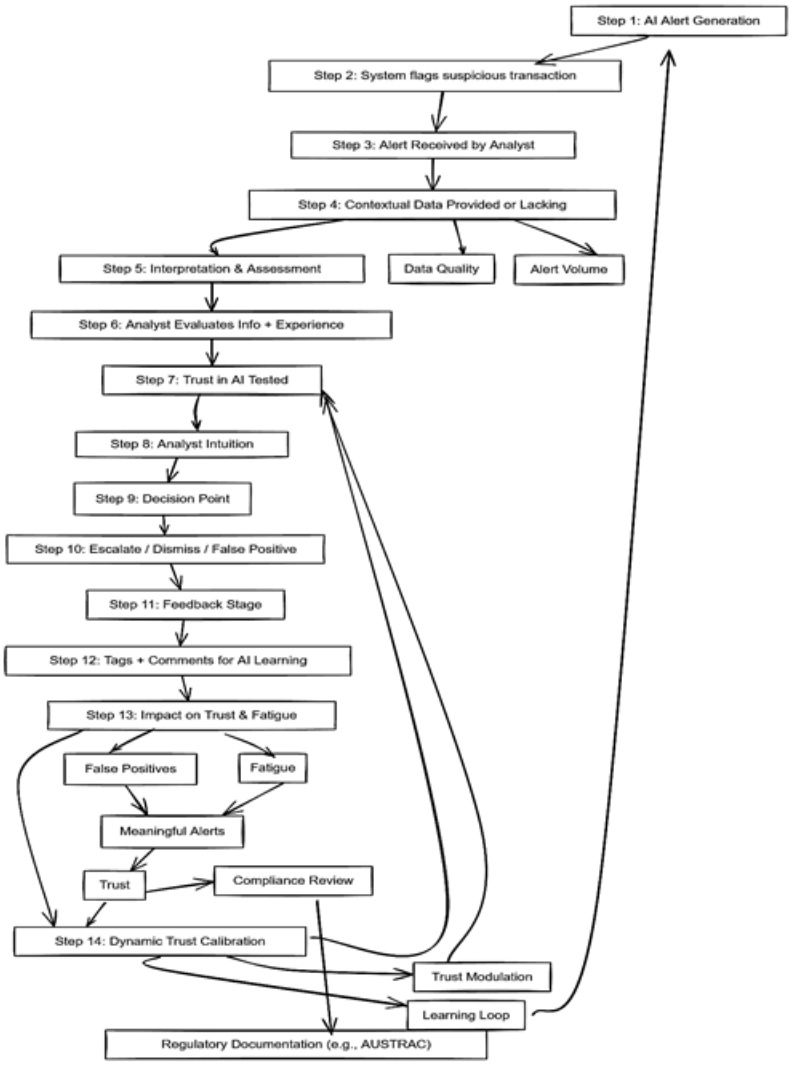


Fig. 2. Conceptual framework: AML analyst journey.

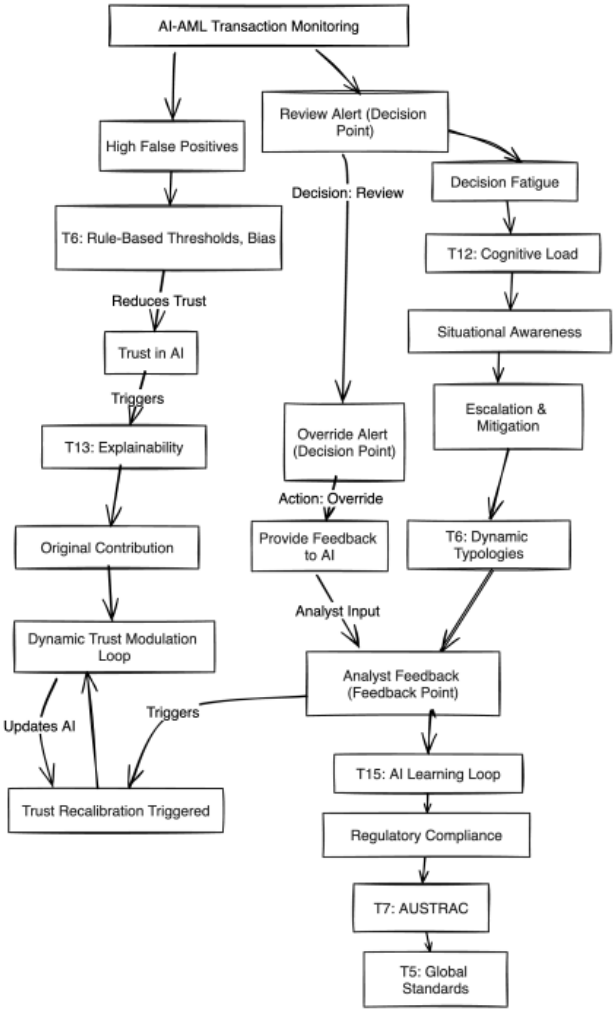


Fig. 3. Analyst workflow model for AI-supported AML decision-making.

The previous discussion on practical strategies, alert fatigue, and regulatory frameworks laid the foundation for the conceptual model. This model integrates theoretical constructs such as human-AI trust, sensemaking, and regulatory alignment, and is illustrated in Fig. 3.

This framework seeks to improve the interaction between human and artificial intelligence decisions in anti-money laundering (AML) settings by dynamically calibrating trust, decision fatigue, and continuously enhancing situational awareness during the alert review process. The goal is to shorten the time between static compliance checkpoints and real-world analytical understanding by integrating explicit feedback loops, trust-based escalation thresholds, and adaptive compliance monitoring.

As shown in Fig. 3, the feedback loop mechanism illustrates this integration. The framework introduces two novel contributions absent in most current AML models:

- A dynamic trust modulation cycle, in which trust in AI declines in response to repeated false positives and is gradually restored through feedback-driven improvements; and
- Explicit feedback loops, whereby analysts' responses and insights are integrated into the model's learning process, thereby narrowing the gap between human decision execution and system adaptation. This process is illustrated in Fig. 4.

A. Contribution to Anti-Money Laundering (AML) Research and Practice

This study contributes to the AML field by introducing a dynamic, human-centered conceptual framework that operationalizes critical analyst–AI interaction variables such as trust calibration, decision fatigue, explainability, and regulatory alignment. Unlike previous models that treat human review as a static checkpoint, the framework demonstrates how analyst trust evolves in response to system outputs and feedback integration, and how this process impacts escalation decisions and regulatory defensibility.

The Framework Analytical Layer Mapping (Table XII) ensures systematic traceability from literature synthesis to conceptual modeling. This transparent development process strengthens the framework's credibility and auditability for practical application in real-world AML settings. It also bridges the gap between theoretical constructs and operational tools,

offering a structure that aligns with AUSTRAC principles and regulatory trends in high-risk financial environments.

Furthermore, the framework provides practical value for compliance officers and AML teams by embedding explainability, analyst confidence, and oversight into daily operations. Through trusted nodes, feedback loops, and threshold calibration, it addresses key gaps identified in AUSTRAC's expectations and supports more defensible Suspicious Matter Reports (SMR).

TABLE XII. FRAMEWORK ANALYTICAL LAYER MAPPING

Table/Figure	Title	Framework Stage	Key Construct(s)
Table I	Literature Review Source Overview	Included in all stages	All Constructs
Table II	Methodologies in Reviewed Studies	Included in all stages	All Constructs
Table III	Literature Classification by Themes	Stage 1: Supporting Theme Extraction	Trust, Fatigue, Situational Awareness
Table IV	Mapping of Case Studies to Framework Components	Stage 1: Theme-to-Framework Alignment	Trust, Explainability, Feedback Loops
Table V	Thematic Assertions from Participant Responses Aligned with AML Theory	Stage 1: Practitioner Theme Extraction	Trust, Fatigue, Situational Awareness
Table VI	Summary of False Positive Causes and Mitigation Strategies	Stage 2–3: Problem–Solution Mapping	Decision Fatigue, Trust, Feedback Loops
Table VII	Cross-Comparison of AI Techniques in AML	Stage 2: Technical System Evaluation	Explainability, Trust
Table VIII	Practitioner Themes from Interviews	Stage 1–2: Theme Validation	Trust, Fatigue, Explainability
Table IX	AI Features vs. AUSTRAC Principles: An Operational Alignment	Stage 3: Regulatory Gap Alignment	Compliance Defensibility, Oversight
Table X	Operational Alignment: AUSTRAC Principles and AI Features Analysis	Stage 3: Regulatory Analysis	Situational Awareness, Oversight
Table XI	Global AI-AML Regulatory Comparison	Stage 3: Regulatory Comparison	Oversight, Trust Calibration
Table XII	Framework Analytical Layer Mapping	Stage 4: Analytical Impl.	All Constructs
Table XIII	Contribution to Explainable AI in AML	Stage 3–4: Novelty Justif.	Explainability, Trust
Table XIV	AI Error Types and Human Responses	Stage 2: Problem Id.	Trust, Decision Fatigue
Table XV	Linking Theory–Objective Mapping	Included in all stages	Trust, Fatigue, Situational Awareness
Table XVI	Summary of Identified Gaps	Stage 3: Gap Synthesis	Trust, Oversight, Feedback, Explainability
Table XVII	Alignment of Regulatory Expectations with AML System Capabilities	Stage 3: Regulatory Fit–Gap Closure	Compliance Defensibility, Oversight
Table XVIII	Mapping of Framework Constructs to Potential Measurable Indicators	Stage 4: Operational Metrics Layer	Trust, Feedback, Decision Fatigue, Explainability
Table XIX	Appendix A – Likert-Scale Survey for AI-AML Constructs	Future Empirical Layer	All Constructs
Table XX	Appendix C: Constructs and Measurement for Empirical Validation	Future Empirical Layer	Trust, Feedback, Decision Fatigue, Explainability
Table XXI	Appendix C: Mapping of Interview Questions to Research Objectives and Theoretical Constructs	Future Empirical Layer	Trust, Fatigue, Situational Awareness
Figure 1	PRISMA Flow Diagram of Literature Selection Process	Stage 1: Literature Selection Justification	All Constructs
Figure 2	Conceptual Framework: AML Analyst Journey	Stage 4: Framework Synthesis	Trust, Explainability, Feedback, Compliance
Figure 3	Analyst Workflow Model for AI-Supported AML Decision-Making	Stage 4: Process Operationalization	Trust, Feedback Loops, Situational Awareness
Figure 4	Dynamic Trust Modulation Loop	Stage 4: Novel Component Highlight	Trust Depletion/Restoration
Figure 5	Feedback Loop Mechanism	Stage 4: Feedback Operationalization	Analyst Feedback, System Learning

B. Contribution to AI Trust and Human–AI Collaboration

The study advances cognitive trust theory in regulated AI contexts by introducing the Dynamic Trust Modulation Cycle, a core innovation that captures how repeated false positives erode analyst trust and how structured feedback and improved explainability restore it. This contribution builds upon, but extends beyond, models like Chhetri's A²C framework by explicitly incorporating decision fatigue, situational awareness, and escalation confidence into the trust-feedback dynamic.

This process is illustrated in Fig. 4, as analyst confidence declines in response to repeated false positives, but it also demonstrates that confidence can be recalibrated through structured feedback and model improvements. Visualizing this dynamic cycle of trust modulation, human oversight, and feedback integration emphasizes that it functions as a continuous process rather than remaining static as a final checkpoint.

To understand the dynamic process of trust calibration, the framework also incorporates explicit feedback loops that connect analyst decisions to AI. Since traditional AML systems typically consider human review as a final step in the process, this design demonstrates that analyst input, such as the confirmation of false positives or the justification for escalating

an alert, is systematically captured and used to refine the model's thresholds, just like feedback data.

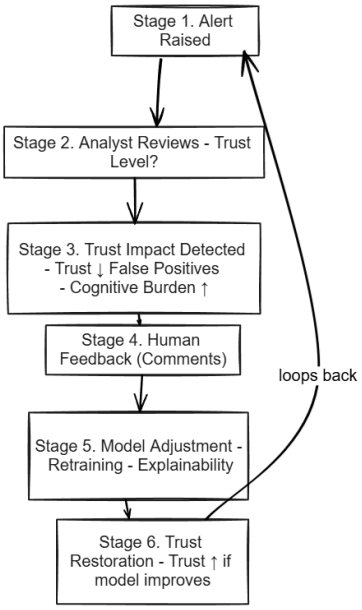


Fig. 4. Dynamic trust modulation loop.

Fig. 5 provides an overview of this mechanism, demonstrating how human judgment continuously shapes system behavior over time and strengthens the compliance case.

Fig. 5 shows the explicit feedback loop for model refinement. It illustrates how analyst feedback on alerts triggers system retraining and threshold adjustments, closing the loop between human judgment and AI model evolution. This cycle enhances the iterative, human-centered approach that distinguishes this framework from static compliance models and ensures that analysts have integrated expertise into the continuous improvement of AI systems.

In the following Table XIII, there are studies that have contributed to the development or application of explainable AI in AML monitoring. It highlights tools such as SHAP values, decision trees, and visual interfaces, and links these contributions to analyst confidence, transparency, and the veracity of effective processes.

As shown in Table XIII, the different AI tools and their explainability, as well as SHAP, LIME, and visual dashboards, directly contribute to analyst efficiency in clarifying model logic and improving alert interpretation. This is especially important in AML/CFT environments, when analysts must justify their case escalation and compliance reporting, following AUSTRAC regulatory standards. When AI decisions are more transparent and interpretable, it reduces decision fatigue, builds cognitive trust, and facilitates human validation, improving operational efficiency and accountability in compliance workflows.

In addition to explicit feedback loops, this framework positions itself as a bridge between algorithmic decision-making and human accountability, in line with AUSTRAC's regulatory expectations. These elements directly support the research objectives, specifically the investigation of analyst behavior in handling alerts, the strategies they adopt to manage false positives, and the regulatory compliance they must follow.

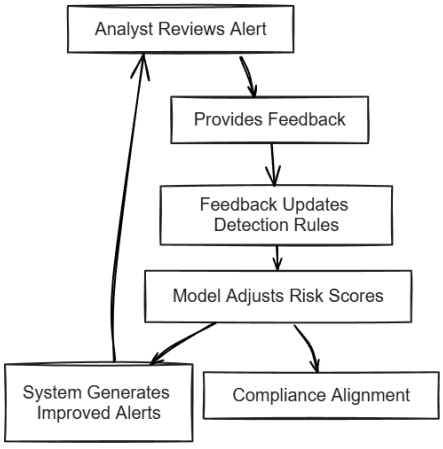


Fig. 5. Feedback loop mechanism.

TABLE XIII. CONTRIBUTION TO EXPLAINABLE AI IN AML

Study	XAI Techniques Used	Contribution to Transparency	Compliance Impact
Kute et al. (2021)	SHAP, LIME, Decision Trees	Improved interpretability of AI-generated alerts for compliance analysts	Supports justifiable SMR decisions; enhances trust in AI recommendations
Bertrand (2024)	Conceptual - Explainability as an ethical requirement	Highlights explainability as key to human trust and accountability	Aligns with AUSTRAC's 'reasonable grounds' requirement for SMRs
Australian Government (2024)	Framework Guidelines (Transparency Standards)	Calls for formal documentation of model logic and intended use	Reinforces AUSTRAC-aligned auditability and oversight expectations
Ghimire (2025)	Precision-recall, threshold tuning	Optimizes model performance visibility	Helps reduce false positives, supports model defensibility

TABLE XIV. AI ERROR TYPES AND HUMAN RESPONSES

Study	Error Type Focused	Human Response Strategy	Tools/Models Used
Mounika et al. (2024)	False Positives	Time-frequency features to reduce alert overload	Random Forest + Skewness/Kurtosis
Eddin et al. (2021)	False Positives	AI enhancement with human validation loop	Machine learning classifier ensemble
Ghimire (2025)	False Positives	Precision-recall optimization to reduce noise	Rule-based + simulated AI outputs
Ketenci et al. (2021)	False Positives	Data integration to reduce alert redundancy	Decision Trees, Logistic Regression
Bertrand (2024)	Cognitive Overload / Alert Fatigue	Human-AI trust calibration and workload awareness	Theoretical (no models)
Deloitte & UOB (2021)	Alert overload	Human-in-the-loop feedback for dynamic tuning	Anomaly Detection + Feedback Loops

Table XIV shows the main types of errors generated by AI in AML systems, such as false positives and the errors it can make when misclassifying them. It also summarizes how analysts respond in practice, highlighting the importance of explainability and a structured process to prevent overload and improve compliance outcomes.

Table XIV shows a comparative summary of studies highlighting the types of artificial intelligence errors, particularly false positives and cognitive overload in analysts, and the human response mechanisms used to mitigate their impact in AML contexts. For a better understanding, each row links a specific error type, such as false positives and alert fatigue, with corresponding strategies, such as feedback gaps, data integrations, or confidence calibration. This comparison between the reference error type and the response mechanism reveals a need to balance technical optimization with human-centered design. Importantly, the table reveals that since most studies focus on technical refinement, not many include confidence as a dynamic and modifiable variable.

The Theory Objective Mapping (Table XV) demonstrates how constructs such as trust, fatigue, and situational awareness are not abstract but are directly linked to AML professionals' lived experiences. Each theoretical construct is aligned with specific research objectives and supports the framework's relevance for both practitioners and scholars seeking to understand human–AI interaction in compliance-driven domains.

As shown in Table XV, a structured mapping between the study's research objectives and their corresponding theoretical foundations ensures the conceptual integrity of the proposed framework. Each objective, ranging from managing false positives to strengthening compliance defensibility, is explicitly linked to established theories such as cognitive trust, human–AI collaboration, and explainability.

The framework transforms conceptual elements of trust and human oversight into measurable, actionable tools for AML professionals. By integrating analyst trust levels, real-time confidence scores, and feedback loops into system retraining protocols, it offers a nuanced mechanism for ensuring compliance that is both adaptive and explainable.

C. Practical and Policy Implications

From a practical standpoint, the architecture offers AML practitioners a clear mechanism for managing false positives, establishing trust levels, and directly incorporating analyst feedback to retrain the system. Through trusted nodes, explainability tools, and feedback loops in daily operations, the framework facilitates real-world compliance defenses based on AUSTRAC's "reasonable grounds" principle. Institutions can demonstrate to regulators that human judgment is not only present but consistently guiding the evolution of AI systems over time.

The framework also contributes policy insights by highlighting the absence of specific regulatory thresholds and explainability standards in existing AUSTRAC guidance. By embedding trust calibration and analyst feedback into the compliance lifecycle, it sets the stage for regulatory advancements aligned with global best practices.

Tables such as the Summary of Identified Gaps (Table XVI), Framework Analytical Layer Mapping (Table XII), and Alignment with Regulatory Expectations (Table XVII) provide empirical support for how the framework addresses persistent challenges in AML operations and policymaking.

Table XVI summarizes these critical gaps and demonstrates their direct relevance to the study's framework.

TABLE XV. LINKING THEORY-OBJECTIVE MAPPING

Theory / Construct	Description	Linked Research Objectives
Trust Theory	Trust in AI systems and cognitive trust determine how analysts accept that decision, override the alert, or otherwise escalate the AI alert. This includes the responsibility for monitoring and calibration after each alert.	RO1: Understand how professionals detect FPs RO2: Understand how professionals evaluate AI alerts RO3: Assess confidence in AI-based alerts
Decision Fatigue Theory	The cognitive load and mental fatigue caused by frequent false positives affect analysts' concentration, willingness to investigate, and the accuracy with which they escalate each alert or case.	RO1: Understand impact of FPs on workload RO2: Understand how professionals evaluate AI alerts RO4: Improve human-AI collaboration and effectiveness
Situational Awareness Theory	When we talk about analysts' ability to perceive, interpret, and act on contextual information, it can impact judgment, confidence, escalation confidence, and compliance defensibility.	RO2: Understand how professionals evaluate AI alerts RO3: Assess confidence in AI-based alerts RO4: Improve human-AI collaboration and effectiveness

TABLE XVI. SUMMARY OF IDENTIFIED GAPS

Framework Component	Gap in Literature
Feedback loops to AI systems	Most studies addressing AI-AML view trust as something static, something that doesn't improve or makes little difference, which means that how analysts' trust evolves isn't explored (Fig. 4).
Analyst fatigue	Cognitive fatigue is often underexplored in AML research, especially in the context of AI false positives (Q5).
Explainability	How analyst feedback changes AI results are rarely investigated in the literature; for example, AUSTRAC lacks feedback norms or standards.
Regulatory compliance	Some technical articles describe the different tools that exist and are included in some research, but not how practitioners use or interpret them (Table XIII).
Human decision after the alert	Academic works usually lack a link to the regulatory context; a clear example can be seen in Table XII on AUSTRAC's obligations.
Trust calibration	In the previous models, a limitation to the generation of alerts is observed, this change, this framework includes a complete human escalation process (Fig. 3)

Table XVI functions as a conceptual tracing map, linking the "why" of the framework to the gaps in the literature, and the "what" of the components, thereby providing a foundation for future empirical testing. Table XVI shows how each component of the proposed conceptual framework directly addresses unanswered questions in the existing AML and AI literature, linking features such as the trust modulation cycle, adaptive compliance thresholds, and feedback mechanisms to specific scholarly and operational gaps.

Table XVII illustrates how each component of the framework addresses specific knowledge gaps in the literature and regulation, highlighting the originality of the model and its contribution to both theory and practice in the field of regulatory compliance within the area of anti-money laundering.

TABLE XVII. ALIGNMENT OF REGULATORY EXPECTATIONS WITH AML SYSTEM CAPABILITIES

AUSTRAC Principle	System Capability	Compliance Gap	Example
Explainability	Black-box alerts limit transparency	Trust and auditability issues	Westpac
Timely SMRs	Alerts are not always escalated in time	Regulatory risk in SMR timing	CBA
Ongoing Oversight	Feedback loops are not always implemented	Lack of analyst feedback loop	Elliptic
Accountability	Responsibility unclear between the system and analyst	Ambiguity in fault ownership	Tabcorp

As shown in Table XVII, each component of the proposed framework addresses the gaps specifically identified through the literature review and analysis of regulatory practices. When these gaps are combined with important elements of the framework, such as adaptive trust calibration, feedback loops, and explainability, this table demonstrates how the framework not only aligns with current regulatory expectations in AML prevention but also offers new contributions to the system.

D. Limitations and Future Work

While the framework provides a robust foundation for AML-AI system design, it remains conceptual and context-specific. Its development is grounded in 61 literature sources and Australian regulatory guidelines, but its generalizability across jurisdictions still needs validation. Moreover, the framework has not yet been tested with primary empirical data, which currently limits real-world applicability.

Future work should focus on operationalizing the framework's constructs into measurable indicators to support empirical evaluation. These indicators, spanning trust calibration, explainability, decision fatigue, and oversight, are designed to reflect actual AML workflows and can inform both qualitative studies, for example, practitioner interviews, and quantitative assessments using operational data.

While prior studies have identified issues such as trust erosion or analyst fatigue (Alahmadi, 2022), few offer mechanisms for real-time trust recalibration or system adaptivity. This framework uniquely incorporates feedback loops as functional components that not only address cognitive strain but also support oversight continuity. In effect, it fills a critical gap in the intersection between compliance design and human-AI interaction.

TABLE XVIII. MAPPING OF FRAMEWORK CONSTRUCTS TO POTENTIAL MEASURABLE INDICATORS

Framework Construct	Proposed Measurable Indicator	Example Data Source	Potential Use Case
Trust Calibration	Percentage of AI-generated alerts overridden or escalated by analysts	Internal AML system logs	Assessing how analyst confidence in AI decisions evolves over time
Explainability	Average time analysts take to resolve an AI-generated alert	Case management system	Evaluating impact of explainability tools on decision speed
Decision Fatigue	Number of alerts processed per analyst per shift and error rates	Analyst workload reports	Identifying workload thresholds that degrade decision quality
Feedback Loop Integration	Frequency and type of analyst feedback incorporated into model retraining	Model governance records	Measuring the effectiveness of human-in-the-loop system updates
Regulatory Alignment	Proportion of escalations meeting AUSTRAC reporting criteria	Compliance audit reports	Tracking alignment of AI decisions with statutory obligations

Table XVIII explains that once the indicators are defined, the framework becomes testable in operational AML environments. It is suggested that future research could employ a mixed-methods design, combining practitioner surveys on trust and fatigue with quantitative analysis of system logs to help validate the relationships between the constructs and help refine the model for broad implementation.

Table XIX presents a draft of a Likert-scale survey developed to measure the key theoretical constructs explored in this study, such as trust in AI, decision fatigue, explainability, and perceptions of supervision. Each item of this scale survey is designed to capture practitioner attitudes using a 5-point scale (1 = Strongly Disagree to 5 = Strongly Agree). This survey aims to support future quantitative extensions of the current research framework.

Future research should address these limitations by:

- Deploying the Likert-scale survey instruments (Table XIX) to gather practitioner data across diverse financial institutions.
- Conducting scenario-based testing and interviews to validate trust calibration, escalation confidence, and decision fatigue in practice.
- Testing the model in other regulated industries, such as healthcare, cybersecurity, or insurance, to examine cross-domain relevance.

- Integrating findings from quantitative log data and qualitative feedback into a mixed-methods study design for broader validation.

The measurement mapping (Table XX) confirms that each construct in the model can be tested using well-established methods and tools. This ensures that the framework is not only theoretically sound but also empirically actionable, a rare feature among current AI-AML models.

As shown in Table XX, the components of the framework are directly linked to a measurable construct, supported by established variables and practical methods that reflect practices in AML and XAI research. This mapping demonstrates that the framework is not only conceptually sound but also empirically testable by asking clear survey questions and scenario-based tasks. When constructs such as confidence calibration, analyst fatigue, and explainability are aligned with validation methods by [18], [31], [32], among others, the study reinforces its commitment to evidence-based design and provides a solid foundation for future quantitative validations. This clarity ensures the framework's relevance to both academic and practitioner settings.

When there is a clear definition of what is to be measured and how, the study provides a roadmap for future researchers. While this study was developed for AML transaction monitoring, the framework's core principles are broadly applicable across sectors where AI and human oversight intersect in high-stakes decision-making environments.

TABLE XIX. LIKERT-SCALE SURVEY FOR AI-AML CONSTRUCTS

Construct	Questionnaire Item (5-point Likert Scale)
Trust in AI	I trust the AI alerting system to correctly identify suspicious transactions.
Trust in AI	I believe the AI system supports my decision-making process.
Decision Fatigue	I feel mentally exhausted after reviewing numerous AI-generated alerts.
Decision Fatigue	I rush through alerts when I know most are false positives.
Explainability	I understand why the AI system flags certain transactions.
Explainability	The AI system provides clear and understandable explanations.
Oversight & Responsibility	I feel personally responsible for verifying the accuracy of AI alerts.
Oversight & Responsibility	Responsibility for AI alert errors lies with the analyst more than the system.

TABLE XX. CONSTRUCTS AND MEASUREMENT FOR EMPIRICAL VALIDATION

Framework	Construct	Example Measurement Variable	Method
Feedback Loops to AI Systems	Feedback quality and frequency	Analyst perceptions of how feedback is integrated into model updates.	Likert-scale items or Frequency scale Example: How often do you provide feedback?
Analyst Fatigue	Decision fatigue and Cognitive load	Perceptions of the amount of workload due to the constant repetition of false positives.	Cognitive Load Scale Example: Rate the mental effort required for daily alert review
Explainability	Explainability Satisfaction	Greater clarity and interpretation of alerts generated by the AI.	Likert-scale items Example: I understand how the AI reached its decision for each alert
Regulatory Compliance	Compliance	Measurement of analysts' confidence in the decisions they make and whether they align with internal or AUSTRAC policies.	Likert-scale agreement items Example: I believe my decisions would be defensible in a compliance audit.
Human Decision After the Alert	Escalation confidence	Measurement of analyst confidence in deciding whether to escalate or dismiss the alert.	Scenario-based questions + Likert items Example: Given this scenario, how confident are you in escalating this alert?
Trust Calibration	Trust in AI Systems	Perceptions of system reliability and analyst confidence levels	Likert-scale items Example: I trust the AI system's output when explanations are clear and consistent.

XIII. CONCLUSION

This study examined how trust, decision fatigue, and explainability interact within AI-driven anti-money laundering (AML) transaction monitoring systems, addressing a critical gap in the literature that has traditionally examined these constructs in isolation. Through a structured synthesis of academic research, regulatory guidance, and industry practice, the study highlighted how high false positive rates, sustained alert pressure, and opaque system behavior undermine both analyst performance and compliance defensibility.

To address these challenges, the study introduced the Dynamic Trust Modulation framework, which conceptualizes trust as a feedback-driven and context-dependent construct shaped by system performance, analyst workload, explainability mechanisms, and regulatory constraints. By framing trust calibration, decision fatigue, and explainability as interdependent elements of AML workflows, the framework provides a socio-technical lens for understanding human–AI collaboration in high-stakes compliance environments.

The contributions of this work are both theoretical and design-oriented, with implications for practice. The framework extends human-AI collaboration research into the AML domain and offers design-relevant insights for developing AI systems that support accountability, decision defensibility, and sustainable human oversight. While this study is conceptual in

nature, it establishes a foundation for future empirical validation and mixed-methods research aimed at operationalizing trust dynamics and feedback mechanisms in real-world AML settings.

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REFERENCES

[1] AUSTRAC, AUSTRAC Money Laundering in Australia National Risk Assessment, 2024. [Online]. Available: https://www.pmc.gov.au/government/its-honour

[2] A. Bello and K. Olufemi, "Artificial intelligence in fraud prevention: Exploring techniques, applications, challenges and opportunities," Computer Science & IT Research Journal, vol. 5, no. 6, pp. 1505–1520, Jun. 2024, doi: 10.51594/csitrj.v5i6.1252.

[3] D Goldbarsht and E. Sheedy, "Money laundering and the risk in the risk-based approach: The Australian context," 2024. [Online]. Available: https://www.cfatf-gafic.org

[4] D Goldbarsht, "Leveraging AI to mitigate money laundering risks in the banking system," in Money, Power, and AI. Cambridge University Press, 2023, pp. 51–69, doi: 10.1017/9781009334297.006.

[5] L Leontjeva and Z. Oubari, "Maximizing anti-money laundering compliance through AI: Assessing the obligations and responsibilities of financial institutions under the proposed EU AI Act," May 2024. [Online]. Available: https://www.diva-portal.org

[6] A J. Ajayi et al., "The impact of artificial intelligence on cyber security in digital currency transactions," Archives of Current Research International, vol. 25, no. 2, pp. 329–351, Feb. 2025, doi: 10.9734/acri/2025/v25i21090.

[7] A Alqudah et al., "Mitigating financial crimes: How anti-money laundering mechanisms shape bank outcomes," 2025. [Online]. Available: https://papers.ssrn.com

[8] N. Sawangnetr, "The implementation and effects of international AML/CTF standards in Thailand: A case study of banking institutions," May 2025. [Online]. Available: https://sussex.figshare.com

[9] M. E. Lokanan, "Unveiling sentiments of the Cullen Commission: Exploring AML compliance and regulation through deep learning," Journal of Economic Criminology, vol. 7, p. 100138, Mar. 2025, doi: 10.1016/j.jeconc.2025.100138.

[10] J. S. Dote-Pardo and P. Severino-González, "Money laundering in emerging countries: Patterns, trends, and knowledge gaps," Journal of Money Laundering Control, 2025, doi: 10.1108/JMLC-01-2025-0002.

[11] S. K. Vududala, "Enhancing anti-money laundering compliance using NICE Actimize: A data-driven approach," International Journal of Computer Techniques, vol. 11, no. 2, 2024.

[12] H. Shah and H. Sadiya, "Predictive analytics and AI integration: Revolutionizing AML and fraud detection," 2024, doi: 10.13140/RG.2.2.10702.27205.

[13] V Boateng, "Harnessing artificial intelligence for combating money laundering and fraud," Finance & Accounting Research Journal, vol. 7, no. 1, pp. 37–49, Feb. 2025, doi: 10.51594/farj.v7i1.1814.

[14] M Celestin and J. Asamoah, A Study on Fintech–RegTech Integration for Combating Money Laundering and Terrorist Financing, 2020.

[15] P Weber, K. V. Carl, and O. Hinz, "Applications of explainable artificial intelligence in finance: A systematic review," Management Review Quarterly, vol. 74, no. 2, pp. 867–907, Jun. 2024, doi: 10.1007/s11301-023-00320-0.

[16] P Lakkarasu, "Advancing explainable AI for AI-driven security and compliance in financial transactions," 2024.

[17] A Bertrand, "Misplaced trust in AI: The explanation paradox and human-centric paths," Ph.D. dissertation, 2024.

[18] H Wang, "Trust in human–AI interaction: How AI's identity affects judicial decisions," master's thesis, 2024.

[19] C Agorbia-Atta and I. Atalor, "Enhancing AML capabilities: Strategic use of AI and cloud technologies," World Journal of Advanced Research and Reviews, vol. 23, no. 2, pp. 2035–2047, Aug. 2024, doi: 10.30574/wjarr.2024.23.2.2508.

[20] B A. Alahmadi et al., "99% false positives: A qualitative study of SOC analysts' perspectives," USENIX Security Symposium, 2022.

[21] A N. Eddin et al., "Anti-money laundering alert optimization using machine learning with graphs," arXiv:2112.07508, 2021.

[22] T C. King et al., "Artificial intelligence crime: An interdisciplinary analysis," Science and Engineering Ethics, vol. 26, no. 1, pp. 89–120, 2020, doi: 10.1007/s11948-018-00081-0.

[23] D A. Zetzsche, "Artificial intelligence in finance: Putting the human in the loop," 2020.

[24] K. Boudt et al., "A news monitoring system for AML supervision," Risk Sciences, p. 100018, Apr. 2025, doi: 10.1016/j.risk.2025.100018.

[25] A Ghimire, "AI-powered anomaly detection for AML compliance in U.S. banking," Global Trends in Science and Technology, vol. 1, no. 1, pp. 95–120, Feb. 2025.

[26] W Maxwell, A. Bertrand, and X. Vamparys, "Are AI-based AML systems compatible with European fundamental rights?" Vienna, 2020.

[27] M Alkhalili et al., "Machine learning for watch-list filtering in AML," IEEE Access, vol. 9, pp. 18481–18496, 2021, doi: 10.1109/ACCESS.2021.3052313.

[28] V Mounika et al., "Detecting AML using time–frequency and transaction abstraction," 2024.

[29] S Aidoo, "Evaluating the effectiveness of AML regulations: A critical review," May 2025.

[30] U G. Ketenci et al., "Time–frequency-based suspicious activity detection for AML," IEEE Access, vol. 9, pp. 59957–59967, 2021, doi: 10.1109/ACCESS.2021.3072114.

[31] Deloitte, Advanced Analytics and Innovation in Financial Crime Compliance, 2020.

[32] B Oztas et al., "Transaction monitoring in AML: Industry perspectives," Future Generation Computer Systems, vol. 159, pp. 161–171, Oct. 2024, doi: 10.1016/j.future.2024.05.027.

[33] K Powelson and A. Capstone, "The impact of artificial intelligence on AML programs," 2022.

[34] Momenta Group, "What will AML Tranche 2 mean for your business?" 2022.

[35] Australian Government, National Framework for the Assurance of Artificial Intelligence in Government, 2024.

[36] B Scott and M. Webster, "AML/CTF Tranche 2 reform in Australia," International Journal of Contemporary Intelligence Issues, 2024.

A Systematic Review of Functional Requirements, Modelling Practices, and Validation Strategies in IoT Application Development

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***Abstract*—The rapid development of the Internet of Things (IoT) requires systematic development methods that address complex functional, architectural, and validation concerns. This review synthesized research published between 2016 and 2023 to characterize common functional requirements (FRs), current modelling techniques, and validation practices. From an initial corpus of 1,598 articles, 425 publications were selected for in-depth analysis. The results demonstrated a consistent emphasis on data handling, inter-device communication, analytics, and system management. Nevertheless, critical gaps persisted in end-to-end security and context-aware computing. Sequence, class, and use case diagrams dominated modelling practices, which indicated attention to system behavior and interactions. Conversely, state machine and deployment diagrams were underutilized despite their potential to better capture runtime states and architectural configurations. The validation approaches in IoT development were primarily empirical, with experiments and case studies predominating. Expert reviews are valuable for early-stage assessment, but were rarely applied, which indicated missed opportunities for early improvement of design quality in the lifecycle. Overall, the results reflected the maturity and limitations of current practices in IoT engineering. These limitations can be addressed by diversifying modelling techniques, enhancing security integration, and using hybrid validation frameworks. This review presented a foundational reference to guide the systematic development of scalable, secure, and context-aware IoT systems, and contributed to the evolving body of IoT software engineering knowledge.**

***Keywords*—Functional requirements; Unified Modeling Language; validation; Internet of Things; systematic review**

I. Introduction

The Internet of Things (IoT) represents a significant technological advancement that enables the interconnection of physical devices equipped with sensors and communication interfaces capable of data exchange across a network. This transformation of physical systems into smart environments has led to the emergence of complex systems that require rigorous requirements engineering (RE) practices to ensure successful IoT application development and deployment [1], [2]. The diverse hardware, software, and communication protocols requires a comprehensive understanding of functional requirements (FRs), which define the essential behaviors, capabilities, and services an IoT system must deliver to reliably meet stakeholder expectations across varying operational contexts [3], [4].

The literature determining the essential FRs in IoT has classified them into thematic groups crucial to the success of the system. The main themes include service discovery and orchestration, device management and security, communication and data management, and context-aware features [3], [5]. The theme-based organization aids developers and stakeholders in addressing the multifaceted integration challenges presented by heterogeneous elements of the system systematically [6], [7]. Several applications in IoT do not systematically define these FRs, which results in errors that could negatively affect user satisfaction and system performance [4], [8].

Modelling is essential in the RE process. Unified Modelling Language (UML) is effective for demonstrating IoT system functionalities and presents a visual representation that enables developer and stakeholder communication [9]. The UML adaptations through the IoTReq extension improve its pertinence in addressing the specific challenges that characterize IoT environments, such as distributed control, heterogeneity, and context-awareness [8], [10]. These modelling approaches are essential to ensure that the FRs defined are captured and understood adequately before a system is implemented.

The FR validation is critical in the lifecycle of IoT system development. The designed systems are confirmed to perform as planned in their chosen contexts through experimental prototypes, simulations, and expert evaluations [11], [12]. Each approach is subject to compromises concerning generalizability and empirical rigor and thereby requires a carefully personalized approach to address specific IoT application situations [13], [14]. The process of validation confirms functional adherence and identifies possible areas for enhancement, thus encouraging the continuous improvement of IoT applications.

This systematic review charts the present landscape of FRs in IoT development and reveals underexplored areas. This review presents actionable observations to create stronger and

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more adaptable IoT systems that can meet the evolving requirements of varied application areas. Sustained focus on the definition, modelling, and validation of FR will be essential in addressing IoT complexities and fully realizing its potential.

II. METHODS

A. Research Questions

This study was organized in three research questions (RQs) to guide the investigation. The RQs provided a structured framework to examine which functional requirements are prioritized in existing research, and how they are modelled and validated within the IoT context. Table I summarizes the RQs and their underlying motivations and highlights their importance to the overall study objectives.

TABLE I. THE RESEARCH QUESTIONS AND MOTIVATIONS

Research Question	*Motivation*
RQ1: What are the common FRs in IoT application development?	This question aims to analyze the distribution of studies regarding the FRs addressed in IoT development. The study aimed to determine to which these identified FRs have been practically applied and integrated into IoT development, which highlights their practical application and relevance within the field.
RQ2: Which UML models are most used for modelling FRs in the development of IoT applications?	The answer to RQ2 would facilitate the identification of the UML diagrams adopted to support the FRs of IoT applications. The answer would also aid the identification of the approaches that have gained IoT development practitioners' attention and assessment of its effectiveness in representing the FRs of IoT projects.
RQ3: What are the strategies applied in IoT FR validation?	To identify the validation methodologies used for verifying the FRs in IoT projects.

B. Literature Search Strategy

The literature was searched using the Web of Science, Scopus, and IEEE Xplore databases. The search targeted titles, keywords, and abstracts, and applied a consistent set of search terms across all databases: ("Internet of Things" OR "IoT") AND ("functional requirement" OR "requirements model" OR "UML" OR "Unified Modelling Language") AND ("validation" OR "verification" OR "evaluation"). The search was limited to articles published between January 2016 and December 2023.

C. Inclusion and Exclusion Criteria

Rigor and relevance in the study selection were ensured by applying specific inclusion and exclusion criteria.

1) Inclusion criteria: Studies were considered eligible for inclusion if they satisfied the following conditions:

- Publication date: Published between January 2016 and December 2023;
- Database: Indexed in Web of Science, Scopus, or IEEE Xplore;
- Topic relevance: Addressed the IoT in the context of FR or UML, and discussed aspects of validation or verification related to these requirements or models;
- Search scope: Appeared in titles, abstracts, or keywords containing the defined search terms;
- Publication type: Peer-reviewed journal articles, conference papers, or book chapters;
- Language: Published in English to maintain interpretation and analysis consistency.

2) Exclusion criteria: Studies were excluded from this review if they met any of the following conditions:

- Publication date outside range: Published before January 2016 or after December 2023;
- Non-relevant focus: Addressed IoT broadly but did not cover FRs, UML, validation, or verification;
- Publication type: Editorials, opinion pieces, prefaces, tutorials, theses, patents, standards documents, or grey literature and any non-peer-reviewed publications;
- Language: Not published in English;
- Accessibility: Full text was unavailable.

D. Study Selection

The studies were selected in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [15] (see Fig. 1).

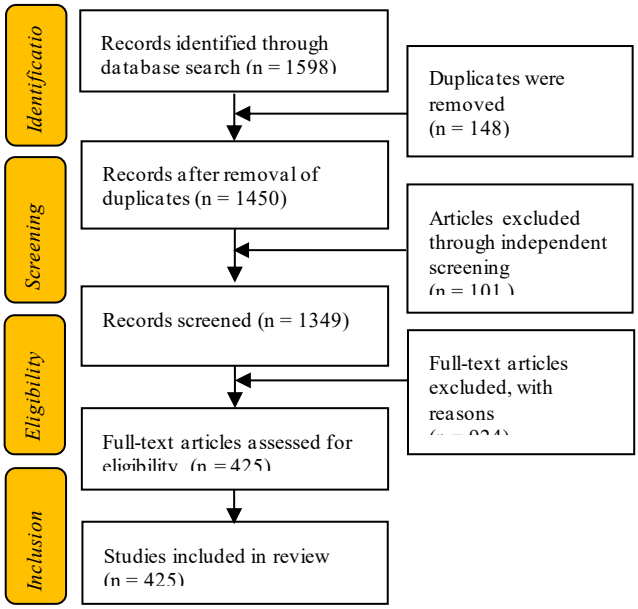


Fig. 1. Flowchart of research process adapted from PRISMA diagram (adapted from [15]).

The process included identification (search results were imported into a reference management tool and duplicates were removed), screening (titles, abstracts, and keywords were reviewed for relevance), eligibility (full-text articles were assessed based on predefined inclusion and exclusion criteria), and inclusion (studies meeting all criteria were selected for final analysis and synthesis). Overall, the database search identified a total of 1,598 publications. After screening, 425 publications were selected and included in the systematic

literature review. Supplementary table (Table II) presents the complete list of included studies.

III. Results and Discussion

A. RQ1: What are the Common FRs in IoT Application Development?

Identifying and analyzing common FRs is crucial for the success and efficiency of IoT ecosystems in the IoT application development domain. This study integrated insights from extensive literature and assessed the importance of FRs prevalent in IoT applications. A consensus emerged around 24 FRs, which can be viewed through their occurrence frequencies within the existing body of knowledge (summarized in Fig. 2).

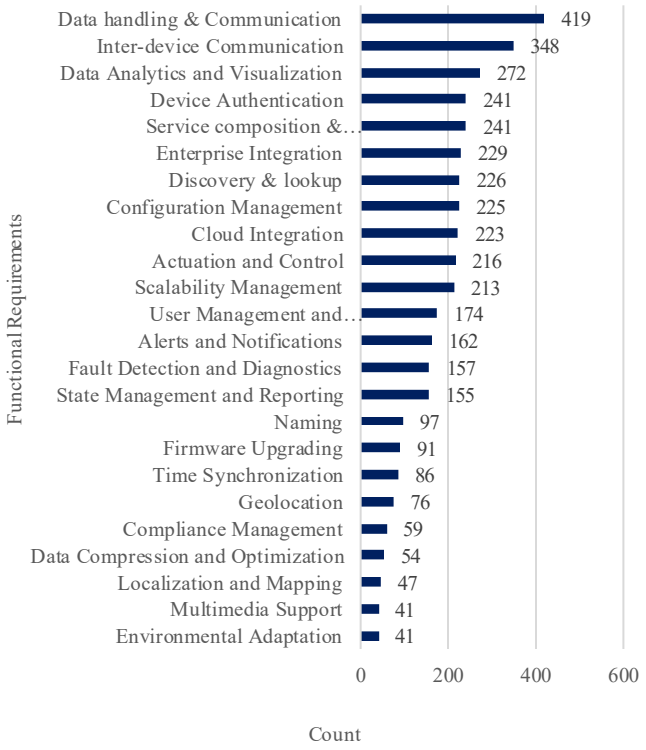


Fig. 2. The FRs of IoT application development.

The foundational FRs of data handling and communication (n = 419) and inter-device communication (n = 348) highlighted the necessity of robust and reliable connectivity for effective IoT operations. These FRs are essential for enabling seamless data flow and interoperability between IoT devices, cloud platforms, and edge nodes. A comprehensive understanding of these communication frameworks was underscored by the requirement for effective data sharing protocols, which was supported by research that emphasized the important role of integrated communication systems and data management in IoT architectures [16]–[18]. Evidently, the prevailing emphasis on communication reflected the fundamental characteristics of IoT systems, whose functionality relies on interconnectedness.

Interoperability and integration requirements, such as service composition and programmability (n = 241), enterprise integration (n = 229), and cloud integration (n = 223), emphasized the need for IoT applications to adapt and operate within heterogeneous environments. This result supported the shift towards more service-oriented architectures within IoT ecosystems. Effective service discovery and integration mechanisms are vital for dynamic integration into existing enterprise systems, and much research supported the necessity of such adaptive frameworks to enhance IoT solution scalability and flexibility [16], [17]. A key priority in the literature was device capacity to effectively communicate and cooperate while autonomously discovering and integrating services.

Data analytics and visualization (n = 272) emerged as a critical requirement that facilitates the conversion of raw data into actionable insights. The prominence of this FR in the literature underscored the integration of advanced analytical capabilities with IoT systems, where artificial intelligence can significantly enhance operational efficiency and decision-making processes [19]–[21]. This result highlighted the trend towards leveraging big data analytics within IoT applications to identify trends and patterns that drive system intelligence.

Actuation and control (n = 216) bridged the gap between data analysis and physical responses in IoT systems. This FR is integral in automated environments, where real-time data processing translates directly into physical actions, thus facilitating interaction with the environment [22], [23]. The importance of such operational management capabilities is correlated with their deployment in important sectors, such as healthcare, smart cities, and industrial operations, where timely responses are dominant.

The emphasis on fleet-level operational management revealed additional significant FRs that included configuration management (n = 225) and scalability management (n = 213). These FRs emphasize the systemic requirements for managing devices over their lifecycle effectively. As IoT technologies mature, device network management collectively becomes essential to ensure reliability and efficiency against potential systemic failures. Given that IoT devices are increasing exponentially, methods for ensuring system observability and maintainability are becoming increasingly important [24], [25].

Regarding security, device authentication (n = 241) and user management and authentication (n = 174) were comparatively well represented, but the shortcomings in other security mechanisms, such as encryption and intrusion detection, highlighted significant gaps in comprehensive security approaches across the IoT landscape [26]–[28]. This imbalance indicated a persistent need for research to evolve toward developing robust, multi-layered security frameworks for IoT environments.

Lastly, several FRs related to context-awareness and optimization, such as geolocation (n = 76) and environmental adaptation (n = 41), were under-represented, which suggested that substantial potential for growth in these domains remains as the IoT ecosystem evolves. Addressing these unfilled niches can enhance the overall functionality of IoT solutions by

tailoring them more closely to the intricacies of application-specific requirements.

The FR analysis revealed a focus on IoT system connectivity, interoperability, analytics, and management. Furthermore, the analyses identified important areas that should be explored further, specifically in security and domain-specific applications. Addressing these shortcomings, particularly in developing comprehensive security strategies and enhancing context-aware capabilities, would be instrumental in advancing IoT application development and ensuring its viability in an increasingly interconnected world.

B. RQ2: Which UML Models are most used for Modelling FRs in the Development of IoT Applications?

In the IoT application development context, the analysis indicated a prevalent utilization of specific UML diagrams for modelling functional requirements. The data (see Fig. 3) demonstrated that sequence, class, and use case diagrams were among the most commonly used diagrams, which supported their importance in IoT systems development [29]–[32].

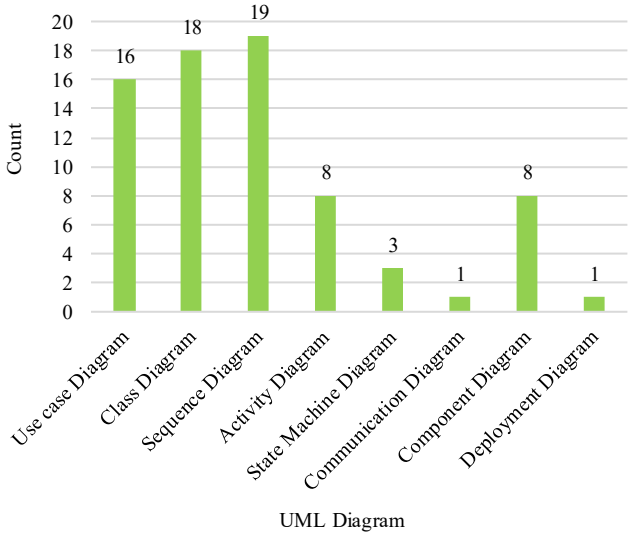


Fig. 3. Frequency of UML models used for modelling FRs in IoT application development.

Sequence diagrams (n = 19) were one of the frequently used modelling tools, and are essential for mapping out time-dependent, message-driven interactions typical within IoT environments. The strength of this diagram is its ability to effectively represent asynchronous communication flows and event-driven IoT systems, which enables a clear depiction of the interaction chain that involves sensors, data processing units, and actuators [29]–[31]. For example, sequence diagrams are visual narrations of the information flow from sensor data capture to cloud processing, and clarify how IoT system components come together in real-time settings [32], [33].

Use case diagrams (n = 16) are effective for capturing functionalities that are user-centric. Such diagrams bridge technical teams and stakeholders, and facilitate a primary comprehension of user interactions and system requirements, especially within smart homes and healthcare domains [29]–[31]. Through this high-level abstraction, stakeholders can articulate and understand the functionalities and purpose of the system more clearly, which ensures that the needs of the user are prioritized in the process of development [29], [30], [32].

The FRs are complemented by class diagrams (n = 18), which articulate the static structure of IoT systems. Class diagrams are influential in defining core objects, such as sensors and actuators, and their characteristics and relations, and act as the foundational design for system implementation in model-driven engineering styles. Integrating class diagrams with use case and sequence diagrams encourages an inclusive perspective of the static framework and dynamic interactions of IoT applications [32], [34], [35].

While the discussion was dominated by the aforementioned diagrams, other UML diagrams [activity diagrams (n = 8) and component diagrams (n = 8)] are also valuable. While activity diagrams were not as widely adopted, they excel in modelling complex workflows, which potentially aids in scenarios involving multi-device interactions or context-aware processes [36][37]. Similarly, component diagrams enhance architectural clarity by defining system decomposition, which is crucial for developing scalable and maintainable IoT solutions [38], [39].

Conversely, the application of state machine diagrams (n = 3), communication diagrams (n = 1), and deployment diagrams (n = 1) was notably limited. This limited application raises concerns about their underutilization despite their potential benefits in representing system states, modularity, and deployment environments. State machine diagrams may be particularly relevant for capturing lifecycle behaviors and reactivity patterns, which are important elements in adaptive IoT applications [40], [41]. The absence of these diagrams indicates a gap in the modelling methodologies that could be corrected by promoting a more diverse usage of UML tools academically and practically [42], [43].

While sequence, use case, and class diagrams are fundamental for articulating functional requirements in IoT applications, a broader adoption of complementary diagrams (activity, component, and state machine diagrams) is required. Researchers and practitioners who bridge this modelling gap can enhance their frameworks and methodologies, ultimately leading to more robust and effective IoT systems.

C. RQ3: What are the Strategies Applied in IoT FR Validation?

The FR validation in IoT application development uses several predominant strategies, which highlight a robust methodological framework in the literature. The analysis (summarized in Fig. 4) revealed that this space was dominated by empirical evaluation techniques, primarily through experiments and case studies, where experiments comprised a significant proportion of the documented methods. This predominance underscored a trend toward validating the performance and behavior metrics of IoT systems in controlled and real-world scenarios, which reflected the necessity of contextually rich data in developing effective IoT applications.

The reliance on experimental methods indicated the emphasis of the IoT community on reproducibility and quantitative performance metrics. Experiments in controlled

environments can precisely measure various system parameters, which include latency, energy consumption, scalability, and interoperability [44], [45]. Such parameters are important given the inherent complexity and dynamic interactions of IoT devices, which operate under diverse and frequently unpredictable conditions [46]. Notably, various empirical analyses demonstrated that prototypes and simulations were frequently used to refine system functionality before deployment. Empirical techniques facilitate continuous integration and iterative development, which align with agile methodologies in software engineering [47].

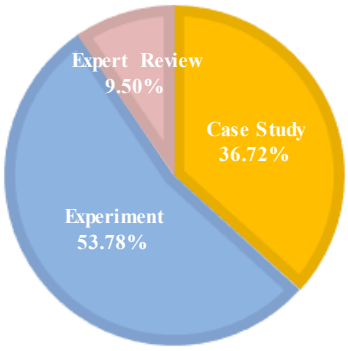


Fig. 4. Strategies used for functional requirement validation in IoT application development.

Case studies provide an enriching contextual lens that enables the validation of IoT FRs. This method allows researchers to embed evaluation efforts within realistic and application-specific environments, such as healthcare and industrial IoT systems [48]. These studies aid the elucidation of domain-specific constraints and user interactions that may be neglected in controlled experiments, thus enhancing the understanding of operational challenges and real-world implications of FRs. Incorporating case studies reflects researchers' awareness of the contextual factors that can influence the success of IoT systems beyond technical validation [49].

Expert reviews comprised a modest proportion of the validation strategies, but have important value, especially in the early stages of requirement elicitation and specification. These reviews aid the identification of ambiguities or inconsistencies within the requirements and contribute to a more thorough validation [50]. Nevertheless, their lower adoption may stem from perceptions of subjectivity and the challenges in assembling a reliable expert panel [51]. Nonetheless, incorporating expert evaluations with empirical approaches can improve validation framework robustness by merging quantitative rigor with qualitative insights [52].

This analysis of present approaches in IoT FR validation revealed that empirical methods were dominant, specifically, experimental approaches that highlight measurable system behaviors, which were accompanied by context-relevant perspectives from case studies and the qualitative contribution from expert appraisals. The evolution of this field demonstrates the clear necessity of frameworks of hybrid validation that simultaneously use the strengths of expert insights and empirical evaluations to develop standardized benchmarks customized to the diverse IoT landscape.

IV. Conclusion and Future Work

This study emphasized the basic trends in IoT application development and focused on FRs, modelling methods, and validation approaches. The analysis suggested that the main focus has been on important capabilities, such as analytics, inter-device communication, data handling, and system-level management. Nonetheless, crucial areas, such as context-awareness and end-to-end security, were notably under-represented, and are important for deployments in the real world. These aforementioned gaps suggest that research priorities are disconnected from operational requirements in the landscape of IoT.

Regarding modelling practices, a clear prevalence of traditional diagram types (sequence and class diagrams) was established, as these diagrams effectively capture functional flows and system structures. Nevertheless, the infrequent use of state machines, deployment, and communication diagrams indicated limitations in the existing modelling frameworks. These diagrams are essential for capturing the full spectrum of functional requirements of IoT applications. Therefore, enhancing modelling practices may be important for addressing architecture-specific challenges and optimizing system resources.

The analysis also revealed that validation strategies within IoT development practices strongly relied on experimental methods and case studies. Although these methods provide valuable empirical insights, incorporating expert reviews, particularly during the early design stages, can strengthen their effectiveness. A combined approach that integrates empirical testing with qualitative assessments can support more holistic evaluations of FRs and system performance.

Future research directions should emphasize the need to expand the focus on FRs, especially in multi-layered security protocols and adaptive computing environments. These elements are vital for supporting advanced applications, such as autonomous systems. Integrating context-aware design practices, coupled with the adoption of modern modelling techniques that can address functional and contextual dynamics, is another promising research direction. Finally, advancing IoT development would rely on the development of adaptive meta-modelling frameworks that can intelligently suggest suitable modelling practices based on system characteristics.

In summary, IoT application development has progressed substantially, but significant operational gaps across FRs, modelling practices, and validation methods remain. Future work should aim to broaden functional scopes, strengthen UML modelling practices, and pioneer advanced validation strategies that promote a more integrated approach to IoT system security and optimization. Addressing these areas would enable researchers and practitioners to better align their efforts with the evolving landscape of IoT technologies and application demands.

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REFERENCES

[1] I. Berrouyne, "CyprIoT project: an open source toolset to model and generate a network of things," Proc. ACM Conference, pp. 1–5, 2020, doi: 10.1145/3417990.3422005.

[2] M. Rana and R. Bo, "IoT-based cyber-physical communication architecture: Challenges and research directions," IET Cyber-Physical Systems: Theory & Applications, vol. 5, no. 1, pp. 25–30, 2019, doi: 10.1049/iet-cps.2019.0028.

[3] C. Perera, M. Barhamgi, A. Bandara, M. Ajmal, B. Price, and B. Nuseibeh, "Designing privacy-aware Internet of Things applications," Information Sciences, vol. 512, pp. 238–257, 2020, doi: 10.1016/j.ins.2019.09.061.

[4] A. Nguyen-Duc, K. Khan, S. Bajwa, and T. Lønnestad, "Minimum viable products for Internet of Things applications: Common pitfalls and practices," Future Internet, vol. 11, no. 2, p. 50, 2019, doi: 10.3390/fi11020050.

[5] R. Hassan, F. Qamar, M. Hasan, A. Aman, and A. Ahmed, "Internet of Things and its applications: A comprehensive survey," Symmetry, vol. 12, no. 10, p. 1674, 2020, doi: 10.3390/sym12101674.

[6] F. Fagroud, L. Ajallouda, E. Benlahmar, A. Zellou, H. Toumi, S. Filali, and Y. Baddi, "Internet of Things search engines: Toward a general architecture," Indonesian Journal of Electrical Engineering and Computer Science, vol. 28, no. 2, pp. 1117–1127, 2022, doi: 10.11591/ijeecs.v28.i2.pp1117-1127.

[7] F. Liang, C. Qian, W. Hatcher, and W. Yu, "Search engine for the Internet of Things: Lessons from web search, vision, and opportunities," IEEE Access, vol. 7, pp. 104673–104691, 2019, doi: 10.1109/ACCESS.2019.2931659.

[8] A. Lekidis and P. Katsaros, "Model-based design of energy-efficient applications for IoT systems," Electronic Proceedings in Theoretical Computer Science, vol. 272, pp. 24–38, 2018, doi: 10.4204/eptcs.272.3.

[9] M. Abadeh, "A semantic axiomatic design for integrity in IoT," Transactions on Emerging Telecommunications Technologies, vol. 35, no. 9, 2024, doi: 10.1002/ett.5032.

[10] K. Küçük, C. Bayılmış, and D. Msongaleli, "Designing real-time IoT system course: Prototyping with cloud platforms, laboratory experiments and term project," International Journal of Electrical Engineering Education, vol. 58, no. 3, pp. 743–772, 2019, doi: 10.1177/0020720919862496.

[11] Z. Li, "Just enough, just in time, just for 'me': Fundamental principles for engineering IoT-native software systems," arXiv preprint arXiv:2201.09931, 2022, doi: 10.48550/arxiv.2201.09931.

[12] M. Hernández, B. Alturki, and S. Reiff-Marganiec, "FABIOT: A flexible agent-based simulation model for IoT environments," Proc. IEEE Cybermatics 2018, pp. 66–73, 2018, doi: 10.1109/Cybermatics_2018.2018.00045.

[13] S. Mondal, P. Jayaraman, P. Haghighi, A. Hassani, and D. Georgakopoulos, "Situation-aware IoT data generation towards performance evaluation of IoT middleware platforms," Sensors, vol. 23, no. 1, p. 7, 2022, doi: 10.3390/s23010007.

[14] H. Korala, D. Georgakopoulos, P. Jayaraman, and A. Yavari, "A time-sensitive IoT data analysis framework," Proc. 54th Hawaii International Conference on System Sciences (HICSS), 2021, doi: 10.24251/HICSS.2021.865.

[15] M. J. Page, J. E. McKenzie, P. M. Bossuyt, I. Boutron, T. C. Hoffmann, C. D. Mulrow, and D. Moher, "The PRISMA 2020 statement: An updated guideline for reporting systematic reviews," BMJ, vol. 372, art. no. n71, 2021, doi: 10.1136/bmj.n71.

[16] A. Khurshid, A. Khan, F. Khan, M. Ali, J. Shuja, and A. Khan, "Secure-CamFlow: A device-oriented security model to assist information flow control systems in cloud environments for IoTs," Concurrency and Computation: Practice and Experience, vol. 31, no. 8, 2018, doi: 10.1002/cpe.4729.

[17] Z. Rehman, N. Tariq, S. Moqurrab, J. Yoo, and G. Srivastava, "Machine learning and Internet of Things applications in enterprise architectures: Solutions, challenges, and open issues," Expert Systems, vol. 41, no. 1, 2023, doi: 10.1111/exsy.13467.

[18] D. Sarabia-Jácome, S. Giménez-Antón, A. Liatifis, E. Grasa, M. Catalán, and D. Pliatsios, "Progressive adoption of RINA in IoT networks: Enhancing scalability and network management via SDN integration," Applied Sciences, vol. 14, no. 6, p. 2300, 2024, doi: 10.3390/app14062300.

[19] J. An, W. Li, F. Gall, E. Kovac, J. Kim, T. Taleb, and J. Song, "EIF: Toward an elastic IoT fog framework for AI services," IEEE Communications Magazine, vol. 57, no. 5, pp. 28–33, 2019, doi: 10.1109/MCOM.2019.1800215.

[20] C. Mouradian, N. Jahromi, and R. Glitho, "NFV and SDN-based distributed IoT gateway for large-scale disaster management," IEEE Internet of Things Journal, vol. 5, no. 5, pp. 4119–4131, 2018, doi: 10.1109/JIOT.2018.2867255.

[21] S. Nasiri, F. Sadoughi, M. Tadayon, and A. Dehnad, "Security requirements of Internet of Things-based healthcare systems: A survey study," Acta Informatica Medica, vol. 27, no. 4, pp. 253–258, 2019, doi: 10.5455/aim.2019.27.253-258.

[22] S. Abedin, M. Alam, S. Kazmi, N. Tran, D. Niyato, and C. Hong, "Resource allocation for ultra-reliable and enhanced mobile broadband IoT applications in fog networks," IEEE Transactions on Communications, vol. 67, no. 1, pp. 489–502, 2019, doi: 10.1109/TCOMM.2018.2870888.

[23] T. Park and W. Saad, "Distributed learning for low-latency machine-type communication in a massive Internet of Things," IEEE Internet of Things Journal, vol. 6, no. 3, pp. 5562–5576, 2019, doi: 10.1109/JIOT.2019.2903832.

[24] T. Heinis, J. Hilario, and M. Meboldt, "Empirical study on innovation motivators and inhibitors of Internet of Things applications for industrial manufacturing enterprises," Journal of Innovation and Entrepreneurship, vol. 7, no. 1, 2018, doi: 10.1186/s13731-018-0090-7.

[25] C. Madalina and A. Petrescu, "IoT modeling for digital enterprises and decision analysis," International Journal of Innovation in the Digital Economy, vol. 15, no. 1, pp. 1–8, 2024, doi: 10.4018/IJIDE.349724.

[26] M. Qutqut, A. Al-Sakran, F. Almasalha, and H. Hassanein, "Comprehensive survey of the IoT open-source OSS," IET Wireless Sensor Systems, vol. 8, no. 6, pp. 323–339, 2018, doi: 10.1049/iet-wss.2018.5033.

[27] H. Son, B. S. Kim, J. Cho, and B. Lee, "ASM: Augmented security module for commercial IoT devices," Tehnički Vjesnik – Technical Gazette, vol. 31, no. 1, 2024, doi: 10.17559/TV-20230608000709.

[28] M. Samaila, J. Sequeiros, T. Simões, M. Freire, and P. Inácio, "IoT-HARPSECA: A framework and roadmap for secure design and development of devices and applications in the IoT space," IEEE Access, vol. 8, pp. 16462–16494, 2020, doi: 10.1109/ACCESS.2020.2965925.

[29] S. Madakam, R. Ramaswamy, and S. Tripathi, "Internet of Things (IoT): A literature review," Journal of Computer and Communications, vol. 3, no. 5, pp. 164–173, 2015, doi: 10.4236/jcc.2015.35021.

[30] R. Lomotey, K. Sofranko, and R. Orji, "Enhancing privacy in wearable IoT through a provenance architecture," Multimodal Technologies and Interaction, vol. 2, no. 2, p. 18, 2018, doi: 10.3390/mti2020018.

[31] M. Hoque and C. Davidson, "Design and implementation of an IoT-based smart home security system," International Journal of Networked and Distributed Computing, vol. 7, no. 2, p. 85, 2019, doi: 10.2991/ijndc.k.190326.004.

[32] T. Nguyễn, D. Min, and E. Choi, "A hierarchical modeling and analysis framework for availability and security quantification of IoT infrastructures," Electronics, vol. 9, no. 1, p. 155, 2020, doi: 10.3390/electronics9010155.

[33] L. Calderoni, A. Magnani, and D. Maio, "IoT Manager: An open-source IoT framework for smart cities," Journal of Systems Architecture, vol. 98, pp. 413–423, 2019, doi: 10.1016/j.sysarc.2019.04.003.

[34] H. Li, K. Ota, and M. Dong, "Learning IoT in edge: Deep learning for the Internet of Things with edge computing," IEEE Network, vol. 32, no. 1, pp. 96–101, 2018, doi: 10.1109/MNET.2018.1700202.

[35] M. Kose and M. Ozkaya, "Towards extending UML's activity diagram for the architectural modeling, analysis, and implementation," Proc. Federated Conference on Computer Science and Information Systems (FedCSIS), vol. 21, pp. 639–648, 2020, doi: 10.15439/2020F199.

[36] Y. Ren, X. Zhang, and G. Lu, "The wireless solution to realize green IoT: Cellular networks with energy-efficient and energy-harvesting schemes," Energies, vol. 13, no. 22, p. 5875, 2020, doi: 10.3390/en13225875.

[37] Z. Shahbazi and Y. Byun, "Improving transactional data systems based on an edge computing–blockchain–machine learning integrated framework," Processes, vol. 9, no. 1, p. 92, 2021, doi: 10.3390/pr9010092.

[38] A. Iftekhar, X. Cui, Q. Tao, and C. Zheng, "Hyperledger Fabric access control system for Internet of Things layer in blockchain-based applications," Entropy, vol. 23, no. 8, p. 1054, 2021, doi: 10.3390/e23081054.

[39] C. Ejike, T. Mathaba, and F. Rand, "General-purpose architectural model for IoT-based in-situ monitoring systems," MATEC Web of Conferences, vol. 370, p. 05006, 2022, doi: 10.1051/matecconf/202237005006.

[40] M. Rehman, P. Jayaraman, S. Malik, A. Khan, and M. Gaber, "RedEdge: A novel architecture for big data processing in mobile edge computing environments," Journal of Sensor and Actuator Networks, vol. 6, no. 3, p. 17, 2017, doi: 10.3390/jsan6030017.

[41] E. Mishra, "Secured novel lightweight IoT end device architecture using confidentiality, integrity, authenticity, and availability-based tight security approach," Turkish Journal of Computer and Mathematics Education (TURCOMAT), vol. 12, no. 10, 2021, doi: 10.17762/turcomat.v12i10.5543.

[42] A. Ibrahim, A. Abbas, A. Hassan, W. Abdel-Rehim, A. Emam, and S. Mohsen, "Design and implementation of a pilot model for IoT smart home networks," IEEE Access, vol. 11, pp. 59701–59728, 2023, doi: 10.1109/ACCESS.2023.3282095.

[43] J. Rubio-Aparicio, F. Cerdán, J. Muro, and J. Ybarra-Moreno, "Design and implementation of a mixed IoT LPWAN network architecture," Sensors, vol. 19, no. 3, p. 675, 2019, doi: 10.3390/s19030675.

[44] S. M. Raza, J. Jeong, M. Kim, B. Kang, and H. Choo, "Empirical performance and energy consumption evaluation of container solutions on resource-constrained IoT gateways," Sensors, vol. 21, no. 4, p. 1378, 2021, doi: 10.3390/s21041378.

[45] S. Hauschild and H. Hellbrück, "Latency and energy consumption of convolutional neural network models from IoT edge perspective," in Proc. Global IoT Summit (GIoTS), Cham, Switzerland: Springer International Publishing, 2022, pp. 385–396, doi: 10.1007/978-3-031-10347-6_31.

[46] W. Wang, J. Cui, R. Ju, X. T. F. Li, B. Tu, G. Li, and L. Han, "A low-latency and high-scalability network with extreme QoS assurance," in Proc. IEEE INFOCOM Workshops (INFOCOM WKSHPS), Apr. 2018, pp. 1–2, doi: 10.1109/INFCOMW.2018.8406982.

[47] A. K. Ranjan and P. Kumar, "Advanced privacy-preserving framework for enhancing fog computing to secure IoT data stream," Journal of Electrical Systems, vol. 20, no. 2s, 2024, doi: 10.52783/jes.1150.

[48] Ulmeanu, M. E., Doicin, C. V., Dugăeșescu, I., Zaharia, C., & Pârvu, G. M. (2024, June). Functional Analysis: A Case Study of an IoT-Based Health Monitoring System. In Macromolecular Symposia (Vol. 413, No. 3, p. 2300207).

[49] Yadegari, F., & Asosheh, A. (2023). Introducing a service model in IoT-based smart hospital. Journal of Health and Biomedical Informatics, 9(4), 267-276.

[50] M. A. Rizkifar, Y. Priyadi, and M. J. Alibasa, "Validating requirement specification using text mining analysis," in Proc. 2023 3rd Int. Conf. on Electronic and Electrical Engineering and Intelligent System (ICE3IS), Aug. 2023, pp. 252–257, doi: 10.1109/ICE3IS58375.2023.10272986.

[51] B. Haq, M. Nadeem, I. Ali, K. Ali, M. Raza, and M. U. Rehmanr, "Use of expert systems in requirements engineering process: A systematic literature review," in Proc. UK/China Emerging Technologies Conf. (UCET), 2019, pp. 1–5, doi: 10.1109/UCET.2019.8881875.

[52] J. Silva and A. Araújo, "The use of OpenEHR archetypes in requirements elicitation: Best practices for engaging domain experts in healthcare software development," IEEE Access, vol. 12, 2024, doi: 10.1109/ACCESS.2024.3387652.

SUPPLEMENTARY TABLE 1

TABLE II. LIST OF INCLUDED STUDIES

Paper ID	Database	Year	References
SID001	IEEE	2016	[Canedo, J., & Skjellum, A. (2016, December). Using machine learning to secure IoT systems. In 2016 14th annual conference on privacy, security and trust (PST) (pp. 219-222). IEEE. https://doi.org/10.1109/ISMSIT50672.2020.9254304
SID002	IEEE	2017	Al-Rubaye, S., Kadhum, E., Ni, Q., & Anpalagan, A. (2017). Industrial internet of things driven by SDN platform for smart grid resiliency. IEEE Internet of Things Journal, 6(1), 267-277. https://doi.org/10.1109/JIOT.2017.2734903
SID003	IEEE	2018	Pathinarupothi, R. K., Durga, P., & Rangan, E. S. (2018). IoT-based smart edge for global health: Remote monitoring with severity detection and alerts transmission. IEEE Internet of things Journal, 6(2), 2449-2462. https://doi.org/10.1109/JIOT.2018.2870068
SID004	IEEE	2018	Banaie, F., Misic, J., Misic, V. B., Moghaddam, M. H. Y., & Seno, S. A. H. (2018). Performance analysis of multithreaded IoT gateway. IEEE Internet of Things Journal, 6(2), 3143-3155. https://doi.org/10.1109/JIOT.2018.2879467
SID005	ACM	2019	Bakshi, A., Chen, L., Srinivasan, K., Koksal, C. E., & Eryilmaz, A. (2019). EMIT: An efficient MAC paradigm for the Internet of Things. IEEE/ACM Transactions on Networking, 27(4), 1572-1583. https://doi.org/10.1109/TNET.2019.2928002
SID006	ACM	2019	Maamar, Z., Baker, T., Faci, N., Ugljanin, E., Khafajiy, M. A., & Burégio, V. (2019, April). Towards a seamless coordination of cloud and fog: illustration through the internet-of-things. In Proceedings of the 34th ACM/SIGAPP symposium on applied computing (pp. 2008-2015). https://doi.org/10.1145/3297280.3297477
SID007	IEEE	2019	Park, K., Park, Y., Das, A. K., Yu, S., Lee, J., & Park, Y. (2019). A dynamic privacy-preserving key management protocol for V2G in social Internet of Things. IEEE Access, 7, 76812–76832. https://doi.org/10.1109/ACCESS.2019.2921399
SID008	IEEE	2019	De Iasio, A., Furno, A., Goglia, L., & Zimeo, E. (2019, December). A microservices platform for monitoring and analysis of iot traffic data in smart cities. In 2019 IEEE International Conference on Big Data (Big Data) (pp. 5223-5232). IEEE. https://doi.org/10.1109/BigData47090.2019.9006025

SID009	IEEE	2019	Banerjee, S., Odelu, V., Das, A. K., Srinivas, J., Kumar, N., Chattopadhyay, S., & Choo, K. K. R. (2019). A provably secure and lightweight anonymous user authenticated session key exchange scheme for Internet of Things deployment. IEEE Internet of Things Journal, 6(5), 8739-8752. https://doi.org/10.1109/JIOT.2019.2923373
SID010	IEEE	2019	Gross, K., & Wang, G. C. (2019, December). AI decision support prognostics for IOT asset health monitoring, failure prediction, time to failure. In 2019 International Conference on Computational Science and Computational Intelligence (CSCI) (pp. 244-248). IEEE. https://doi.org/10.1109/CSCI49370.2019.00050
SID011	IEEE	2019	Fayyaz, H., Rehman, Z. U., & Abbas, S. (2019, November). An IoT enabled framework for smart buildings empowered with cloud & fog infrastructures. In 2019 International Conference on Innovative Computing (ICIC) (pp. 1-8). IEEE. https://doi.org/10.1109/ICIC48496.2019.8966715
SID012	IEEE	2019	De Paula, H. T., Gomes, J. B., Affonso, L. F., Rabelo, R. A., & Rodrigues, J. J. (2019, May). An IoT-based water monitoring system for smart buildings. In 2019 IEEE international conference on communications workshops (ICC workshops) (pp. 1-5). IEEE. https://doi.org/10.1109/ICCW.2019.8756905
SID013	IEEE	2019	Cao, H., & Wachowicz, M. (2019, October). Analytics everywhere for streaming iot data. In 2019 Sixth International Conference on Internet of Things: Systems, Management and Security (IOTSMS) (pp. 18-25). IEEE. https://doi.org/10.1109/IOTSMS48152.2019.8939171
SID014	IEEE	2019	de Puga, J. S., Salvador, C. E. P., & Pellicer, A. B. (2019, July). Architecture and use case for an iot deployment with sdn at the edge and dual physical and virtual gateway. In 2019 28th International Conference on Computer Communication and Networks (ICCCN) (pp. 1-6). IEEE. https://doi.org/10.1109/ICCCN.2019.8847095
SID015	IEEE	2019	Júnior, M. J., Maia, O. B., Oliveira, H., Souto, E., & Barreto, R. (2019, September). Assistive technology through internet of things and edge computing. In 2019 IEEE 9th International Conference on Consumer Electronics (ICCE-Berlin) (pp. 330-332). IEEE. https://doi.org/10.1109/ICCE-Berlin47944.2019.8966148
SID016	IEEE	2019	Latif, S., Rehman, A., & Zafar, N. A. (2019, December). Blockchain and IoT based formal model of smart waste management system using TLA+. In 2019 International conference on frontiers of information technology (FIT) (pp. 304-3045). IEEE. https://doi.org/10.1109/FIT47737.2019.00064
SID017	ACM	2019	Sigwart, M., Borkowski, M., Peise, M., Schulte, S., & Tai, S. (2019, October). Blockchain-based data provenance for the internet of things. In Proceedings of the 9th International Conference on the Internet of Things (pp. 1-8). https://doi.org/10.1145/3365871.3365886
SID018	IEEE	2019	Danilchenko, V., Theobald, M., & Cohen, D. (2019, December). Bootstrapping security configuration for IoT devices on networks with TLS inspection. In 2019 IEEE Globecom Workshops (GC Wkshps) (pp. 1-7). IEEE. https://doi.org/10.1109/GCWkshps45667.2019.9024325
SID019	IEEE	2019	Bonafini, F., Rinaldi, S., Depari, A., Flammini, A., Ferrari, P., & Sisinni, E. (2019, March). Cluster of iot sensors for sma rt cities: impact of the communication infrastructure over computational performance. In 2019 IEEE sensors applications symposium (SAS) (pp. 1-6). IEEE. https://doi.org/10.1109/SAS.2019.8706079
SID020	IEEE	2019	Spanos, G., Giannoutakis, K. M., Votis, K., & Tzovaras, D. (2019, September). Combining statistical and machine learning techniques in IoT anomaly detection for smart homes. In 2019 IEEE 24th International Workshop on Computer Aided Modeling and Design of Communication Links and Networks (CAMAD) (pp. 1-6). IEEE. https://doi.org/10.1109/CAMAD.2019.8858490
SID021	IEEE	2019	Kölsch, J., Ratzke, A., & Grimm, C. (2019, April). Co-Simulating the Internet of Things in a Smart Grid use case scenario. In 2019 7th Workshop on Modeling and Simulation of Cyber-Physical Energy Systems (MSCPES) (pp. 1-6). IEEE. https://doi.org/10.1109/MSCPES.2019.8738795
SID022	IEEE	2019	Aklamanu, F., Randriamasy, S., & Renault, E. (2019, October). Intent-based 5G IoT application network slice deployment. In 2019 10th International Conference on Networks of the Future (NoF) (pp. 141-143). IEEE. 10.1109/NoF47743.2019.9015048
SID023	IEEE	2019	Mekruksavanich, S. (2019, October). Design and implementation of the smart shopping basket based on IoT technology. In 2019 14th International Joint Symposium on Artificial Intelligence and Natural Language Processing (iSAI-NLP) (pp. 1-6). IEEE. https://doi.org/10.1109/iSAI-NLP48611.2019.9045336
SID024	IEEE / ACM	2019	Verghelet, P., & Mocskos, E. (2019, December). First Steps in creating a Methodology to develop and test Scheduling Policies for Internet of Things. In 2019 Winter Simulation Conference (WSC) (pp. 2629-2640). IEEE. https://doi.org/10.1109/WSC40007.2019.9004950
SID025	IEEE	2019	Rescati, M., Scapini, E., DeMatteis, M., Schettini, R., Pau, D., Paganoni, M., & Baschirotto, A. (2019, September). HAEMS: implementation of an intelligent event-driven edge mesh IoT architecture. In 2019 IEEE 5th International forum on Research and Technology for Society and Industry (RTSI) (pp. 39-44). IEEE. https://doi.org/10.1109/RTSI.2019.8895581
SID026	IEEE	2019	Kamiyama, M., Madokoro, H., Nakasho, K., Shimoi, N., Woo, H., & Sato, K. (2019, October). Invisible and Cost-Effective Sensors with a Network Robot for an IoT House for Tourists. In 2019 19th International Conference on Control, Automation and Systems (ICCAS) (pp. 460-465). IEEE. https://doi.org/10.23919/ICCAS47443.2019.8971768
SID027	IEEE	2019	Day, R. J., Salehi, H., & Javadi, M. (2019, December). Iot environmental analyzer using sensors and machine learning for migraine occurrence prevention. In 2019 18th IEEE International Conference On Machine Learning And Applications (ICMLA) (pp. 1460-1465). IEEE. https://doi.org/10.1109/ICMLA.2019.00239
SID028	IEEE	2019	Pereira, R. I., Jucá, S. C., Carvalho, P. C., & Souza, C. P. (2019). Iot network and sensor signal conditioning for meteorological data and photovoltaic module temperature monitoring. IEEE Latin America Transactions, 17(06), 937-944. https://doi.org/10.1109/TLA.2019.8896816
SID029	IEEE	2019	Hamdan, O., Shanableh, H., Zaki, I., Al-Ali, A. R., & Shanableh, T. (2019, January). IoT-based interactive dual mode smart home automation. In 2019 IEEE international conference on consumer electronics (ICCE) (pp. 1-2). IEEE. https://doi.org/10.1109/ICCE.2019.8661935
SID030	IEEE	2019	Zitouni, R., Petit, J., Djoudi, A., & George, L. (2019, July). IoT-based urban traffic-light control: modelling, prototyping and evaluation of MQTT protocol. In 2019 International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData) (pp. 182-189). IEEE. https://doi.org/10.1109/iThings/GreenCom/CPSCom/SmartData.2019.00051
SID031	IEEE	2019	Sanchez-Iborra, R., Covaci, S., Santa, J., Sanchez-Gomez, J., Gallego-Madrid, J., & Skarmeta, A. F. (2019, December). MEC-assisted end-to-end 5G-slicing for IoT. In 2019 IEEE Global Communications Conference (GLOBECOM) (pp. 1-6).

			IEEE. https://doi.org/10.1109/GLOBECOM38437.2019.9013623
SID032	IEEE	2019	Sundharam, S. M. (2019, March). Modeling of high level system requirements-An IoT case-study. In 2019 International Conference on Vision Towards Emerging Trends in Communication and Networking (ViTECoN) (pp. 1-7). IEEE. https://doi.org/10.1109/ViTECoN.2019.8899419
SID033	IEEE	2019	Ajchariyavanich, C., Limpisthira, T., Chanjarasvichai, N., Jareonwatanan, T., Phongphanpanya, W., Wareechuensuk, S., ... & Pipattanasomporn, M. (2019, October). Park king: an IoT-based smart parking system. In 2019 IEEE International Smart Cities Conference (ISC2) (pp. 729-734). IEEE. https://doi.org/10.1109/ISC246665.2019.9071721
SID034	IEEE	2019	Taylor, G. A., Torres, H. B., Ruiz, F., Marin, M. N., Chaves, D. M., Arboleda, L. T., ... & Mouazen, A. M. (2019). pH measurement IoT system for precision agriculture applications. IEEE Latin America Transactions, 17(05), 823-832. https://doi.org/10.1109/TLA.2019.8891951
SID035	IEEE	2019	Mubarakali, A., Jaganathan, S. C. B., Marina, N., & Kumar, A. D. (2019, February). Programmed water management system for irrigation using internet of things. In 2019 International Conference on Intelligent Sustainable Systems (ICISS) (pp. 203-207). IEEE. https://doi.org/10.1109/ISS1.2019.8908110
SID036	IEEE	2019	Abraham, E., Nameer, C. K., Tom, R., Ganesh, Y., & Vidhya, S. S. (2019, July). Pro-Safe: An IoT based Smart Application for Emergency Help. In 2019 2nd International Conference on Intelligent Computing, Instrumentation and Control Technologies (ICICICT) (Vol. 1, pp. 593-597). IEEE. https://doi.org/10.1109/ICICICT46008.2019.8993220
SID037	IEEE	2019	Das, A. K., Wazid, M., Yannam, A. R., Rodrigues, J. J., & Park, Y. (2019). Provably secure ECC-based device access control and key agreement protocol for IoT environment. IEEE Access, 7, 55382-55397. https://doi.org/10.1109/ACCESS.2019.2912998
SID038	IEEE	2019	Alduais, N. A. M., Abdullah, J., & Jamil, A. (2019). RDCM: An efficient real-time data collection model for IoT/WSN edge with multivariate sensors. IEEE Access, 7, 89063-89082. https://doi.org/10.1109/ACCESS.2019.2926209
SID039	IEEE	2019	Khan, S., Alzahrani, A. I., Alfarraj, O., Alalwan, N., & Al-Bayatti, A. H. (2019). Resource efficient authentication and session key establishment procedure for low-resource IoT devices. IEEE Access, 7, 170615-170628. https://doi.org/10.1109/ACCESS.2019.2955604
SID040	ACM	2019	Anantharaman, P., Palani, K., & Smith, S. (2019, October). Scalable identity and key management for publish-subscribe protocols in the Internet-of-Things. In Proceedings of the 9th International Conference on the Internet of Things (pp. 1-7). https://doi.org/10.1145/3365871.3365883
SID041	IEEE	2019	Georgiev, I., & Georgiev, I. (2019, September). Simulation-based self-testing in IoT-enabled manufacturing. In 2019 International Conference on Information Technologies (InfoTech) (pp. 1-4). IEEE. https://doi.org/10.1109/InfoTech.2019.8860882
SID042	IEEE	2019	Patel, N. D., Mehtre, B. M., & Wankar, R. (2019, December). Simulators, emulators, and test-beds for internet of things: A comparison. In 2019 Third International conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC) (pp. 139-145). IEEE. https://doi.org/10.1109/I-SMAC47947.2019.9032519
SID043	IEEE	2019	Tang, S., Gu, Z., Yang, Q., & Fu, S. (2019, December). Smart home iot anomaly detection based on ensemble model learning from heterogeneous data. In 2019 IEEE international conference on big data (Big Data) (pp. 4185-4190). IEEE. https://doi.org/10.1109/BigData47090.2019.9006249
SID044	IEEE	2019	Alghanmi, N., Alotaibi, R., & Buhari, S. M. (2019, June). TCMD: A two-tier classification model for anomaly-based detection in IoT. In 2019 6th Swiss Conference on Data Science (SDS) (pp. 130-135). IEEE. https://doi.org/10.1109/SDS.2019.00013
SID045	IEEE	2019	Hovhannisyan, D., Eltawil, A., & Kurdahi, F. (2019, May). Testing topology adaptive irrigation iot with circuits. In 2019 IEEE International Symposium on Circuits and Systems (ISCAS) (pp. 1-5). IEEE. https://doi.org/10.1109/ISCAS.2019.8702559
SID046	IEEE	2019	Zeeshan, N., Reed, M., & Siddiqui, Z. (2019, August). Three-way security framework for cloud based IoT network. In 2019 International Conference on Computing, Electronics & Communications Engineering (iCCECE) (pp. 183-186). IEEE. https://doi.org/10.1109/iCCECE46942.2019.8941877
SID047	IEEE	2019	Garg, S., Kaur, K., Kaddoum, G., & Choo, K. K. R. (2019). Toward secure and provable authentication for Internet of Things: Realizing industry 4.0. IEEE Internet of Things Journal, 7(5), 4598-4606. https://doi.org/10.1109/JIOT.2019.2942271
SID048	IEEE	2019	Russell, L., Kwamena, F., & Goubran, R. (2019, August). Towards reliable IoT: Fog-based AI sensor validation. In 2019 IEEE Cloud Summit (pp. 37-44). IEEE. https://doi.org/10.1109/CloudSummit47114.2019.00013
SID049	IEEE	2019	Gore, R. N., Elizabeth, N., Dzung, D., & Ashok, S. (2019, January). Towards robust synchronization in IoT networks. In 2019 11th International Conference on Communication Systems & Networks (COMSNETS) (pp. 678-683). IEEE. https://doi.org/10.1109/COMSNETS.2019.8711343
SID050	IEEE	2019	Peniak, P., & Bubeníková, E. (2019, September). Validation of IoT secure communication gateway for constrained devices. In 2019 International Conference on Applied Electronics (AE) (pp. 1-5). IEEE. https://doi.org/10.23919/AE.2019.8866990
SID051	IEEE	2019	Kumar, R., Venkanna, U., & Tiwari, V. (2020). A binary classification approach for time granular traffic in SDWMN based IoT networks. In 2020 12th International Conference on COMmunication Systems & NETworks (COMSNETS) (pp. 531–534). IEEE. https://doi.org/10.1109/COMSNETS48256.2020.9027336
SID052	Springer	2020	Lee, Y., Rathore, S., Park, J. H., & Park, J. H. (2020). A blockchain-based smart home gateway architecture for preventing data forgery. Human-centric Computing and Information Sciences, 10, 9. https://doi.org/10.1186/s13673-020-0214-5
SID053	Springer	2020	Zhang, Z., Jing, J., Wang, X., Choo, K.-K. R., & Gupta, B. B. (2020). A crowdsourcing method for online social networks security assessment based on human-centric computing. Human-centric Computing and Information Sciences, 10, 23. https://doi.org/10.1186/s13673-020-00230-0
SID054	ACM	2020	Etiabi, Y., Amhoud, E. M., & Sabir, E. (2020). A distributed and collaborative localization algorithm for Internet of Things environments. In Proceedings of the 18th International Conference on Advances in Mobile Computing & Multimedia (MoMM '20) (pp. 114–118). Association for Computing Machinery. https://doi.org/10.1145/3428690.3429161
SID055	Scopus	2020	Shapsough, S. Y., & Zualkernan, I. A. (2020). A generic IoT architecture for ubiquitous context-aware learning. IEEE Transactions on Learning Technologies, 13(3), 449–464. https://doi.org/10.1109/TLT.2020.3007708
SID056	IEEE	2020	Olatinwo, D. D., Abu-Mahfouz, A. M., & Hancke, G. P. (2021). A hybrid multi-class MAC protocol for IoT-enabled WBAN systems. IEEE Sensors Journal, 21(5), 6761–6774. https://doi.org/10.1109/JSEN.2020.3037788

SID057	Springer	2020	Bureš, T., Gerostathopoulos, I., Hnětynka, P., Plášil, F., Krijt, F., Vinárek, J., & Kofroň, J. (2020). A language and framework for dynamic component ensembles in smart systems. International Journal on Software Tools for Technology Transfer, 22, 497–509. https://doi.org/10.1007/s10009-020-00558-z
SID058	IEEE / Scopus	2020	Aman, M. N., Basheer, M. H., & Sikdar, B. (2020). A lightweight protocol for secure data provenance in the Internet of Things using wireless fingerprints. IEEE Systems Journal, 15(2), 2948-2958. https://doi.org/10.1109/JSYST.2020.3000269
SID059	Scopus	2020	Hagos, D. H., Yazidi, A., Kure, Ø., & Engelstad, P. E. (2020). A machine-learning-based tool for passive os fingerprinting with tcp variant as a novel feature. IEEE Internet of Things Journal, 8(5), 3534-3553. https://doi.org/10.1109/JIOT.2020.3024293
SID060	IEEE / Scopus	2020	Ciliberti, F., Giusto, F., Accetta, L., Vergari, G., Sergi, I., & Patrono, L. (2020, September). A New Approach to Monitor Sarcopenic Patients based on IoT Technologies. In 2020 5th International Conference on Smart and Sustainable Technologies (SpliTech) (pp. 1-5). IEEE. https://doi.org/10.23919/SpliTech49282.2020.9243692
SID061	Scopus	2020	Keerthi, A. M., Raksha, R., & Rakesh, N. (2020, November). A novel remote monitoring smart system for the elderly using internet of things. In 2020 4th International Conference on Electronics, Communication and Aerospace Technology (ICECA) (pp. 596-602). IEEE. https://doi.org/10.1109/ICECA49313.2020.9297403
SID062	IEEE	2020	Roy, S. K., Misra, S., Raghuwanshi, N. S., & Das, S. K. (2020). AgriSens: IoT-based dynamic irrigation scheduling system for water management of irrigated crops. IEEE Internet of Things Journal, 8(6), 5023-5030. https://doi.org/10.1109/JIOT.2020.3036126
SID063	IEEE/ Scopus	2020	Jacob, S., Alagirisamy, M., Menon, V. G., Kumar, B. M., Jhanjhi, N. Z., Ponnusamy, V., ... & Balasubramanian, V. (2020). An adaptive and flexible brain energized full body exoskeleton with IoT edge for assisting the paralyzed patients. IEEE Access, 8, 100721-100731. https://doi.org/10.1109/ACCESS.2020.2997727
SID064	ACM	2020	Santos, L., Silva, E., Batista, T., Cavalcante, E., Leite, J., & Oquendo, F. (2020, March). An architectural style for internet of things systems. In Proceedings of the 35th Annual ACM Symposium on applied computing (pp. 1488-1497). https://doi.org/10.1145/3341105.3374030
SID065	Scopus	2020	Otoom, M., Otoum, N., Alzubaidi, M. A., Etoom, Y., & Banihani, R. (2020). An IoT-based framework for early identification and monitoring of COVID-19 cases. Biomedical signal processing and control, 62, 102149. https://doi.org/10.1016/j.bspc.2020.102149
SID066	IEEE	2020	Li, J. Y., Qi, S., Ji, K. Q., Zhang, Y., Liang, S. T., & Lu, J. T. (2020, October). Application Research on Internet-of-Things in Park-Level Intelligent Energy Protection and Control. In 2020 IEEE 20th International Conference on Communication Technology (ICCT) (pp. 813-817). IEEE. https://doi.org/10.1109/ICCT50939.2020.9295679
SID067	IEEE	2020	Fiorentino, G., Occhipinti, C., Corsi, A., Moro, E., Davies, J., & Duke, A. (2020). Blockchain: Enabling trust on the internet of things. The Internet of Things: From Data to Insight, 141-157. https://doi.org/10.1002/9781119545293.ch11
SID068	IEEE	2020	Goyat, R., Kumar, G., Alazab, M., Conti, M., Rai, M. K., Thomas, R., ... & Kim, T. H. (2020). Blockchain-based data storage with privacy and authentication in internet of things. IEEE Internet of Things Journal, 9(16), 14203-14215. https://doi.org/10.1109/JIOT.2020.3019074
SID069	IEEE / Scopus	2020	Hosen, A. S., Singh, S., Sharma, P. K., Ghosh, U., Wang, J., Ra, I. H., & Cho, G. H. (2020). Blockchain-based transaction validation protocol for a secure distributed IoT network. IEEE Access, 8, 117266-117277. https://doi.org/10.1109/ACCESS.2020.3004486
SID070	Scopus	2020	Mongelli, M., Orani, V., Cambiaso, E., Vaccari, I., Paglialonga, A., Braido, F., & Catalano, C. E. (2020, August). Challenges and Opportunities of IoT and AI in Pneumology. In 2020 23rd Euromicro Conference on Digital System Design (DSD) (pp. 285-292). IEEE. https://doi.org/10.1109/DSD51259.2020.00054
SID071	Scopus	2020	Rojas, E., Bastidas, V., & Cabrera, C. (2020). Cities-board: a framework to automate the development of smart cities dashboards. IEEE Internet of Things Journal, 7(10), 10128-10136. https://doi.org/10.1109/JIOT.2020.3002581
SID072	IEEE / Scopus / WoS	2020	Wang, M., Qian, C., Li, X., Shi, S., & Chen, S. (2020). Collaborative validation of public-key certificates for IoT by distributed caching. IEEE/ACM Transactions on Networking, 29(1), 92-105. https://doi.org/10.1109/INFOCOM.2019.8737423
SID073	IEEE / Scopus	2020	Ayeb, N., Rutten, E., Bolle, S., Coupaye, T., & Douet, M. (2020, September). Coordinated autonomic loops for target identification, load and error-aware Device Management for the IoT. In 2020 15th Conference on Computer Science and Information Systems (FedCSIS) (pp. 491-500). IEEE. https://doi.org/10.15439/2020F154
SID074	Scopus	2020	Kumar, A., & Hariharan, N. (2020). DCRL-RPL: Dual context-based routing and load balancing in RPL for IoT networks. IET Communications, 14(12), 1869-1882. https://doi.org/10.1049/iet-com.2020.0091
SID075	Scopus	2020	Baena-Navarro, R., Torres-Hoyos, F., Uc–Rios, C., & Colmenares-Quintero, R. F. (2020). Design and assembly of an IoT-based device to determine the absorbed dose of gamma and UV radiation. Applied Radiation and Isotopes, 166, 109359. https://doi.org/10.1016/j.apradiso.2020.109359
SID076	Scopus	2020	Sha, P., Chen, S., Zheng, L., Liu, X., Tang, H., & Li, Y. (2020). Design and implement of microservice system for edge computing. IFAC-PapersOnLine, 53(5), 507-511. https://doi.org/10.1016/j.ifacol.2021.04.137
SID077	Scopus	2020	Chen, G., Jiang, T., Wang, M., Tang, X., & Ji, W. (2020). Design and model checking of timed automata oriented architecture for Internet of thing. International Journal of Distributed Sensor Networks, 16(5), 1550147720911008. https://doi.org/10.1177/1550147720911008
SID078	Scopus / WoS	2020	Amitrano, F., Coccia, A., Ricciardi, C., Donisi, L., Cesarelli, G., Capodaglio, E. M., & D'Addio, G. (2020). Design and validation of an e-textile-based wearable sock for remote gait and postural assessment. Sensors, 20(22), 6691. https://doi.org/10.3390/s20226691
SID079	IEEE / Scopus	2020	Shorfuzzaman, M. (2020, October). Detection of cyber attacks in IoT using tree-based ensemble and feedforward neural network. In 2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC) (pp. 2601-2606). IEEE. https://doi.org/10.1109/SMC42975.2020.9283443
SID080	Scopus	2020	Mialdea-Flor, I., López-Ballester, J., Garcia-Pineda, M., Navarro-Camba, E., Soriano-Asensi, A., Fayos-Jordán, R., ... & Alcaraz-Calero, J. M. (2020, November). Development of a low-cost IoT system to detect and locate lightning strikes. In Proceedings of the 10th Euro-American Conference on Telematics and Information Systems (pp. 1-8). https://doi.org/10.1145/3401895.3401916
SID081	Scopus	2020	Sahlab, N., Jazdi, N., Weyrich, M., Schmid, P., Reichelt, F., Maier, T., ... & Kalka, G. (2020). Development of an intelligent pill dispenser based on an IoT-approach. In Human Systems Engineering and Design II: Proceedings of the 2nd International Conference on Human Systems Engineering and Design (IHSED2019): Future Trends and Applications,

			September 16-18, 2019, Universität der Bundeswehr München, Munich, Germany (pp. 33-39). Springer International Publishing. https://doi.org/10.1007/978-3-030-27928-8_6
SID082	Scopus	2020	Kamel, M. B., Wallis, K., Ligeti, P., & Reich, C. (2020, October). Distributed data validation network in IoT: a decentralized validator selection model. In Proceedings of the 10th International Conference on the Internet of Things (pp. 1-8). https://doi.org/10.1145/3410992.3411027
SID083	IEEE	2020	Niya, S. R., Beckmann, R., & Stiller, B. (2020, November). DLIT: a scalable distributed ledger for iot data. In 2020 Second International Conference on Blockchain Computing and Applications (BCCA) (pp. 100-107). IEEE. https://doi.org/10.1109/BCCA50787.2020.9274456
SID084	IEEE / Scopus	2020	Hamdani, S. W. A., Khan, A. W., Iltaf, N., & Iqbal, W. (2020, August). DTMSim-IoT: A distributed trust management simulator for IoT networks. In 2020 IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress (DASC/PiCom/CBDCom/CyberSciTech) (pp. 491-498). IEEE. https://doi.org/10.1109/DASC-PICom-CBDCom-CyberSciTech49142.2020.00091
SID085	Scopus	2020	Xin, X., Keoh, S. L., Sevegnani, M., & Saerbeck, M. (2020, August). Dynamic probabilistic model checking for sensor validation in Industry 4.0 applications. In 2020 IEEE International Conference on Smart Internet of Things (SmartIoT) (pp. 43-50). IEEE. https://doi.org/10.1109/SmartIoT49966.2020.00016
SID086	Scopus	2020	Debauche, O., Mahmoudi, S., Mahmoudi, S. A., Manneback, P., & Lebeau, F. (2020). Edge computing and artificial intelligence semantically driven. application to a climatic enclosure. Procedia Computer Science, 175, 542-547. https://doi.org/10.1016/j.procs.2020.07.077
SID087	IEEE	2020	Seng, L. G., Wei, K. L. K., & Narciso, S. J. (2020, April). Effective industry ready iot applied courseware-teaching iot design and validation. In 2020 IEEE Global Engineering Education Conference (EDUCON) (pp. 1579-1583). IEEE. https://doi.org/10.1109/EDUCON45650.2020.9125366
SID088	Scopus	2020	Ballesteros, J., Ayala, I., Caro-Romero, J. R., Amor, M., & Fuentes, L. (2020). Evolving dynamic self-adaptation policies of mhealth systems for long-term monitoring. Journal of Biomedical Informatics, 108, 103494. https://doi.org/10.1016/j.jbi.2020.103494
SID089	ACM	2020	Guedey, M., & Uckelmann, D. (2020, October). Exploring smart home and internet of things technologies for smart public buildings. In Proceedings of the 10th International Conference on the Internet of Things (pp. 1-8). https://doi.org/10.1145/3410992.3411009
SID090	Springer	2020	Yang, X., Liu, Y., Wang, J., Yao, Z., Zhou, Y., & Fu, S. (2020). Flexible automatic detection for security management of dispatching data network. Journal of Cloud Computing, 9(1), 20. https://doi.org/10.1186/s13677-020-00163-0
SID091	Scopus	2020	Olmsted, J., & Al-Masri, E. (2020, August). FogWeaver: Task allocation optimization strategy across hybrid fog environments. In 2020 3rd IEEE International Conference on Knowledge Innovation and Invention (ICKII) (pp. 156-159). IEEE. https://doi.org/10.1109/ICKII50300.2020.9318846
SID092	IEEE	2020	Becerril, J. A., Ramírez-delReal, T. A., Villanueva, D., & Arellano-Vázquez, M. (2020, November). Gateway design based on IoT Methodology using a Beaglebone Black Wireless. In 2020 IEEE International Autumn Meeting on Power, Electronics and Computing (ROPEC) (Vol. 4, pp. 1-6). IEEE. https://doi.org/10.1109/ROPEC50909.2020.9258764
SID093	Scopus	2020	Cai, W. Y., Guo, J. H., Zhang, M. Y., Ruan, Z. X., Zheng, X. C., & Lv, S. S. (2020). GBDT-Based Fall Detection with Comprehensive Data from Posture Sensor and Human Skeleton Extraction. Journal of healthcare engineering, 2020(1), 8887340. https://doi.org/10.1155/2020/8887340
SID094	IEEE / Scopus	2020	Nurminen, A., & Malhi, A. (2020, December). Green Thumb Engineering: Artificial intelligence for managing IoT enabled houseplants. In 2020 IEEE Global Conference on Artificial Intelligence and Internet of Things (GCAIoT) (pp. 01-07). IEEE. https://doi.org/10.1109/GCAIoT51063.2020.9345850
SID095	IEEE	2020	Fama, F., Santos, D. F., & Perkusich, A. (2020, September). Integrating an iot application middleware with a fog and edge computing simulator. In 2020 International Conference on Software, Telecommunications and Computer Networks (SoftCOM) (pp. 1-6). IEEE. https://doi.org/10.23919/SoftCOM50211.2020.9238245
SID096	IEEE / Scopus	2020	Sergi, I., Malagnino, A., Rosito, R. C., Lacasa, V., Corallo, A., & Patrono, L. (2020, September). Integrating BIM and IoT technologies in innovative fire management systems. In 2020 5th International Conference on Smart and Sustainable Technologies (SpliTech) (pp. 1-5). IEEE. https://doi.org/10.23919/SpliTech49282.2020.9243838
SID097	Scopus	2020	Sarmiento, A., & Diakité, A. A. (2020). Integration of IoT sensors to 3D indoor models with IndoorGML. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 44, 135-142. https://doi.org/10.5194/isprs-archives-XLIV-4-W1-2020-135-2020
SID098	IEEE	2020	Ranjan, R., Sinha, R., Khot, L. R., Peters, R. T., & Salazar-Gutierrez, M. R. (2020, November). Internet of Things enabled crop physiology sensing system for abiotic crop stress management in apple and sweet cherry. In 2020 IEEE International Workshop on Metrology for Agriculture and Forestry (MetroAgriFor) (pp. 273-277). IEEE. https://doi.org/10.1109/MetroAgriFor50201.2020.9277581
SID099	Scopus	2020	Alqahtani, M., Mathkour, H., & Ben Ismail, M. M. (2020). IoT botnet attack detection based on optimized extreme gradient boosting and feature selection. Sensors, 20(21), 6336. https://doi.org/10.3390/s20216336
SID100	IEEE / Scopus	2020	Tham, O. Y., Markom, M. A., Bakar, A. A., Tan, E. M. M., & Markom, A. M. (2020, October). IoT health monitoring device of oxygen saturation (SpO2) and heart rate level. In 2020 1st International conference on information technology, advanced mechanical and electrical engineering (ICITAMEE) (pp. 128-133). IEEE. https://doi.org/10.1109/ICITAMEE50454.2020.9398455
SID101	IEEE / Scopus	2020	Doss, J. K. S., & Kamalakkannan, S. (2020, October). IoT system accomplishment using blockchain in validating and data security with cloud. In 2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC) (pp. 60-64). IEEE. https://doi.org/10.1109/I-SMAC49090.2020.9243412
SID102	Scopus	2020	Vieira, E., Bartolomeu, P. C., Hosseini, S. M., & Ferreira, J. (2020, June). IOTApass: Enabling public transport payments with IOTA. In 2020 IEEE 6th World Forum on Internet of Things (WF-IoT) (pp. 1-6). IEEE. https://doi.org/10.1109/WF-IoT48130.2020.9221224
SID103	IEEE / Scopus	2020	Catarinucci, L., Colella, R., Consalvo, S. I., Patrono, L., Rollo, C., & Sergi, I. (2020). IoT-aware waste management system based on cloud services and ultra-low-power RFID sensor-tags. IEEE Sensors Journal, 20(24), 14873-14881. https://doi.org/10.1109/JSEN.2020.3010675

SID104	IEEE	2020	Bhatia, M. (2020). Iot-inspired framework for athlete performance assessment in smart sport industry. IEEE Internet of Things Journal, 8(12), 9523-9530. https://doi.org/10.1109/JIOT.2020.3012440
SID105	IEEE	2020	Park, K., Noh, S., Lee, H., Das, A. K., Kim, M., Park, Y., & Wazid, M. (2020). LAKS-NVT: Provably secure and lightweight authentication and key agreement scheme without verification table in medical internet of things. IEEe Access, 8, 119387-119404. https://doi.org/10.1109/ACCESS.2020.3005592
SID106	IEEE	2020	Dasiga, S., Bhatia, A. A. R., Bhirangi, A., & Siddiqua, A. (2020, December). LoRa for the last mile connectivity in IoT. In 2020 9th International Conference System Modeling and Advancement in Research Trends (SMART) (pp. 195-200). IEEE. https://doi.org/10.1109/SMART50582.2020.9337114
SID107	IEEE / Scopus	2020	Ali, S., Glass, T., Parr, B., Potgieter, J., & Alam, F. (2020). Low cost sensor with IoT LoRaWAN connectivity and machine learning-based calibration for air pollution monitoring. IEEE Transactions on Instrumentation and Measurement, 70, 1-11. https://doi.org/10.1109/TIM.2020.3034109
SID108	Scopus	2020	Han, H. J., Labbaf, S., Borelli, J. L., Dutt, N., & Rahmani, A. M. (2020). Objective stress monitoring based on wearable sensors in everyday settings. Journal of Medical Engineering & Technology, 44(4), 177-189. https://doi.org/10.1080/03091902.2020.1759707
SID109	IEEE / Scopus / WoS	2020	Makhdoom, I., Tofigh, F., Zhou, I., Abolhasan, M., & Lipman, J. (2020, November). PLEDGE: An IoT-oriented proof-of-honesty based blockchain consensus protocol. In 2020 IEEE 45th Conference on Local Computer Networks (LCN) (pp. 54-64). IEEE. https://doi.org/10.1109/LCN48667.2020.9314794
SID110	IEEE	2020	Christou, I. T., Kefalakis, N., Zalonis, A., & Soldatos, J. (2020, May). Predictive and explainable machine learning for industrial internet of things applications. In 2020 16th international conference on distributed computing in sensor systems (DCOSS) (pp. 213-218). IEEE. https://doi.org/10.1109/DCOSS49796.2020.00043
SID111	IEEE	2020	Maitra, S., Yanambaka, V. P., Abdelgawad, A., Puthal, D., & Yelamarthi, K. (2020, June). Proof-of-authentication consensus algorithm: Blockchain-based IoT implementation. In 2020 IEEE 6th World Forum on Internet of Things (WF-IoT) (pp. 1-2). IEEE. https://doi.org/10.1109/WF-IoT48130.2020.9221187
SID112	IEEE / Scopus	2020	Postolache, O., Hemanth, D. J., Alexandre, R., Gupta, D., Geman, O., & Khanna, A. (2020). Remote monitoring of physical rehabilitation of stroke patients using IoT and virtual reality. IEEE Journal on Selected Areas in Communications, 39(2), 562-573. https://doi.org/10.1109/JSAC.2020.3020600
SID113	Scopus	2020	Al-Ali, M. S., Al-Mohammed, H. A., & Alkaeed, M. (2020, February). Reputation based traffic event validation and vehicle authentication using blockchain technology. In 2020 IEEE International Conference on Informatics, IoT, and Enabling Technologies (ICIoT) (pp. 451-456). IEEE. https://doi.org/10.1109/ICIoT48696.2020.9089639
SID114	Scopus	2020	Zhiyong, S., Weiping, L., Yanghua, Z., & Yanshan, H. (2020). Research on intelligent power automation technology based on edge computing of power Internet of things. In E3S Web of Conferences (Vol. 204, p. 02006). EDP Sciences. https://doi.org/10.1051/e3sconf/202020402006
SID115	Scopus	2020	Feng, X., & Hu, J. (2020). Research on the identification and management of vehicle behaviour based on Internet of things technology. Computer Communications, 156, 68-76. https://doi.org/10.1016/j.comcom.2020.03.035
SID116	IEEE	2020	Abbas, A. W., & Marwat, S. N. K. (2020). Scalable emulated framework for IoT devices in smart logistics based cyber-physical systems: bonded coverage and connectivity analysis. IEEE Access, 8, 138350-138372. https://doi.org/10.1109/ACCESS.2020.3012458
SID117	ACM	2020	Sagar, S., Mahmood, A., Sheng, Q. Z., & Siddiqui, S. A. (2020, November). SCaRT-SIoT: towards a scalable and robust trust platform for social internet of things: demo abstract. In Proceedings of the 18th Conference on Embedded Networked Sensor Systems (pp. 635-636). https://doi.org/10.1145/3384419.3430434
SID118	Scopus	2020	Liaqat, S., Akhunzada, A., Shaikh, F. S., Giannetsos, A., & Jan, M. A. (2020). SDN orchestration to combat evolving cyber threats in Internet of Medical Things (IoMT). Computer Communications, 160, 697-705. https://doi.org/10.1016/j.comcom.2020.07.006
SID119	Scopus / WoS	2020	Hu, J., Reed, M., Thomos, N., AI-Naday, M. F., & Yang, K. (2020). Securing SDN-controlled IoT networks through edge blockchain. IEEE Internet of Things Journal, 8(4), 2102-2115. https://doi.org/10.1109/JIOT.2020.3017354
SID120	IEEE	2020	Kavitha, A., Reddy, V. B., Singh, N., Gunjan, V. K., Lakshmanna, K., Khan, A. A., & Wechtaisong, C. (2022). Security in IoT mesh networks based on trust similarity. IEEE Access, 10, 121712-121724. https://doi.org/10.1109/ACCESS.2022.3220678
SID121	Scopus	2020	Liu, Z., Qiu, X., Zhang, S., Deng, S., & Liu, G. (2020). Service Scheduling Based on Edge Computing for Power Distribution IoT. Computers, materials & continua, 62(3). https://doi.org/10.32604/cmc.2020.07334
SID122	IEEE / Scopus	2020	Sharma, S., Sharma, A., Goel, T., Deoli, R., & Mohan, S. (2020, July). Smart home gardening management system: A cloud-based internet-of-things (iot) application in vanet. In 2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT) (pp. 1-5). IEEE. https://doi.org/10.1109/ICCCNT49239.2020.9225573
SID123	Springer	2020	Xiao-wei, X. (2020). Study on the intelligent system of sports culture centers by combining machine learning with big data. Personal and Ubiquitous Computing, 24(1), 151-163. https://doi.org/10.1007/s00779-019-01307-z
SID124	IEEE	2020	Mahlous, A. R., & Ara, A. (2020, March). The adoption of blockchain technology in iot: An insight view. In 2020 6th Conference on Data Science and Machine Learning Applications (CDMA) (pp. 100-105). IEEE. https://doi.org/10.1109/CDMA47397.2020.00023
SID125	Springer	2020	Bibri, S. E. (2020). The eco-city and its core environmental dimension of sustainability: green energy technologies and their integration with data-driven smart solutions. Energy Informatics, 3(1), 4. https://doi.org/10.1186/s42162-020-00107-7
SID126	Springer	2020	Aufner, P. (2020). The IoT security gap: a look down into the valley between threat models and their implementation. International Journal of Information Security, 19(1), 3-14. https://doi.org/10.1007/s10207-019-00445-y
SID127	Scopus	2020	Rajendran, A., & Rajappa, M. (2020). Topological Ordering Signal Selection Technique for Internet of Things based on Combinational Gate for Visibility Enhancement. Scalable Computing: Practice and Experience, 21(1), 33-40. https://doi.org/10.12694/SCPE.V21I1.1607
SID128	Scopus	2020	Sauer, D., Jumar, R., Lutz, R., Schlachter, T., Schmitt, C., & Hagenmeyer, V. (2020, October). Towards Smart Buildings: A Versatile Acquisition Setup for Indoor Climate Data. In 2020 IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe) (pp. 1196-1200). IEEE. https://doi.org/10.1109/ISGT-Europe47291.2020.9248925
SID129	Springer	2020	Ahlström, C., Wachtmeister, J., Nyman, M., Nordenström, A., & Kircher, K. (2020). Using smartphone logging to gain

			insight about phone use in traffic. Cognition, Technology & Work, 22(1), 181-191. https://doi.org/10.1007/s10111-019-00547-6
SID130	Scopus / WoS	2020	Faust, O., Kareem, M., Shenfield, A., Ali, A., & Acharya, U. R. (2020). Validating the robustness of an internet of things based atrial fibrillation detection system. Pattern Recognition Letters, 133, 55-61. https://doi.org/10.1016/j.patrec.2020.02.005
SID131	IEEE	2020	Karaagac, A., Camerlynck, P., Crombez, P., & Hoebeke, J. (2020, June). Viot: voice over internet of things. In 2020 Global Internet of Things Summit (GIoTS) (pp. 1-6). IEEE. https://doi.org/10.1109/GIOTS49054.2020.9119616
SID132	Springer	2021	Andrienko, G., Andrienko, N., Boldrini, C., Caldarelli, G., Cintia, P., Cresci, S., ... & Trasarti, R. (2021). (So) Big Data and the transformation of the city. International Journal of Data Science and Analytics, 11(4), 311-340. https://doi.org/10.1007/s41060-020-00207-3
SID133	Springer	2021	Anthony Jnr, B. (2021). A case-based reasoning recommender system for sustainable smart city development. AI & Society, 36, 159–183. https://doi.org/10.1007/s00146-020-00984-2
SID134	Springer	2021	Haghgoo, M., Dognini, A., Storek, T., Plamanescu, R., Rahe, U., Gheorghe, S., Albu, M., Monti, A., & Müller, D. (2021). A cloud-based service-oriented architecture to unlock smart energy services. Energy Informatics, 4, 8. https://doi.org/10.1186/s42162-021-00143-x
SID135	Springer	2021	Ahmad, I., Noor, R. M., Ahmed, Z., Habiba, U.-e., Akram, N., & García Márquez, F. P. (2021). A cooperative heterogeneous vehicular clustering framework for efficiency improvement. Frontiers of Information Technology & Electronic Engineering, 22(9), 1247–1259.
SID136	Scopus / Springer	2021	Parri, J., Patara, F., Sampietro, S., & Vicario, E. (2021). A framework for model-driven engineering of resilient software-controlled systems. Computing, 103, 589–612. https://doi.org/10.1007/s00607-020-00841-6
SID137	Scopus	2021	Vaccari, I., Orani, V., Paglialonga, A., Cambiaso, E., & Mongelli, M. (2021). A generative adversarial network (GAN) technique for Internet of Medical Things data. Sensors, 21(11), 3726. https://doi.org/10.3390/s21113726
SID138	Scopus	2021	Javeed, D., Gao, T., Khan, M. T., & Ahmad, I. (2021). A hybrid deep learning-driven SDN enabled mechanism for secure communication in Internet of Things (IoT). Sensors, 21(14), 4884. https://doi.org/10.3390/s21144884
SID139	Scopus	2021	Meng, X., Xu, J., Liang, W., Xu, Z., & Li, K.-C. (2021). A lightweight anonymous cross-regional mutual authentication scheme using blockchain technology for internet of vehicles. Computers & Electrical Engineering, 95, 107431. https://doi.org/10.1016/j.compeleceng.2021.107431
SID140	IEEE	2021	Ramson, S. J., Vishnu, S., Kirubaraj, A. A., Anagnostopoulos, T., & Abu-Mahfouz, A. M. (2021). A LoRaWAN IoT-enabled trash bin level monitoring system. IEEE Transactions on Industrial Informatics, 18(2), 786-795. https://doi.org/10.1109/TII.2021.3078556
SID141	IEEE / Scopus	2021	Sreevidya, P., Abhilash, C. S., Paul, J., & Rejithkumar, G. (2021, January). A machine learning-based early landslide warning system using IoT. In 2021 4th Biennial International Conference on Nascent Technologies in Engineering (ICNTE) (pp. 1-6). IEEE. https://doi.org/10.1109/ICNTE51185.2021.9487669
SID142	IEEE / Scopus	2021	Amato, F., Cozzolino, G., Moscato, F., Moscato, V., & Xhafa, F. (2021). A model for verification and validation of law compliance of smart contracts in IoT environment. IEEE Transactions on Industrial Informatics, 17(11), 7752-7759. https://doi.org/10.1109/TII.2021.3057595
SID143	IEEE	2021	Asare, B. T., Quist-Aphetsi, K., Nana, L., & Simpson, G. (2021, December). A nodal authentication iot data model for heterogeneous connected sensor nodes within a blockchain network. In 2021 International Conference on Cyber Security and Internet of Things (ICSIoT) (pp. 65-71). IEEE. https://doi.org/10.1109/ICSIoT55070.2021.00021
SID144	IEEE	2021	Khan, R., McLaughlin, K., Kang, B., Laverty, D., & Sezer, S. (2021, July). A novel edge security gateway for end-to-end protection in industrial internet of things. In 2021 IEEE Power & Energy Society General Meeting (PESGM) (pp. 1-5). IEEE. https://doi.org/10.1109/PESGM46819.2021.9638002
SID145	IEEE	2021	Hussain, S., Ullah, S. S., Gumaei, A., Al-Rakhami, M., Ahmad, I., & Arif, S. M. (2021). A novel efficient certificateless signature scheme for the prevention of content poisoning attack in named data networking-based internet of things. IEEE access, 9, 40198-40215. https://doi.org/10.1109/ACCESS.2021.3063490
SID146	Springer	2021	Madsen, S. S., Santos, A. Q., & Jørgensen, B. N. (2021). A QR code based framework for auto-configuration of IoT sensor networks in buildings. Energy Inform. https://doi.org/10.1186/s42162-021-00152-w
SID147	Scopus	2021	Zhang, Y., Chen, Z., Tian, H., Kido, K., Ono, N., Chen, W., ... & Huang, M. (2021). A Real-Time Portable IoT System for Telework Tracking. Frontiers in Digital Health, 3, 643042. https://doi.org/10.3389/fdgth.2021.643042
SID148	Scopus	2021	Mahajan, S., Gabrys, J., & Armitage, J. (2021). Airkit: A citizen-sensing toolkit for monitoring air quality. Sensors, 21(12), 4044. https://doi.org/10.3390/s21124044
SID149	Scopus	2021	Son, S. O., Park, J., Oh, C., & Yeom, C. (2021). An algorithm for detecting collision risk between trucks and pedestrians in the connected environment. Journal of advanced transportation, 2021(1), 9907698. https://doi.org/10.1155/2021/9907698
SID150	Springer	2021	Repetto, M., Striccoli, D., Piro, G., Carrega, A., Boggia, G., & Bolla, R. (2021). An autonomous cybersecurity framework for next-generation digital service chains. Journal of Network and Systems Management, 29(4), 37. https://doi.org/10.1007/s10922-021-09607-7
SID151	Springer	2021	Croatti, A., Montagna, S., Lombardi, C., Parati, G., Pengo, M. F., & Silvani, A. (2021). An Internet of Medical Things System to Increase Continuous Positive Airway Pressure Usage in Patients with Sleep-Disordered Breathing. SN Computer Science, 2(2), 117. https://doi.org/10.1007/s42979-021-00522-x
SID152	IEEE	2021	Sakti, W. W., Anam, K., Utomo, S. B., Marhaenanto, B., & Nahela, S. (2021, October). Artificial intelligence IoT based EEG application using deep learning for movement classification. In 2021 8th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI) (pp. 192-196). IEEE. https://doi.org/10.23919/EECSI53397.2021.9624269
SID153	IEEE	2021	Kashif, M., & Kalkan, K. (2021, November). BCPriPIoT: BlockChain utilized privacy-preservation mechanism for IoT devices. In 2021 Third international conference on blockchain computing and applications (BCCA) (pp. 201-209). IEEE. https://doi.org/10.1109/BCCA53669.2021.9657016
SID154	IEEE	2021	de Lope, L. R., Choque, J., Sandaza, A. S., Valdes, J. F., Terzi, S., Votis, K., ... & Muñoz, L. (2021, June). Boosting IoT data valorization through the adoption of DLT. In 2021 IEEE International Conference on Communications Workshops (ICC Workshops) (pp. 1-5). IEEE. https://doi.org/10.1109/ICCWorkshops50388.2021.9473741
SID155	IEEE	2021	Reátegui, J. L., & Herrera, P. C. (2021, August). Customized IoT devices for the architectural education future in

			connectivity for smart cities. In 2021 2nd Sustainable Cities Latin America Conference (SCLA) (pp. 1-6). IEEE. https://doi.org/10.1109/SCLA53004.2021.9540124
SID156	IEEE	2021	Sharifi, A. Z., Vanijja, V., Pal, D., & Anantasabkit, W. (2021, December). CyberIoT: An initial conceptualization of a web-based cyber range for IoT. In 2021 international conference on computational performance evaluation (comPE) (pp. 091-096). IEEE. https://doi.org/10.1109/ComPE53109.2021.9752401
SID157	IEEE	2021	Alvarenga, I. D., Camilo, G. F., De Souza, L. A., & Duarte, O. C. M. (2021, December). DAGSec: A hybrid distributed ledger architecture for the secure management of the Internet of Things. In 2021 IEEE International Conference on Blockchain (Blockchain) (pp. 266-271). IEEE. https://doi.org/10.1109/Blockchain53845.2021.00043
SID158	IEEE	2021	Rahmantyo, D. T., Erfianto, B., & Satrya, G. B. (2021, September). Deep residual cnn for preventing botnet attacks on the internet of things. In 2021 4th International Conference of Computer and Informatics Engineering (IC2IE) (pp. 462-466). IEEE. https://doi.org/10.1109/IC2IE53219.2021.9649314
SID159	Scopus	2021	Ramanathan, G., Husmann, M., & Mayer, S. (2021, November). Web of Things in Building Automation. In Proceedings of the 11th International Conference on the Internet of Things (pp. 181-184). https://doi.org/10.1145/3494322.3494355
SID160	Scopus	2021	Nagy, S. J., Szabó, R., Vajda, M. L., & Vörös, A. (2021, November). Demonstrator for dependable edge-based cyber-physical systems. In 2021 10th Latin-American Symposium on Dependable Computing (LADC) (pp. 1-8). IEEE. https://doi.org/10.1109/LADC53747.2021.9672569
SID161	IEEE	2021	Bo, L., Zhang, Z., Liu, Y., Zhu, D., & Yue, Y. (2021, December). Design and implementation of an experimental platform for online monitoring of mine water based on the internet of things. In 2021 2nd International Conference on Electronics, Communications and Information Technology (CECIT) (pp. 437-442). IEEE. https://doi.org/10.1109/CECIT53797.2021.00083
SID162	Scopus	2021	Liu, Y., Wang, X., She, X., Yi, M., Li, Y., & Jiang, F. (2021). Design of intelligent mosquito nets based on deep learning algorithms. https://doi.org/10.32604/cmc.2021.015501
SID163	IEEE	2021	Shallari, I., Leal, I. S., Krug, S., Jantsch, A., & O'Nils, M. (2021). Design space exploration for an IoT node: Trade-offs in processing and communication. IEEE Access, 9, 65078-65090. https://doi.org/10.1109/ACCESS.2021.3074875
SID164	IEEE	2021	Saleem, M. U., Usman, M. R., & Shakir, M. (2021). Design, implementation, and deployment of an IoT based smart energy management system. IEEE Access, 9, 59649-59664. https://doi.org/10.1109/ACCESS.2021.3070960
SID165	Scopus	2021	Lopes, S. I., Nunes, L. J., & Curado, A. (2021). Designing an indoor radon risk exposure indicator (IRREI): an evaluation tool for risk management and communication in the IoT age. International journal of environmental research and public health, 18(15), 7907. https://doi.org/10.3390/ijerph18157907
SID166	IEEE	2021	Krishnaswamy, D., Bhardwaj, N., & Srivastava, S. (2021, June). Distc: Distributed quantum-safe consensus for secure iot data processing. In 2021 IEEE International Conference on Communications Workshops (ICC Workshops) (pp. 1-6). IEEE. https://doi.org/10.1109/ICCWorkshops50388.2021.9473875
SID167	IEEE	2021	Michaelides, C., Adame, T., & Bellalta, B. (2021, December). ECTS: Enhanced centralized TSCH scheduling with packet aggregation for Industrial IoT. In 2021 IEEE Conference on Standards for Communications and Networking (CSCN) (pp. 40-45). IEEE. https://doi.org/10.1109/CSCN53733.2021.9686162
SID168	Scopus	2021	Yuhas, M., Feng, Y., Ng, D. J. X., Rahiminasab, Z., & Easwaran, A. (2021, May). Embedded out-of-distribution detection on an autonomous robot platform. In Proceedings of the Workshop on Design Automation for CPS and IoT (pp. 13-18). https://doi.org/10.1145/3445034.3460509
SID169	IEEE / Scopus	2021	Zonios, C., & Tenentes, V. (2021, July). Energy efficient speech command recognition for private smart home iot applications. In 2021 10th International Conference on Modern Circuits and Systems Technologies (MOCAST) (pp. 1-4). IEEE. https://doi.org/10.1109/MOCAST52088.2021.9493392
SID170	Scopus	2021	Găitan, V. G., & Zagan, I. (2021). Experimental implementation and performance evaluation of an IoT access gateway for the modbus extension. Sensors, 21(1), 246. https://doi.org/10.3390/s21010246
SID171	Scopus	2021	Medjek, F., Tandjaoui, D., Djedjig, N., & Romdhani, I. (2021). Fault-tolerant AI-driven intrusion detection system for the internet of things. International Journal of Critical Infrastructure Protection, 34, 100436. https://doi.org/10.1016/j.ijcip.2021.100436
SID172	Scopus	2021	Lilli, M., Braghin, C., & Riccobene, E. (2021, July). Formal Proof of a Vulnerability in Z-Wave IoT Protocol. In SECRYPT (pp. 198-209). https://doi.org/10.5220/0010553301980209
SID173	IEEE	2021	Tehseen, A., Zafar, N. A., & Ali, T. (2021, September). Graph Theory-Based Formal Modeling of Forest Fire Management System using IoT and Drone. In 2021 International Conference on Communication Technologies (ComTech) (pp. 132-137). IEEE. https://doi.org/10.1109/ComTech52583.2021.9616876
SID174	Springer	2021	Howard, D. A., Ma, Z., Veje, C., Clausen, A., Aaslyng, J. M., & Jørgensen, B. N. (2021). Greenhouse industry 4.0–digital twin technology for commercial greenhouses. Energy Informatics, 4, 1-13. https://doi.org/10.1186/s42162-021-00161-9
SID175	IEEE	2021	Sanchez-Gomez, J., Marin-Perez, R., Ross, M., & Gomez, A. F. S. (2021, August). Holistic IoT architecture for secure lightweight communication, firmware update, and trust monitoring. In 2021 IEEE International Conference on Smart Internet of Things (SmartIoT) (pp. 353-358). IEEE. https://doi.org/10.1109/SmartIoT52359.2021.00066
SID176	Scopus	2021	Song, Q., & Li, L. (2021). Home Robot Control System Based on Internet of Things and Fuzzy Control. Mobile Information Systems, 2021(1), 9409556. https://doi.org/10.1155/2021/9409556
SID177	Scopus	2021	Noura, M., Gyrard, A., Klotz, B., Troncy, R., Datta, S. K., & Gaedke, M. (2021). How to Understand Better "Smart Vehicle"? Knowledge Extraction for the Automotive Sector Using Web of Things. Semantic IoT: Theory and Applications: Interoperability, Provenance and Beyond, 303-321. https://doi.org/10.1007/978-3-030-64619-6_13
SID178	Springer	2021	Qin, J., Li, Z., Wang, R., Li, L., Yu, Z., He, X., & Liu, Y. (2021). Industrial Internet of Learning (IIoL): IIoT based pervasive knowledge network for LPWAN—concept, framework and case studies. CCF Transactions on Pervasive Computing and Interaction, 3(1), 25-39. https://doi.org/10.1007/s42486-020-00050-2
SID179	IEEE	2021	AI-Okby, M. F. R., Neubert, S., Roddelkopf, T., & Thurow, K. (2021, November). Integration and testing of novel MOX gas sensors for IoT-based indoor air quality monitoring. In 2021 IEEE 21st International Symposium on Computational Intelligence and Informatics (CINTI) (pp. 000173-000180). IEEE. https://doi.org/10.1109/CINTI53070.2021.9668462
SID180	Scopus	2021	Shakeel, P. M., Baskar, S., Fouad, H., Manogaran, G., Saravanan, V., & Montenegro-Marin, C. E. (2021). Internet of things forensic data analysis using machine learning to identify roots of data scavenging. Future Generation Computer Systems, 115, 756-768. https://doi.org/10.1016/j.future.2020.10.001

SID181	IEEE	2021	Mir, M. N. H., Kayesh, N. I., Khan, T. M., & Sattar, A. (2021, March). IoT based digital toll collection system: A perspective. In 2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS) (pp. 1406-1410). IEEE. https://doi.org/10.1109/ICAIS50930.2021.9395996
SID182	IEEE	2021	Shafi, M. K. I., Sultan, M. R., Rahman, S. M. M., & Hoque, M. M. (2021, December). IoT based smart home: a machine learning approach. In 2021 24th International Conference on Computer and Information Technology (ICCIT) (pp. 1-6). IEEE. https://doi.org/10.1109/ICCIT54785.2021.9689786
SID183	IEEE	2021	Rai, R. S., Indumathi, S. K., Pritima, D., & Rani, S. S. (2021, November). IoT secure framework for wearable sensor data for e-health system. In 2021 Fifth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC) (pp. 211-215). IEEE. https://doi.org/10.1109/I-SMAC52330.2021.9640977
SID184	Scopus	2021	Gupta, A., & Al-Anbuky, A. (2021). IoT-based patient movement monitoring: the post-operative hip fracture rehabilitation model. Future Internet, 13(8), 195. https://doi.org/10.3390/fi13080195
SID185	IEEE	2021	Pal, P., Parvathy, A. K., Devabalaji, K. R., Antony, S. J., Ocheme, S., Babu, T. S., ... & Yuvaraj, T. (2021). IoT-based real time energy management of virtual power plant using PLC for Transactive energy framework. IEEE Access, 9, 97643-97660. https://doi.org/10.1109/ACCESS.2021.3093111
SID186	Scopus	2021	Sekine, H., Kanai, K., Katto, J., Kanemitsu, H., & Nakazato, H. (2021, January). Iot-centric service function chainingorchestration and its performance validation. In 2021 IEEE 18th Annual Consumer Communications & Networking Conference (CCNC) (pp. 1-4). IEEE. https://doi.org/10.1109/CCNC49032.2021.9369538
SID187	IEEE / Scopus	2021	Baccarelli, E., Scarpiniti, M., Momenzadeh, A., & Ahrabi, S. S. (2021). Learning-in-the-fog (LiFo): Deep learning meets fog computing for the minimum-energy distributed early-exit of inference in delay-critical IoT realms. IEEE Access, 9, 25716-25757. https://doi.org/10.1109/ACCESS.2021.3058021
SID188	Scopus	2021	Zaric, N., Spalevic, V., Bulatovic, N., Pavlicevic, N., & Dudic, B. (2021). Measurement of air pollution parameters in montenegro using the ecomar system. International Journal of Environmental Research and Public Health, 18(12), 6565. https://doi.org/10.3390/ijerph18126565
SID189	IEEE	2021	Lawson, V. J., & Banerjee, M. (2021, November). Measuring the Impact of an IoT Temperature Sensor Framework for Tracking Contagious Diseases. In 2021 IEEE 5th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE) (pp. 332-337). IEEE. https://doi.org/10.1109/ICITISEE53823.2021.9655853
SID190	Springer	2021	Yin, Y., Lin, J., Sun, N., Zhu, Q., Zhang, S., Zhang, Y., & Liu, M. (2021). Method for detection of unsafe actions in power field based on edge computing architecture. Journal of Cloud Computing, 10, 1-14. https://doi.org/10.1186/s13677-021-00234-w
SID191	Springer	2021	Ullah, A., Dagdeviren, H., Ariyattu, R. C., DesLauriers, J., Kiss, T., & Bowden, J. (2021). Micado-edge: Towards an application-level orchestrator for the cloud-to-edge computing continuum. Journal of Grid Computing, 19(4), 47. https://doi.org/10.1007/s10723-021-09589-5
SID192	IEEE / Scopus	2021	Sharanappa, P. H., & Kakkasageri, M. S. (2021, October). Multiagent based Information Validation Scheme in Internet of Things. In 2021 International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON) (pp. 1-5). IEEE. https://doi.org/10.1109/SMARTGENCON51891.2021.9645776
SID193	IEEE	2021	da Silveira, J. D. F., Martins, T. R., da Silva, C. N., & dos Reis, J. V. (2021, July). New solution based on fuzzy system for planning iot communication infrastructure for rural areas. In 2021 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE) (pp. 1-6). IEEE. https://doi.org/10.1109/FUZZ45933.2021.9494578
SID194	IEEE	2021	Gabsi, S., Kortli, Y., Beroulle, V., Kieffer, Y., Alasiry, A., & Hamdi, B. (2021). Novel ECC-based RFID mutual authentication protocol for emerging IoT applications. IEEE access, 9, 130895-130913. https://doi.org/10.1109/ACCESS.2021.3112554
SID195	Springer	2021	Klikovits, S., & Buchs, D. (2021). Pragmatic reuse for DSML development: Composing a DSL for hybrid CPS modeling. Software and Systems Modeling, 20(3), 837-866. https://doi.org/10.1007/s10270-020-00831-4
SID196	IEEE	2021	Atitallah, N., Hakim, H., & Abid, M. (2021, June). Prototyping of an efficient and energy-aware IoT-based sensor node for water pipeline monitoring. In 2021 International Wireless Communications and Mobile Computing (IWCMC) (pp. 2115-2120). IEEE. https://doi.org/10.1109/IWCMC51323.2021.9498932
SID197	Springer	2021	Calvaresi, D., Dicente Cid, Y., Marinoni, M., Dragoni, A. F., Najjar, A., & Schumacher, M. (2021). Real-time multi-agent systems: rationality, formal model, and empirical results. Autonomous agents and multi-agent systems, 35(1), 12. https://doi.org/10.1007/s10458-020-09492-5
SID198	Scopus	2021	Darvishi, H., Ciuonzo, D., & Rossi, P. S. (2021, December). Real-time sensor fault detection, isolation and accommodation for industrial digital twins. In 2021 IEEE International Conference on Networking, Sensing and Control (ICNSC) (Vol. 1, pp. 1-6). IEEE. https://doi.org/10.1109/ICNSC52481.2021.9702175
SID199	Springer	2021	Ngamboé, M., Berthier, P., Ammari, N., Dyrda, K., & Fernandez, J. M. (2021). Risk assessment of cyber-attacks on telemetry-enabled cardiac implantable electronic devices (CIED). International Journal of Information Security, 20, 621-645. https://doi.org/10.1007/s10207-020-00522-7
SID200	Scopus	2021	Priya, V., Thaseen, I. S., Gadekallu, T. R., Aboudaif, M. K., & Nasr, E. A. (2021). Robust attack detection approach for IIoT using ensemble classifier. arXiv preprint arXiv:2102.01515. https://doi.org/10.32604/cmc.2021.013852
SID201	Springer	2021	Howell, S., Beach, T., & Rezgui, Y. (2021). Robust requirements gathering for ontologies in smart water systems. Requirements Engineering, 26(1), 97-114. https://doi.org/10.1007/s00766-020-00335-z
SID202	Scopus	2021	Shi, M., Chen, Q., Li, H., Wei, G., Yang, X., & Wang, H. (2021, May). SD-MIRS: SDN-based Multi-Identifier Routing Strategy. In Proceedings of the 2021 2nd International Conference on Computing, Networks and Internet of Things (pp. 1-6). https://doi.org/10.1145/3468691.3468695
SID203	IEEE	2021	Shodiq, F. A., Pahlevi, R. R., & Sukarno, P. (2021, December). Secure mqtt authentication and message exchange methods for iot constrained device. In 2021 International Conference on Intelligent Cybernetics Technology & Applications (ICICyTA) (pp. 70-74). IEEE. https://doi.org/10.1109/ICICyTA53712.2021.9689126
SID204	Springer	2021	Risco, S., Moltó, G., Naranjo, D. M., & Blanquer, I. (2021). Serverless workflows for containerised applications in the cloud continuum. Journal of Grid Computing, 19, 1-18. https://doi.org/10.1007/s10723-021-09570-2
SID205	Scopus	2021	Zhao, Y., Ge, S., & Feng, Y. (2021). RETRACTED: Smart IoT data platform in hospital and postoperative analgesic effects of orthopedic patients. https://doi.org/10.1016/j.micpro.2020.103653

SID206	Scopus	2021	Bertoli, A., Cervo, A., Rosati, C. A., & Fantuzzi, C. (2021). Smart node networks orchestration: a new e2e approach for analysis and design for agile 4.0 implementation. Sensors, 21(5), 1624. https://doi.org/10.3390/s21051624
SID207	Springer	2021	Yan, Z., Cao, W., & Ji, J. (2021). Social behavior prediction with graph U-Net+. Discover Internet of Things, 1, 1-18. https://doi.org/10.1007/s43926-021-00018-3
SID208	Springer	2021	Ferrara, P., Mandal, A. K., Cortesi, A., & Spoto, F. (2021). Static analysis for discovering IoT vulnerabilities. International Journal on Software Tools for Technology Transfer, 23(1), 71-88. https://doi.org/10.1007/s10009-020-00592-x
SID209	IEEE	2021	Hasan, D., & Driss, M. (2021, November). SUBLμME: Secure blockchain as a service and microservices-based framework for IoT environments. In 2021 IEEE/ACS 18th International Conference on Computer Systems and Applications (AICCSA) (pp. 1-9). IEEE. https://doi.org/10.1109/AICCSA53542.2021.9686757
SID210	IEEE	2021	Silva, H. D. A., Adriano, E., Scatolini, D., & Braga, R. T. V. (2021, June). Supporting IoT-based applications to combat the Aedes aegypti mosquito: a case in Brazil. In 2021 IEEE 34th International Symposium on Computer-Based Medical Systems (CBMS) (pp. 330-335). IEEE. https://doi.org/10.1109/CBMS52027.2021.00029
SID211	Springer	2021	Li, Z., Millar-Bilbao, F., Rojas-Durán, G., & Ladra, S. (2021). Take one for the team: on the time efficiency of application-level buffer-aided relaying in edge cloud communication. Journal of Cloud Computing, 10, 1-18. https://doi.org/10.1186/s13677-021-00241-x
SID212	Scopus	2021	Pop, P., Zarrin, B., Barzegaran, M., Schulte, S., Punnekkat, S., Ruh, J., & Steiner, W. (2021). The FORA fog computing platform for industrial IoT. Information Systems, 98, 101727. https://doi.org/10.1016/j.is.2021.101727
SID213	Springer	2021	Tusa, F., & Clayman, S. (2021). The impact of encoding and transport for massive real-time IoT data on edge resource consumption. Journal of Grid Computing, 19(3), 32. https://doi.org/10.1007/s10723-021-09577-9
SID214	IEEE	2021	Bălăceanu, C., Negoiță, A., Drăgulinescu, A. M., Roșcăneanu, R., Chedea, V. S., & Suciu, G. (2021, May). The use of IoT technology in Smart Viticulture. In 2021 23rd International Conference on Control Systems and Computer Science (CSCS) (pp. 362-369). IEEE. https://doi.org/10.1109/CSCS52396.2021.00066
SID215	Springer	2021	Tomarchio, O., Calcaterra, D., Di Modica, G., & Mazzaglia, P. (2021). Torch: a tosca-based orchestrator of multi-cloud containerised applications. Journal of Grid Computing, 19(1), 5. https://doi.org/10.1007/s10723-021-09549-z
SID216	Scopus	2021	Sudharsan, B., Patel, P., Breslin, J., Ali, M. I., Mitra, K., Dustdar, S., ... & Ranjan, R. (2021). Toward distributed, global, deep learning using iot devices. IEEE Internet Computing, 25(3), 6-12. https://doi.org/10.1109/MIC.2021.3053711
SID217	Springer	2021	Sirjani, M., Provenzano, L., Asadollah, S. A., Moghadam, M. H., & Saadatmand, M. (2021). Towards a verification-driven iterative development of software for safety-critical cyber-physical systems. Journal of Internet Services and Applications, 12(1), 2. https://doi.org/10.1186/s13174-021-00132-z
SID218	IEEE	2021	Agajo, J., Thomas, S., Gafai, N., Lukman, A. A., Obadiah, N. A., & Okafor, K. C. (2021, July). Towards Prediction model for iot-wireless sensor network packet transmission using soft computing technique. In 2021 1st International Conference on Multidisciplinary Engineering and Applied Science (ICMEAS) (pp. 1-4). IEEE. https://doi.org/10.1109/ICMEAS52683.2021.9692316
SID219	IEEE	2021	Boutot, P., Tabassum, M. R., & Mustafiz, S. (2021, October). UCM4IoT: A use case modelling environment for IoT systems. In 2021 ACM/IEEE International Conference on Model Driven Engineering Languages and Systems Companion (MODELS-C) (pp. 767-776). IEEE. https://doi.org/10.1109/MODELS-C53483.2021.00123
SID220	Scopus	2021	Kaur, B., Dadkhah, S., Xiong, P., Iqbal, S., Ray, S., & Ghorbani, A. A. (2021, December). Verification based scheme to restrict iot attacks. In Proceedings of the 2021 IEEE/ACM 8th International Conference on Big Data Computing, Applications and Technologies (pp. 63-68). https://doi.org/10.1145/3492324.3494170
SID221	IEEE	2022	da Silva, D. C., de Sousa, M. A. F., Bressan, G., & Silveira, R. M. (2022). 5G network slice selector in IoT services scenarios with QoS requirements guarantee. 2022 IEEE Wireless Communications and Networking Conference (WCNC) (pp. 90–95). IEEE. https://doi.org/10.1109/WCNC51071.2022.9771744
SID222	Springer	2022	Marchese, A., & Tomarchio, O. (2022). A blockchain-based system for agri-food supply chain traceability management. SN Computer Science, 3, 279. https://doi.org/10.1007/s42979-022-01148-3
SID223	IEEE	2022	Cheng, X., Tian, W., Shi, F., Zhao, M., Chen, S., & Wang, H. (2022). A blockchain-empowered cluster-based federated learning model for blade icing estimation on IoT-enabled wind turbine. IEEE Transactions on Industrial Informatics, 18(12), 9184–9195. https://doi.org/10.1109/TII.2022.3159684
SID224	IEEE	2022	Al-Maani, M., Frisbie, G., Shippy, F., Tiseo, M., Darwish, O., & Abualkibash, M. (2022). A classifier to detect number of machines performing DoS attack against Arduino Oplà device in IoT environment. In 2022 5th International Conference on Advanced Communication Technologies and Networking (CommNet) (pp. 1–9). IEEE. https://doi.org/10.1109/CommNet56067.2022.9993816
SID225	IEEE	2022	Ahluwalia, J. K., Mouradian, C., Alam, M. N., & Glitho, R. H. (2022). A cloud infrastructure as a service for an efficient usage of sensing and actuation capabilities in Internet of Things. In Proceedings of the 2022 IEEE/IFIP Network Operations and Management Symposium (NOMS) (pp. 1–6). IEEE. https://doi.org/10.1109/NOMS54207.2022.9789805
SID226	Springer	2022	Coccoli, M., De Francesco, V., Fusco, A., & Maresca, P. (2022). A cloud-based cognitive computing solution with interoperable applications to counteract illegal dumping in smart cities. Multimedia Tools and Applications, 81, 95–113. https://doi.org/10.1007/s11042-021-11238-8
SID227	IEEE	2022	Nagdewani, H., & Mehra, P. S. (2022). A complete Internet of Things based home security system. In 2022 Second International Conference on Computer Science, Engineering and Applications (ICCSEA) (pp. 348–352). IEEE. https://doi.org/10.1109/ICCSEA54677.2022.9936168
SID228	IEEE / Scopus	2022	Yin, F., & Fu, Z. (2022). A data provenance scheme based on blockchain for Internet of Things. In 2022 2nd International Conference on Computer Science and Blockchain (CCSB) (pp. 42–45). IEEE. https://doi.org/10.1109/CCSB58128.2022.00014
SID229	IEEE	2022	Avadut, S., & Udgata, S. K. (2022). A deep learning based IoT framework for assistive healthcare using gesture based interface. In 2022 IEEE International Conference on Internet of Things and Intelligence Systems (IoTaIS) (pp. 6–12). IEEE. https://doi.org/10.1109/IoTaIS56727.2022.9975885
SID230	IEEE	2022	Arunprathap, S., Nithya, R., & Nivetha, S. (2022, May). A Fog Computing Architecture Integrating Blockchain and Internet of Things for Securing Bank Accounts. In 2022 International Conference on Applied Artificial Intelligence and Computing (ICAAIC) (pp. 1326-1330). IEEE. https://doi.org/10.1109/ICAAIC53929.2022.9792983
SID231	Springer	2022	Zschörnig, T., Windolph, J., Wehlitz, R., Dumont, Y., & Franczyk, B. (2022). A fog-based multi-purpose Internet of Things

			analytics platform. SN Computer Science, 3, Article 213. https://doi.org/10.1007/s42979-022-01110-3
SID232	Scopus	2022	Nyangaresi, V. O., & Ma, J. (2022). A formally verified message validation protocol for intelligent IoT e-health systems. In 2022 IEEE World Conference on Applied Intelligence and Computing (AIC) (pp. 416–422). IEEE. https://doi.org/10.1109/AIC55036.2022.9848874
SID233	IEEE	2022	Bhattacharya, P., Patel, K., Zuhair, M., & Trivedi, C. (2022). A lightweight authentication via unclonable functions for Industrial Internet-of-Things. In 2022 2nd International Conference on Innovative Practices in Technology and Management (ICIPTM) (pp. 657–662). IEEE. https://doi.org/10.1109/ICIPTM54933.2022.9754198
SID234	Springer	2022	Pérez-Castillo, R., Delgado, A., Ruiz, F., Bacigalupe, V., & Piattini, M. (2022). A method for transforming knowledge discovery metamodel to ArchiMate models. Software And Systems Modeling, 1-26. https://doi.org/10.1007/s10270-021-00912-y
SID235	Scopus / WoS	2022	Aldalur, I., Arrieta, A., Agirre, A., Sagardui, G., & Arratibel, M. (2024). A microservice-based framework for multi-level testing of cyber-physical systems. Software Quality Journal, 32(1), 193-223. https://doi.org/10.1007/s11219-023-09639-z
SID236	Springer	2022	Lin, J., Xie, D., Huang, J., Liao, Z., & Ye, L. (2022). A multi-dimensional extensible cloud-native service stack for enterprises. Journal of Cloud Computing, 11(1), 83. https://doi.org/10.1186/s13677-022-00366-7
SID237	Scopus	2022	Fatimah, B., Singhal, A., & Singh, P. (2022). A multi-modal assessment of sleep stages using adaptive Fourier decomposition and machine learning. Computers in Biology and Medicine, 148, 105877. https://doi.org/10.1016/j.compbiomed.2022.105877
SID238	Springer	2022	Pang, J., Wang, S., Tang, Z., Qin, Y., Tao, X., You, X., & Zhu, J. (2022). A new 5G radio evolution towards 5G-Advanced. Science China Information Sciences, 65(9), 191301. https://doi.org/10.1007/s11432-021-3470-1
SID239	Scopus	2022	Bahaa, A., Sayed, A., Elfangary, L., & Fahmy, H. (2022). A novel hybrid optimization enabled robust CNN algorithm for an IoT network intrusion detection approach. Plos one, 17(12), e0278493. https://doi.org/10.1371/journal.pone.0278493
SID240	IEEE	2022	Shang, S., Li, X., Lu, R., Niu, J., Zhang, X., & Guizani, M. (2022). A privacy-preserving multidimensional range query scheme for edge-supported industrial IoT. IEEE Internet of Things Journal, 9(16), 15285-15296. https://doi.org/10.1109/JIOT.2022.3149638
SID241	Springer	2022	Muschalik, M., Fumagalli, F., Hammer, B., & Hüllermeier, E. (2022). Agnostic explanation of model change based on feature importance. KI-Künstliche Intelligenz, 36(3), 211-224. https://doi.org/10.1007/s13218-022-00766-6
SID242	IEEE / Scopus	2022	Dutta, J., Puthal, D., & Damiani, E. (2022, December). Ai-based block identification and classification in the blockchain integrated iot. In 2022 OITS International Conference on Information Technology (OCIT) (pp. 415-421). IEEE. https://doi.org/10.1109/OCIT56763.2022.00084
SID243	IEEE	2022	Almeida, E. M., Peres, L. M., & L'Erario, A. (2022, October). An Approach to Use Comic Strips To Support IoT Systems Requirements Engineering. In 2022 IEEE Frontiers in Education Conference (FIE) (pp. 1-6). IEEE. https://doi.org/10.1109/FIE56618.2022.9962579
SID244	Scopus	2022	Puli, S., & Chaparala, S. C. (2022). An efficient swift routing model with node trust identity factor (SRM-NTIF) to perform secure data transmission among IoT gadgets. Revue d'Intelligence Artificielle, 36(1), 31. https://doi.org/10.18280/ria.360104
SID245	IEEE	2022	Passos, J. M., Lopes, S. I., Moreira, P. M., Clemente, F. M., Bezerra, P., Silva, R., & Rodrigues, L. P. (2022, July). An IoT-enabled Portable System for Field-based Endurance Run Testing. In 2022 IEEE International Workshop on Sport, Technology and Research (STAR) (pp. 7-12). IEEE. https://doi.org/10.1109/STAR53492.2022.9859636
SID246	Scopus	2022	Muhammad, Y., Almoteri, M., Mujlid, H., Alharbi, A., Alqurashi, F., Dutta, A. K., ... & Almohamedh, H. (2022). [Retracted] An ML-Enabled Internet of Things Framework for Early Detection of Heart Disease. BioMed research international, 2022(1), 3372296. https://doi.org/10.1155/2022/3372296
SID247	IEEE	2022	Pallivalappil, A. S., Ahmad, S. S., Raju, Y., Kumar, C. K., & Krishnaiah, N. (2022, April). Applications of Ensuring Security and Privacy Using Block Chain with IoT for Health Record. In 2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE) (pp. 1911-1917). IEEE. https://doi.org/10.1109/ICACITE53722.2022.9823735
SID248	IEEE	2022	Vangala, A., Roy, S., & Das, A. K. (2022, November). Blockchain-based lightweight authentication protocol for IoT-enabled smart agriculture. In 2022 International Conference on Cyber-Physical Social Intelligence (ICCSI) (pp. 110-115). IEEE. https://doi.org/10.1109/ICCSI55536.2022.9970603
SID249	Springer	2022	Khan, K. M., Arshad, J., Iqbal, W., Abdullah, S., & Zaib, H. (2022). Blockchain-enabled real-time SLA monitoring for cloud-hosted services. Cluster Computing, 1-23. https://doi.org/10.1007/s10586-021-03416-y
SID250	IEEE	2022	Feng, H., Cui, Z., & Yang, T. (2022, March). Cache optimization strategy for mobile edge computing in maritime IoT. In 2022 5th Conference on Cloud and Internet of Things (CIoT) (pp. 213-219). IEEE. https://doi.org/10.1109/CIoT53061.2022.9766604
SID251	IEEE / Scopus	2022	Ullah, I., Alomari, A., Abdullah, A. M., Kumar, N., Alsirhani, A., Noor, F., ... & Khan, M. A. (2022). Certificate-based signcryption scheme for securing wireless communication in industrial internet of things. IEEE Access, 10, 105182-105194. https://doi.org/10.1109/ACCESS.2022.3211257
SID252	IEEE	2022	Sharma, A. (2022, September). Civic centered heuristic early warning system fashioned using artificial intelligence and Internet of Things. In 2022 Second International Conference on Computer Science, Engineering and Applications (ICCSEA) (pp. 1-6). IEEE. https://doi.org/10.1109/ICCSEA54677.2022.9936300
SID253	Scopus	2022	Haq, A. U., Li, J. P., Khan, I., Agbley, B. L. Y., Ahmad, S., Uddin, M. I., ... & Alam, I. (2022). DEBCM: deep learning-based enhanced breast invasive ductal carcinoma classification model in IoMT healthcare systems. IEEE Journal of Biomedical and Health Informatics, 28(3), 1207-1217. https://doi.org/10.1109/JBHI.2022.3228577
SID254	Springer	2022	Zampognaro, P., Paragliola, G., & Falanga, V. (2022). Definition of an FHIR-based multiprotocol IoT home gateway to support the dynamic plug of new devices within instrumented environments. Journal of Reliable Intelligent Environments, 1-13. https://doi.org/10.1007/s40860-021-00161-2
SID255	Scopus	2022	Melero-Muñoz, F. J., Bueno-Delgado, M. V., Martínez-Carreras, R., Maestre-Ferriz, R., Beteta-Medina, M. Á., Puebla-Martínez, T., ... & Álvarez-Leon, M. (2022). Design and development of a heterogeneous active assisted living solution for monitoring and following up with chronic heart failure patients in Spain. Sensors, 22(22), 8961. https://doi.org/10.3390/s22228961
SID256	IEEE	2022	Silapunt, R., Panpanyatep, W., & Boonsothonsatit, G. (2022, March). Design and development of the smart object for the

			IoT-enabled smart warehouse. In 2022 International Electrical Engineering Congress (iEECON) (pp. 1-4). IEEE. https://doi.org/10.1109/iEECON53204.2022.9741566
SID257	IEEE	2022	Bhavani, G. L., Ramu, M., Gupta, S., Akula, S. P., Gomathi, S., & Yadav, A. (2022, April). Development and Performance Evaluation of a Blockchain Associated E-Voting System in IoT-Enabled Smart-Cities. In 2022 3rd International Conference on Intelligent Engineering and Management (ICIEM) (pp. 935-941). IEEE. https://doi.org/10.1109/ICIEM54221.2022.9853068
SID258	IEEE	2022	Al Momani, M. M. A., & Puttaswamy, P. S. (2022, December). Development of Secured Authentication Contract Communication Network Protocol for IoT Environment. In 2022 Fourth International Conference on Emerging Research in Electronics, Computer Science and Technology (ICERECT) (pp. 1-6). IEEE. https://doi.org/10.1109/ICERECT56837.2022.10060005
SID259	Springer	2022	Pérez, J., Díaz, J., Berrocal, J., López-Viana, R., & González-Prieto, A. (2022). Edge computing: A grounded theory study. Computing, 104(12), 2711-2747. https://doi.org/10.1007/s00607-022-01104-2
SID260	IEEE	2022	Amutha, R., Damodar, N., Sivasankari, G. G., & Kalshetty, J. N. (2022, October). Embedded Based Health Monitoring Secure System on IoT with Artificial Intelligence. In 2022 IEEE 2nd Mysore Sub Section International Conference (MysuruCon) (pp. 1-8). IEEE. https://doi.org/10.1109/MysuruCon55714.2022.9972696
SID261	IEEE	2022	Guo, X., & Wu, X. (2022, October). Entrepreneurial Optimization Sharing Platform Based on IoT and AI Algorithms. In 2022 International Conference on Artificial Intelligence of Things and Crowdsensing (AIoTCs) (pp. 250-255). IEEE. https://doi.org/10.1109/AIoTCs58181.2022.00045
SID262	ACM	2022	Hakim, I. M., Singgih, M. L., & Gunarta, I. K. (2022, September). Evaluating critical success factors for implementation of internet of things (IoT) using DEMATEL: A case of Indonesian automotive company. In Proceedings of the 2022 international conference on engineering and information technology for sustainable industry (pp. 1-7). https://doi.org/10.1145/3557738.3557867
SID263	Scopus	2022	Mehta, M., & Patel, K. (2022). Experimental study of location spoofing and identity spoofing attack in internet of things network. International Journal of Intelligent Information Technologies (IJIIT), 18(3), 1-13. https://doi.org/10.4018/IJIIT.309587
SID264	IEEE / Scopus	2022	Cardenas, H., Zimmerman, R., Viesca, A. R., Al Lail, M., & Perez, A. J. (2022, October). Formal UML-based modeling and analysis for securing location-based IoT applications. In 2022 IEEE 19th International Conference on Mobile Ad Hoc and Smart Systems (MASS) (pp. 722-723). IEEE. https://doi.org/10.1109/MASS56207.2022.00109
SID265	IEEE / Scopus	2022	Erfan, F., Bellaiche, M., & Halabi, T. (2022, August). Game-theoretic designs for blockchain-based iot: Taxonomy and research directions. In 2022 IEEE International Conference on Decentralized Applications and Infrastructures (DAPPS) (pp. 27-37). IEEE. https://doi.org/10.1109/DAPPS55202.2022.00012
SID266	IEEE	2022	Pour, M. S., Khoury, J., & Bou-Harb, E. (2022, April). HoneyComb: A darknet-centric proactive deception technique for curating IoT malware forensic artifacts. In NOMS 2022-2022 IEEE/IFIP Network Operations and Management Symposium (pp. 1-9). IEEE. https://doi.org/10.1109/NOMS54207.2022.9789827
SID267	IEEE	2022	Basso, A., Bortoluzzi, D., & Torta, G. (2022, September). Implementation of an iot wearable prototype on a standard ai architecture. In 2022 IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress (DASC/PiCom/CBDCom/CyberSciTech) (pp. 1-5). IEEE. https://doi.org/10.1109/DASC/PiCom/CBDCom/Cy55231.2022.9927767
SID268	IEEE	2022	Li, M., Hollifield, S. C., & Iannacone, M. D. (2023, October). Incremental threshold scheme enabled iot group key management. In 2023 7th Cyber Security in Networking Conference (CSNet) (pp. 123-129). IEEE. https://doi.org/10.1109/CSNet59123.2023.10339701
SID269	Springer	2022	Burzagli, L., Emiliani, P. L., Antona, M., & Stephanidis, C. (2022). Intelligent environments for all: a path towards technology-enhanced human well-being. Universal access in the information society, 1-20. https://doi.org/10.1007/s10209-021-00797-0
SID270	IEEE	2022	Anindya, D. S., Yuliana, M., & Hadi, M. Z. S. (2022, August). IoT Based Climate Prediction System Using Long Short-Term Memory (LSTM) Algorithm as Part of Smart Farming 4.0. In 2022 International Electronics Symposium (IES) (pp. 255-260). IEEE. https://doi.org/10.1109/IES55876.2022.9888486
SID271	IEEE	2022	Mohapatra, H., & Dalai, A. K. (2022, February). IoT based V2I framework for accident prevention. In 2022 2nd international conference on artificial intelligence and signal processing (AISP) (pp. 1-4). IEEE. https://doi.org/10.1109/AISP53593.2022.9760623
SID272	IEEE	2022	Ribeiro, F., Metrôlho, J., & Cabral, S. (2022, June). IoT technologies to promote tourism experiences in low-density territories. In 2022 17th Iberian conference on information systems and technologies (CISTI) (pp. 1-7). IEEE. https://doi.org/10.23919/CISTI54924.2022.9820237
SID273	IEEE	2022	Kirikkayis, Y., Gallik, F., & Reichert, M. (2022, May). IoTDM4BPMN: an IoT-enhanced decision making framework for BPMN 2.0. In 2022 International Conference on Service Science (ICSS) (pp. 88-95). IEEE. https://doi.org/10.1109/ICSS55994.2022.00022
SID274	Scopus	2022	Patel, C., & Doshi, N. (2022). LDA-IoT: a level dependent authentication for IoT paradigm. Information Security Journal: A Global Perspective, 31(6), 629-656. https://doi.org/10.1080/19393555.2021.1931573
SID275	IEEE	2022	Mueller, S., Plociennik, M., Zacharczuk, M., Fojud, A., Blaszczak, M., Laskowska, A., ... & Wojtowicz, A. (2022, August). Leveraging IoT solutions as a base for development of the agriculture advisory services. In 2022 IEEE International Conference on Omni-layer Intelligent Systems (COINS) (pp. 1-6). IEEE. https://doi.org/10.1109/COINS54846.2022.9854950
SID276	Scopus	2022	Ali, J., Zafar, M. H., Hewage, C., Hassan, R., & Asif, R. (2022). Mathematical modeling and validation of retransmission-based mutant MQTT for improving quality of service in developing smart cities. Sensors, 22(24), 9751. https://doi.org/10.3390/s22249751
SID277	IEEE	2022	Neves, J., Postolache, O., Monge, J., & Pereira, J. M. D. (2022, November). Mixed Reality and IoT for Physical Rehabilitation. In 2022 E-Health and Bioengineering Conference (EHB) (pp. 01-06). IEEE. https://doi.org/10.1109/EHB55594.2022.9991681
SID278	Springer	2022	Gómez, A., Iglesias-Urkia, M., Belategi, L., Mendialdua, X., & Cabot, J. (2022). Model-driven development of asynchronous message-driven architectures with AsyncAPI. Software and Systems Modeling, 1-29.

			https://doi.org/10.1007/s10270-021-00945-3
SID279	Scopus	2022	Kang, E. Y., Brix, M., Szenczi, D., Kováts, Á., Formosa, R., Melsen, C. W., & Nørgård, M. A. (2022, November). Model-driven software development approach: Ensuring safety of an iot-based plant health monitoring system. In 2022 6th International Conference on System Reliability and Safety (ICSRS) (pp. 251-258). IEEE. https://doi.org/10.1109/ICSRS56243.2022.10067493
SID280	IEEE	2022	Ghosh, A., Misra, S., & Udutalapally, V. (2022). Multiobjective optimization and sensor correlation framework for IoT data validation. IEEE Sensors Journal, 22(23), 23581-23589. https://doi.org/10.1109/JSEN.2022.3215993
SID281	Springer	2022	Di Ciccio, C., Meroni, G., & Plebani, P. (2022). On the adoption of blockchain for business process monitoring. Software and Systems Modeling, 21(3), 915-937. https://doi.org/10.1007/s10270-021-00959-x
SID282	IEEE	2022	Roy, S., Das, D., Mondal, A., Mahalat, M. H., Sen, B., & Sikdar, B. (2022). PLAKE: PUF-based secure lightweight authentication and key exchange protocol for IoT. IEEE Internet of Things Journal, 10(10), 8547-8559. https://doi.org/10.1109/JIOT.2022.3202265
SID283	IEEE	2022	Vieira, D. F., & Júnior, H. G. (2022, October). Public Transportation passengers accounting at university by IoT device. In 2022 Symposium on Internet of Things (SIoT) (pp. 1-5). IEEE. https://doi.org/10.1109/SIoT56383.2022.10070138
SID284	IEEE	2022	Tan, C., Wang, P., Zhang, J., Bai, S., Zhang, Z., & Sun, H. (2022, April). Research and Application of Low-Voltage Smart Circuit Breaker for Power Distribution Internet of Things. In 2022 5th International Conference on Energy, Electrical and Power Engineering (CEEPE) (pp. 182-186). IEEE. https://doi.org/10.1109/CEEPE55110.2022.9783443
SID285	IEEE	2022	Huang, Z., Wen, X., & Wang, N. (2022, August). Research on Intelligent Monitoring Technology of Substation Equipment Based on Power IoT. In 2022 6th International Conference on Wireless Communications and Applications (ICWCAPP) (pp. 63-66). IEEE. https://doi.org/10.1109/ICWCAPP57292.2022.00023
SID286	Springer	2022	Coppolino, L., Sgaglione, L., D'Antonio, S., Magliulo, M., Romano, L., & Pacelli, R. (2022). Risk assessment driven use of advanced SIEM technology for cyber protection of critical e-health processes. SN Computer Science, 3, 1-13. https://doi.org/10.1007/s42979-021-00858-4
SID287	IEEE	2022	Hasan, T., Malik, J., Bibi, I., Khan, W. U., Al-Wesabi, F. N., Dev, K., & Huang, G. (2022). Securing industrial internet of things against botnet attacks using hybrid deep learning approach. IEEE Transactions on Network Science and Engineering, 10(5), 2952-2963. https://doi.org/10.1109/TNSE.2022.3168533
SID288	Scopus	2022	Zhang, Z., Xia, C., & Chen, S. (2022). Security and privacy with opacity-based state observation for finite state machine. Asian Journal of Control, 24(2), 614-625. https://doi.org/10.1002/asjc.2570
SID289	IEEE	2022	Aguiar, A., & Rodrigues, J. (2022, January). Sensemycity: a mobile iot tool for researching intelligent urban mobility. In 2022 14th International Conference on COMmunication Systems & NETworkS (COMSNETS) (pp. 725-733). IEEE. https://doi.org/10.1109/COMSNETS53615.2022.9668516
SID290	IEEE	2022	[S290] Iqbal, A., & Rana, M. E. (2022, March). Smart health technology model for adoption of IoT in automobiles for driver's safety. In 2022 International Conference on Decision Aid Sciences and Applications (DASA) (pp. 1018-1022). IEEE. https://doi.org/10.1109/DASA54658.2022.9765239
SID291	Springer	2022	Ilyas, A., Alatawi, M. N., Hamid, Y., Mahfooz, S., Zada, I., Gohar, N., & Shah, M. A. (2022). Software architecture for pervasive critical health monitoring system using fog computing. Journal of Cloud Computing, 11(1), 84. https://doi.org/10.1186/s13677-022-00371-w
SID292	IEEE / Scopus / WoS	2022	Ismail, S., & Dawoud, D. W. (2022, January). Software development models for IoT. In 2022 IEEE 12th Annual Computing and Communication Workshop and Conference (CCWC) (pp. 0524-0530). IEEE. https://doi.org/10.1109/CCWC54503.2022.9720750
SID293	Scopus	2022	Hofman, J., Do, T. H., Qin, X., Bonet, E. R., Philips, W., Deligiannis, N., & La Manna, V. P. (2022). Spatiotemporal air quality inference of low-cost sensor data: Evidence from multiple sensor testbeds. Environmental Modelling & Software, 149, 105306. https://doi.org/10.1016/j.envsoft.2022.105306
SID294	IEEE	2022	Andreas, A., Mavromoustakis, C. X., Mastorakis, G., Batalla, J. M., Pallis, E., & Chatzimisios, P. (2022, September). Sustainable framework for smart assistive living improvement through IoT-based integration model. In 2022 IEEE International Mediterranean Conference on Communications and Networking (MeditCom) (pp. 31-36). IEEE. https://doi.org/10.1109/MeditCom55741.2022.9928640
SID295	IEEE	2022	Charilaou, C., Ioannou, C. I., & Vassiliou, V. (2022, June). System for operational technology attack detection in industrial IoT. In 2022 20th Mediterranean Communication and Computer Networking Conference (MedComNet) (pp. 84-93). IEEE. https://doi.org/10.1109/MedComNet55087.2022.9810446
SID296	IEEE	2022	Lee, S., Roh, B. H., & Kim, S. J. (2022, January). The convergence system of an IoT standard service platform and an autonomous drone. In 2022 IEEE International Conference on Consumer Electronics (ICCE) (pp. 1-3). IEEE. https://doi.org/10.1109/ICCE53296.2022.9730389
SID297	Springer	2022	Essel, H. B., Vlachopoulos, D., Tachie-Menson, A., Johnson, E. E., & Baah, P. K. (2022). The impact of a virtual teaching assistant (chatbot) on students' learning in Ghanaian higher education. International Journal of Educational Technology in Higher Education, 19(1), 57. https://doi.org/10.1186/s41239-022-00362-6
SID298	IEEE / Scopus	2022	Sharma, S., Urumkar, S., Fontanesi, G., Karanam, V. S. S. L., Hu, B., Ramamurthy, B., & Nag, A. (2022, July). Towards Emulation of Intelligent IoT Networks on EU-US Testbeds. In 2022 International Seminar on Intelligent Technology and Its Applications (ISITIA) (pp. 484-489). IEEE. https://doi.org/10.1109/ISITIA56226.2022.9855352
SID299	Springer	2022	Garcia-Garcia, J. M., Penichet, V. M., Lozano, M. D., & Fernando, A. (2022). Using emotion recognition technologies to teach children with autism spectrum disorder how to identify and express emotions. Universal Access in the Information Society, 21(4), 809-825. https://doi.org/10.1007/s10209-021-00818-y
SID300	IEEE	2023	Xu, G., Zhou, Z., Dong, J., Zhang, L., & Song, X. (2023). A blockchain-based federated learning scheme for data sharing in industrial Internet of Things. IEEE Internet of Things Journal, 10(24), 21467–21478. https://doi.org/10.1109/JIOT.2023.3298196
SID301	Springer	2023	Sober, M., Scaffino, G., Schulte, S., & Kanhere, S. S. (2023). A blockchain-based IoT data marketplace. Cluster Computing, 26, 3523–3545. https://doi.org/10.1007/s10586-022-03745-6
SID302	Springer	2023	Albshri, A., Alzubaidi, A., Alharby, M., Awaji, B., Mitra, K., & Solaiman, E. (2023). A conceptual architecture for simulating blockchain-based IoT ecosystems. Journal of Cloud Computing: Advances, Systems and Applications, 12, 103. https://doi.org/10.1186/s13677-023-00481-z

SID303	Springer	2023	González-Abad, J., López García, Á., & Kozlov, V. Y. (2023). A container-based workflow for distributed training of deep learning algorithms in HPC clusters. Cluster Computing, 26, 2815–2834. https://doi.org/10.1007/s10586-022-03798-7
SID304	Springer	2023	Ghrab, S., Lahyani, I., Yangui, S., & Jmaiel, M. (2023). A core IoT ontology for automation support in edge computing. Service Oriented Computing and Applications, 17, 25–37. https://doi.org/10.1007/s11761-022-00356-2
SID305	IEEE	2023	Rath, C. K., Mandal, A. K., & Sarkar, A. (2023). A feature-weighted clustering approach for context discovery and selection of devices in IoT. In 2023 4th International Conference on Computing and Communication Systems (I3CS) (pp. 97–102). IEEE. https://doi.org/10.1109/I3CS58314.2023.10127469
SID306	Springer	2023	Aguzzi, G., Audrito, G., Casadei, R., Damiani, F., Torta, G., & Viroli, M. (2023). A field-based computing approach to sensing-driven clustering in robot swarms. Swarm Intelligence, 17, 27–62. https://doi.org/10.1007/s11721-022-00215-y
SID307	Scopus	2023	Kerin, M., Pham, D. T., Huang, J., & Hadall, J. (2023). A generic asset model for implementing product digital twins in smart remanufacturing. The International Journal of Advanced Manufacturing Technology, 124, 3021–3038. https://doi.org/10.1007/s00170-022-09295-w
SID308	Springer	2023	Hu, Q., Qi, H., Huang, W., & Liu, M. (2023). A method to recommend cloud manufacturing service based on the spectral clustering and improved Slope one algorithm. Journal of Cloud Computing, 12(1), 115. https://doi.org/10.1186/s13677-023-00489-5
SID309	Springer	2023	Alfonso, I., Garcés, K., Castro, H., & Cabot, J. (2023). A model-based infrastructure for the specification and runtime execution of self-adaptive IoT architectures. Computing, 105(9), 1883-1906. https://doi.org/10.1007/s00607-022-01145-7
SID310	IEEE / Scopus	2023	AbdelQader, A., Lafi, M., Awad, K., & AbedelQader, M. A. (2023, August). A Novel Approach to Elicit Software Requirements for IoT Systems Using SVM Classifier. In 2023 International Conference on Information Technology (ICIT) (pp. 779-782). IEEE. https://doi.org/10.1109/ICIT58056.2023.10225969
SID311	Scopus	2023	Subha, S., Inbamalar, T. M., Suresh, L. R., Boopathi, S., & Alaskar, K. (2023, February). A Remote Health Care Monitoring system using internet of medical things (IoMT). In 2023 3rd International Conference on Innovative Practices in Technology and Management (ICIPTM) (pp. 1-6). IEEE. https://doi.org/10.1109/ICIPTM57143.2023.10118103
SID312	Springer	2023	Makkonen, J., Latikka, R., Kaukonen, L., Laine, M., & Väänänen, K. (2023). Advancing residents' use of shared spaces in Nordic superblocks with intelligent technologies. AI & society, 38(3), 1167-1184. https://doi.org/10.1007/s00146-022-01604-x
SID313	Springer	2023	Georgievski, I., Shahid, M. Z., & Aiello, M. (2023). AI temporal planning for energy smart buildings. Energy Informatics, 6(Suppl 1), 18. https://doi.org/10.1186/s42162-023-00289-w
SID314	Springer	2023	El-Rashidy, N., Sedik, A., Siam, A. I., & Ali, Z. H. (2023). An efficient edge/cloud medical system for rapid detection of level of consciousness in emergency medicine based on explainable machine learning models. Neural Computing and Applications, 35(14), 10695-10716. https://doi.org/10.1007/s00521-023-08258-w
SID315	IEEE	2023	Laha, S. R., Pattanayak, B. K., Pattnaik, S., Mishra, D., Nayak, D. S. K., & Dash, B. B. (2023, September). An IOT-based soil moisture management system for precision agriculture: real-time monitoring and automated irrigation control. In 2023 4th International Conference on Smart Electronics and Communication (ICOSEC) (pp. 451-455). IEEE. https://doi.org/10.1109/ICOSEC58147.2023.10276266
SID316	Springer	2023	Mahroo, A., Greci, L., Mondellini, M., & Sacco, M. (2023). Assessment of a mixed reality smart home controller: HoloHome pilot study on healthy adults. Virtual Reality, 27(3), 2673-2690. https://doi.org/10.1007/s10055-023-00834-8
SID317	IEEE	2023	Macrì, D., & Gentile, A. F. (2023, October). Avoiding information disorder in disaster recovery through internet of things. In 2023 IEEE/WIC International Conference on Web Intelligence and Intelligent Agent Technology (WI-IAT) (pp. 469-473). IEEE. https://doi.org/10.1109/WI-IAT59888.2023.00077
SID318	Scopus	2023	Lee, J., Kim, M., Park, K., Noh, S., Bisht, A., Das, A. K., & Park, Y. (2023). Blockchain-based data access control and key agreement system in iot environment. Sensors, 23(11), 5173. https://doi.org/10.3390/s23115173
SID319	IEEE / Scopus	2023	Maurya, V., Rishiwal, V., Yadav, M., Jat, D. S., Agarwal, U., & Verma, V. R. (2023, August). Blockchain-powered solution to safeguard iot devices against attacks. In 2023 International conference on emerging trends in networks and computer communications (ETNCC) (pp. 209-215). IEEE. https://doi.org/10.1109/ETNCC59188.2023.10284784
SID320	Springer	2023	Lipps, C., Herbst, J., Klingel, S., Franke, L., Wolff, A., Rüb, M., ... & Schotten, H. D. (2023). Connectivity in the era of the (I) IoT: about security, features and limiting factors of reconfigurable intelligent surfaces. Discover Internet of Things, 3(1), 16. https://doi.org/10.1007/s43926-023-00046-1
SID321	IEEE	2023	Yadav, T., Kulkarni, P., & Chirputkar, A. (2023, August). Continuous Bank Audit Using Internet of Things. In 2023 5th International Conference on Inventive Research in Computing Applications (ICIRCA) (pp. 1412-1417). IEEE. https://doi.org/10.1109/ICIRCA57980.2023.10220640
SID322	Springer	2023	Roy, M., Das, S., Deb, N., Cortesi, A., Chaki, R., & Chaki, N. (2023). Correlating contexts and NFR conflicts from event logs. Software and Systems Modeling, 22(6), 1987-2010. https://doi.org/10.1007/s10270-023-01087-4
SID323	IEEE	2023	Kaur, A., Sahu, R., & Anand, D. (2023, August). Deep Reinforcement Base Multi Context Routing in Social IoT. In 2023 International Conference on Circuit Power and Computing Technologies (ICCPCT) (pp. 675-682). IEEE. https://doi.org/10.1109/ICCPCT58313.2023.10245117
SID324	Scopus	2023	Alarcón-Maza, K., Herrera-Perez, V., Rodriguez-Flores, J., Pacheco-Cunduri, M., & Hernandez-Ambato, J. (2023, April). Design and experimental validation of an IoT data-logger device for indirect measurement of solar irradiance based on a correlation model. In 2023 IEEE Green Technologies Conference (GreenTech) (pp. 40-45). IEEE. https://doi.org/10.1109/GreenTech56823.2023.10173825
SID325	Scopus	2023	Moran, J. P. O., Cortez, J. D. L. C., De La Cruz, S. E. C., Mendoza, P. A. M., & Quijano, S. A. C. (2023, October). Design of a Prevention and Monitoring System for People with Hypertension. In 2023 IEEE 14th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON) (pp. 0783-0787). IEEE. https://doi.org/10.1109/UEMCON59035.2023.10316051
SID326	Springer	2023	[S326] Albrecht, R., Overbeek, S., & van de Weerd, I. (2023). Designing a Data Quality Management Framework for CRM Platform Delivery and Consultancy. SN Computer Science, 4(6), 742. https://doi.org/10.1007/s42979-023-02196-z
SID327	IEEE	2023	Vijayarangan, R., Loganathan, S., Thirumurugan, V., Poonguzhali, I., & Ramachandra, A. C. (2023, June). Detection of Denial of Service Attacks Using SNMP-MIB in Internet of Things Environment. In 2023 International Conference on Applied Intelligence and Sustainable Computing (ICAISC) (pp. 1-5). IEEE. https://doi.org/10.1109/ICAISC58445.2023.10199348

SID328	IEEE	2023	Sánchez, I. C. G., Bacovich, R. A., López, J. G., Cuevas, C. Á., Cocozza, C., & Álvarez-Taboada, F. (2023, November). Development and Application of an Automated System for Early Detection of Stress and Damage in Poplar Clone Plantations Using Eco-Physiological Sensors and IoT. In 2023 IEEE International Workshop on Metrology for Agriculture and Forestry (MetroAgriFor) (pp. 624-628). IEEE. https://doi.org/10.1109/MetroAgriFor58484.2023.10424391
SID329	Springer	2023	Huang, H. C., Tsai, C. H., & Lin, H. C. (2023). Development of 5G cyber-physical production system. International Journal of Networked and Distributed Computing, 11(1), 9-19. https://doi.org/10.1007/s44227-022-00003-4
SID330	Scopus	2023	Mendonça, R. D. S., De Carvalho, M. M., Machado, G. S., Da Silva, C. S. M., De Medeiros, R. L. P., & De Lucena, V. F. (2023). Development of a novel methodology to retrofit legacy systems in the context of industry 4.0. IEEE Access, 11, 123223-123235. https://doi.org/10.1109/ACCESS.2023.3328537
SID331	IEEE	2023	Olatinwo, D. D., Abu-Mahfouz, A. M., Hancke, G. P., & Myburgh, H. C. (2023). Energy efficient priority-based hybrid MAC protocol for IoT-enabled WBAN systems. IEEE Sensors Journal, 23(12), 13524-13538. https://doi.org/10.1109/JSEN.2023.3273427
SID332	IEEE	2023	Girón, S. A. S., Morales, B. A. C., Lagos, F. D. L. C., & Rodríguez, F. E. N. (2023, April). Environmental monitoring system with wireless sensing and iot technologies for intensive care units. In 2023 8th International Conference on Control and Robotics Engineering (ICCRE) (pp. 150-155). IEEE. https://doi.org/10.1109/ICCRE57112.2023.10155571
SID333	IEEE	2023	Mao, J., Xu, X., Lin, Q., Ma, L., & Liu, J. (2023). EScope: Effective event validation for IoT systems based on state correlation. Big Data Mining and Analytics, 6(2), 218-233. https://doi.org/10.26599/BDMA.2022.9020034
SID334	Scopus	2023	Dehshiri, S. J. H., & Amiri, M. (2023). Evaluating the risks of the internet of things in renewable energy systems using a hybrid fuzzy decision approach. Energy, 285, 129493. https://doi.org/10.1016/j.energy.2023.129493
SID335	Scopus	2023	Ahmad, F., Chaudhry, M. T., Jamal, M. H., Sohail, M. A., Gavilanes, D., Vergara, M. M., & Ashraf, I. (2023). Formal modeling and analysis of security schemes of RPL protocol using colored Petri nets. Plos one, 18(8), e0285700. https://doi.org/10.1371/journal.pone.0285700
SID336	IEEE	2023	Ferrag, M. A., Hamouda, D., Debbah, M., Maglaras, L., & Lakas, A. (2023, June). Generative adversarial networks-driven cyber threat intelligence detection framework for securing internet of things. In 2023 19th International Conference on Distributed Computing in Smart Systems and the Internet of Things (DCOSS-IoT) (pp. 196-200). IEEE. https://doi.org/10.1109/DCOSS-IoT58021.2023.00042
SID337	IEEE	2023	Rudraraju, S. R., Suryadevara, N. K., & Negi, A. (2023). Heterogeneous Sensor Data Acquisition and Federated Learning for Resource Constrained IoT Devices—A Validation. IEEE Sensors Journal, 23(15), 17602-17610. https://doi.org/10.1109/JSEN.2023.3287580
SID338	Springer	2023	Nizamudeen, S. M. T. (2023). Intelligent intrusion detection framework for multi-clouds–IoT environment using swarm-based deep learning classifier. Journal of Cloud Computing, 12(1), 134. https://doi.org/10.1186/s13677-023-00509-4
SID339	Springer	2023	Ntambara, B., Nyambo, D. G., & Solsbach, A. (2023). Internet of things (IoT)-based on real-time and remote boiler fuel monitoring system: a case of Raha Beverages Company Limited, Arusha-Tanzania. Discover Internet of Things, 3(1), 19. https://doi.org/10.1007/s43926-023-00052-3
SID340	IEEE	2023	Slunjski, M., & Sumina, D. (2023, July). Investigation of Internet-of-Things gateway-based solution for protection of industrial control systems. In 2023 3rd International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME) (pp. 1-6). IEEE. https://doi.org/10.1109/ICECCME57830.2023.10253072
SID341	IEEE / Scopus	2023	Laxmaiah, B., Easwaran, B., Sultana, H. P., Praveenadevi, D., & Katragadda, L. S. (2023, May). Iot Enabled Fog Based Computing with Deep Learning Models to Increase The Allocation of Resource. In 2023 International Conference on Disruptive Technologies (ICDT) (pp. 140-143). IEEE. https://doi.org/10.1109/ICDT57929.2023.10151115
SID342	IEEE	2023	Sun, S., Peng, T., Huang, H., Wang, Y., Zhang, X., & Zhou, Y. (2023). IoT motion tracking system for workout performance evaluation: A case study on dumbbell. IEEE Transactions on Consumer Electronics, 69(4), 798-808. https://doi.org/10.1109/TCE.2023.3320183
SID343	IEEE	2023	Almorabea, O. M., Khanzada, T. J. S., Aslam, M. A., Hendi, F. A., & Almorabea, A. M. (2023). IoT Network-Based Intrusion Detection Framework: A Solution to Process Ping Floods Originating From Embedded Devices. IEEE access, 11, 119118-119145. https://doi.org/10.1109/ACCESS.2023.3327061
SID344	IEEE	2023	Kumar, G. R., Ranjani, M., Santhiya, R., & Thamilselvi, S. S. (2023, August). IoT with Cloud Based Breast Cancer Diagnosis Using Deep Learning Techniques. In 2023 5th International Conference on Inventive Research in Computing Applications (ICIRCA) (pp. 938-946). IEEE. https://doi.org/10.1109/ICIRCA57980.2023.10220631
SID345	IEEE	2023	Rukhiran, M., Wong-In, S., & Netinant, P. (2023). IoT-based biometric recognition systems in education for identity verification services: Quality assessment approach. Ieee Access, 11, 22767-22787. https://doi.org/10.1109/ACCESS.2023.3253024
SID346	IEEE	2023	Adhau, J., Adsare, V., Jadhav, D., Kshirsagar, K., & Tamkhade, J. (2023, November). IoT-Based Face Recognition with SNN. In 2023 2nd International Conference on Futuristic Technologies (INCOFT) (pp. 1-6). IEEE. https://doi.org/10.1109/INCOFT60753.2023.10425691
SID347	IEEE	2023	Iqbal, S., Zafar, N. A., & Batool, T. (2023, November). IoT-based Quality Model in which Blockchain Enabled to Analysis and Provide Medicine to COVID-19 Patients by VDM-SL. In 2023 2nd International Conference on Emerging Trends in Electrical, Control, and Telecommunication Engineering (ETECTE) (pp. 1-6). IEEE. https://doi.org/10.1109/ETECTE59617.2023.10396734
SID348	IEEE	2023	Ceenepalli, P., & Chandrasekhar, C. (2023, October). IoT-Enabled Flood Wall: Advancing Real-Time Flash Flood Monitoring and Forecasting. In 2023 International Conference on Self Sustainable Artificial Intelligence Systems (ICSSAS) (pp. 1369-1376). IEEE. https://doi.org/10.1109/ICSSAS57918.2023.10331865
SID349	Scopus	2023	Oliveira, J., Sousa, F., & Almeida, L. (2023, October). IoTNetEMU-A Framework to Emulate and Test IoT Applications. In Proceedings of the 19th ACM International Symposium on QoS and Security for Wireless and Mobile Networks (pp. 33-37). https://doi.org/10.1145/3616391.3622774
SID350	Scopus	2023	Akram, U., Sharif, W., Shahroz, M., Mushtaq, M. F., Aray, D. G., Thompson, E. B., ... & Ashraf, I. (2023). IoTTPS: Ensemble RKSVM model-based Internet of Things threat protection system. Sensors, 23(14), 6379. https://doi.org/10.3390/s23146379
SID351	IEEE	2023	Malik, M., Dutta, M., & Granjal, J. (2023). L-ecqv: Lightweight ecqv implicit certificates for authentication in the internet of things. IEEE Access, 11, 35517-35540. https://doi.org/10.1109/ACCESS.2023.3261666

SID352	IEEE	2023	Khaing, M. S., Aye, Z. M., & Tun, T. (2023, February). Machine Learning-Based Performance Analysis for IoT Attacks in IDS. In 2023 IEEE Conference on Computer Applications (ICCA) (pp. 375-380). IEEE. https://doi.org/10.1109/ICCA51723.2023.10181629
SID353	Springer	2023	Wang, C., & Wang, D. (2023). Managing the integration of teaching resources for college physical education using intelligent edge-cloud computing. Journal of Cloud Computing, 12(1), 82. https://doi.org/10.1186/s13677-023-00455-1
SID354	IEEE	2023	De Oliveira, R. R., Soares, M. F., De Souza, A. S., & Gomes, K. D. C. (2023). Methodology to control iot smart devices driven by digital tv video scene. IEEE Access, 11, 27806-27815. https://doi.org/10.1109/ACCESS.2023.3257856
SID355	Scopus	2023	Sankaranarayanan, S., Swaminathan, G., Radhakrishnan, T. K., & Sivakumaran, N. (2023). Missing data estimation and IoT-based flyby monitoring of a water distribution system: Conceptual and experimental validation. International Journal of Communication Systems, 36(12), e4135. https://doi.org/10.1002/dac.4135
SID356	IEEE	2023	Nwadiugwu, W. P., Ejaz, W., Kaneko, M., & Anpalagan, A. (2023). Neural-network-assisted packet accelerators for Internet of Things network systems. IEEE Internet of Things Journal, 10(17), 15238-15251. https://doi.org/10.1109/JIOT.2023.3265344
SID357	IEEE	2023	Lee, S., & Kim, J. H. (2023). Opportunistic block validation for iot blockchain networks. IEEE Internet of Things Journal, 11(1), 666-676. https://doi.org/10.1109/JIOT.2023.3287166
SID358	Scopus	2023	Padmavilochanan, D., Pathinarupothi, R. K., Menon, K. U., Kumar, H., Guntha, R., Ramesh, M. V., & Rangan, P. V. (2023). Personalized diabetes monitoring platform leveraging IoMT and AI for non-invasive estimation. Smart Health, 30, 100428. https://doi.org/10.1016/j.smhl.2023.100428
SID359	IEEE	2023	Balaji, S., Raju, N. K. K., Tarun, S., Karthikeyan, R., Shankar, T., & Santhakumar, R. (2023, May). Precision Agriculture Crop Recommendation System Using IoT and Machine Learning. In 2023 2nd International Conference on Vision Towards Emerging Trends in Communication and Networking Technologies (ViTECoN) (pp. 1-6). IEEE. https://doi.org/10.1109/ViTECoN58111.2023.10157577
SID360	Springer	2023	Haghshenas, A., Hasan, A., Osen, O., & Mikalsen, E. T. (2023). Predictive digital twin for offshore wind farms. Energy Informatics, 6(1), 1. https://doi.org/10.1186/s42162-023-00257-4
SID361	IEEE	2023	Regi, R. J., Joseph, J., & Thomas, P. (2023, November). Predictive Modeling of Residential Energy Usage with Deep Learning and IoT Devices. In 2023 IEEE International Conference on Recent Advances in Systems Science and Engineering (RASSE) (pp. 1-6). IEEE. https://doi.org/10.1109/RASSE60029.2023.10363582
SID362	IEEE	2023	Zhang, S., & Zhu, J. (2023, June). Privacy protection federated learning framework based on blockchain and committee consensus in IoT devices. In 2023 IEEE 47th Annual Computers, Software, and Applications Conference (COMPSAC) (pp. 627-636). IEEE. https://doi.org/10.1109/COMPSAC57700.2023.00088
SID363	IEEE	2023	Chakraborty, A., Gupta, R. D., Roy, D., Kabir, M. Z., Bablu, M. S. I., & Gupta, R. D. (2023, December). Radiation Monitoring and Environmental Assessment in Precision Agriculture: Development of an Integrated IoT Device with Comprehensive Data Analysis Capabilities. In 2023 26th International Conference on Computer and Information Technology (ICCIT) (pp. 1-6). IEEE. https://doi.org/10.1109/ICCIT60459.2023.10441341
SID364	IEEE	2023	Chanal, P. M., & Kakkasageri, M. S. (2023, July). Random forest algorithm based device authentication in IoT. In 2023 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT) (pp. 1-6). IEEE. https://doi.org/10.1109/CONECCT57959.2023.10234738
SID365	Springer	2023	Muñiz, R., Nuño, F., Díaz, J., González, M., J. Prieto, M., & Menéndez, Ó. (2023). Real-time monitoring solution with vibration analysis for industry 4.0 ventilation systems. The Journal of Supercomputing, 79(6), 6203-6227. https://doi.org/10.1007/s11227-022-04897-3
SID366	IEEE	2023	Zhang, K., Zheng, J., Fu, J., Zhang, Y., & Ji, W. (2023, September). Research and application of zero trust based secure access to the power Internet of Things. In 2023 IEEE 7th Information Technology and Mechatronics Engineering Conference (ITOEC) (Vol. 7, pp. 2356-2360). IEEE. https://doi.org/10.1109/ITOEC57671.2023.10291965
SID367	IEEE	2023	Liao, X. (2023, November). Research on Network Security Dynamic Defense Technology for Power Iot Terminals. In 2023 5th International Conference on Artificial Intelligence and Computer Applications (ICAICA) (pp. 876-880). IEEE. https://doi.org/10.1109/ICAICA58456.2023.10405519
SID368	IEEE	2023	Salas, H., Ramirez, O., & Wong, L. (2023, November). SafeSteps: A mobile app for monitoring and tracking the elderly with Alzheimer's using an IoT device. In 2023 IEEE XXX International Conference on Electronics, Electrical Engineering and Computing (INTERCON) (pp. 1-7). IEEE. https://doi.org/10.1109/INTERCON59652.2023.10326076
SID369	Scopus	2023	Lu, C. H., Liu, C. H., & Chen, Z. H. (2023). Secure and efficient firmware update for increasing IoT-enabled smart devices. Journal of Ambient Intelligence and Humanized Computing, 14(5), 4987-5000. https://doi.org/10.1007/s12652-020-02492-z
SID370	IEEE	2023	Biró, V., Chiu, W. Y., & Meng, W. (2023, December). Securing iot firmware dispatch systems with blockchain. In 2023 IEEE International Conference on Blockchain (Blockchain) (pp. 229-238). IEEE. https://doi.org/10.1109/Blockchain60715.2023.00046
SID371	IEEE	2023	Srivastava, A., & Jain, U. (2023, July). Securing the future of IoT: A comprehensive framework for real-time attack detection and mitigation in IoT networks. In 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT) (pp. 1-6). IEEE. https://doi.org/10.1109/ICCCNT56998.2023.10307306
SID372	Springer	2023	Li, J., & Zhu, S. (2023). Service composition considering energy consumption of users and transferring files in a multicloud environment. Journal of Cloud Computing, 12(1), 43. https://doi.org/10.1186/s13677-023-00423-9
SID373	Springer	2023	Cañizares, P. C., Núñez, A., Bernal, A., Cambronero, M. E., & Barker, A. (2023). Simcan2Cloud: a discrete-event-based simulator for modelling and simulating cloud computing infrastructures. Journal of Cloud Computing, 12(1), 133. https://doi.org/10.1186/s13677-023-00511-w
SID374	Springer	2023	Li, H., Chen, J., Yang, C., Chen, X., Chang, L., & Liu, J. (2023). Smart and efficient EV charging navigation scheme in vehicular edge computing networks. Journal of Cloud Computing, 12(1), 176. https://doi.org/10.1186/s13677-023-00547-y
SID375	IEEE	2023	Mendes, L. F., Aguilar, P. A., & Bezerra, C. I. (2023, March). Software Architecture for IoT-based Indoor Positioning Systems for Ambient Assisted Living. In 2023 IEEE 20th International Conference on Software Architecture (ICSA) (pp. 93-104). IEEE. https://doi.org/10.1109/ICSA56044.2023.00017
SID376	Springer	2023	Talaat, F. M., & El-Balka, R. M. (2023). Stress monitoring using wearable sensors: IoT techniques in medical field. Neural Computing and Applications, 35(25), 18571-18584. https://doi.org/10.1007/s00521-023-08681-z

SID377	Springer	2023	Babović, Z., Bajat, B., Barac, D., Bengin, V., Đokić, V., Đorđević, F., ... & Zak, S. (2023). Teaching computing for complex problems in civil engineering and geosciences using big data and machine learning: synergizing four different computing paradigms and four different management domains. Journal of Big Data, 10(1), 89. https://doi.org/10.1186/s40537-023-00730-7
SID378	IEEE	2023	Williams, K., Hammer, J., & Hudson, S. (2023, October). The IoT Codex: A Book of Programmable Stickers for Authoring and Composing Embedded Computing Applications. In 2023 IEEE Symposium on Visual Languages and Human-Centric Computing (VL/HCC) (pp. 1-11). IEEE. https://doi.org/10.1109/VL-HCC57772.2023.00009
SID379	Springer	2023	Garcia, A., Oregui, X., Franco, J., Arrieta, U., Ferreres, J., & Valencia, J. A. (2023). Time series manufacturing data edge monitoring and visualization to support industrial maintenance teams. SN Computer Science, 5(1), 131. https://doi.org/10.1007/s42979-023-02442-4
SID380	Springer	2023	De Donato, L., Dirnfeld, R., Somma, A., De Benedictis, A., Flammini, F., Marrone, S., ... & Vittorini, V. (2023). Towards AI-assisted digital twins for smart railways: preliminary guideline and reference architecture. Journal of Reliable Intelligent Environments, 9(3), 303-317. https://doi.org/10.1007/s40860-023-00208-6
SID381	Springer	2023	Mena, M., Criado, J., Iribarne, L., Corral, A., Chbeir, R., & Manolopoulos, Y. (2023). Towards high-availability cyber-physical systems using a microservice architecture. Computing, 105(8), 1745-1768. https://doi.org/10.1007/s00607-023-01165-x
SID382	Scopus	2023	Mishra, S. K., & Sarkar, A. (2023, March). Validating User-Centric Business Process based Service Composition. In 2023 4th International Conference on Computing and Communication Systems (I3CS) (pp. 1-6). IEEE. https://doi.org/10.1109/I3CS58314.2023.10127225
SID383	IEEE	2023	Johar, A., & Lahari, S. A. (2023, December). Water Quality Index Prediction System Using IoT Enabled Sensor Suite and Machine Learning. In 2023 16th International Conference on Sensing Technology (ICST) (pp. 1-6). IEEE. https://doi.org/10.1109/ICST59744.2023.10460817
SID384	Springer	2024	Aldalur, I., Arrieta, A., Agirre, A., Sagardui, G., & Arratibel, M. (2024). A microservice-based framework for multi-level testing of cyber-physical systems. Software Quality Journal, 32(1), 193-223. https://doi.org/10.1007/s11219-023-09639-z
SID385	Springer	2024	Michael, J., & Shekhovtsov, V. A. (2024). A model-based reference architecture for complex assistive systems and its application. Software and Systems Modeling, 23(5), 1247-1274. https://doi.org/10.1007/s10270-024-01157-1
SID386	Springer	2024	Sales Mendes, A. F., Sánchez San Blas, H., Pérez Robledo, F., De Paz Santana, J. F., & Villarrubia González, G. (2024). A novel multiagent system for cervical motor control evaluation and individualized therapy: integrating gamification and portable solutions. Multimedia Systems, 30(3), 131. https://doi.org/10.1007/s00530-024-01328-6
SID387	Springer	2024	Karakostas, I., Valakou, A., Gavgiotaki, D., Stefanidi, Z., Pastaltzidis, I., Tsipouridis, G., ... & Tzovaras, D. (2024). A real-time wearable AR system for egocentric vision on the edge. Virtual Reality, 28(1), 44. https://doi.org/10.1007/s10055-023-00937-2
SID388	Springer	2024	Forkan, A. R. M., Kang, Y. B., Marti, F., Banerjee, A., McCarthy, C., Ghaderi, H., ... & Jayaraman, P. P. (2024). AIoT-citysense: AI and IoT-driven city-scale sensing for roadside infrastructure maintenance. Data Science and Engineering, 9(1), 26-40. https://doi.org/10.1007/s41019-023-00236-5
SID389	Springer	2024	Sheeba, A., Bushra, S. N., Rajarajeswari, S., & Subasini, C. A. (2024). An efficient starling murmuration-based secure web service model for smart city application using DBN. Artificial Intelligence Review, 57(3), 72. https://doi.org/10.1007/s10462-023-10689-9
SID390	Springer	2024	Rostami, M., & Goli-Bidgoli, S. (2024). An overview of QoS-aware load balancing techniques in SDN-based IoT networks. Journal of cloud computing, 13(1), 89. https://doi.org/10.1186/s13677-024-00651-7
SID391	Springer	2024	Upadrista, V., Nazir, S., & Tianfield, H. (2024). Automatic edge app placement for personalized heart attack predictions. Iran Journal of Computer Science, 7(2), 241-257. https://doi.org/10.1007/s42044-024-00172-1
SID392	IEEE	2024	Alshaeri, A., & Younis, M. (2024, January). Distributed Hardware-Assisted Authentication and Key Agreement Protocol for Internet of Things. In 2024 IEEE 21st Consumer Communications & Networking Conference (CCNC) (pp. 152-158). IEEE. https://doi.org/10.1109/CCNC51664.2024.10454706
SID393	Springer	2024	Fedeli, A., Fornari, F., Polini, A., Re, B., Torres, V., & Valderas, P. (2024). FloBP: a model-driven approach for developing and executing IoT-enhanced business processes. Software and Systems Modeling, 23(5), 1217-1246. https://doi.org/10.1007/s10270-024-01150-8
SID394	Springer	2024	Gilani, S. M. M., Usman, M., Daud, S., Kabir, A., Nawaz, Q., & Judit, O. (2024). SDN-based multi-level framework for smart home services. Multimedia Tools and Applications, 83(1), 327-347. https://doi.org/10.1007/s11042-023-15678-2
SID395	IEEE	2024	Sadhwani, S., Modi, U. K., Muthalagu, R., & Pawar, P. M. (2024). SmartSentry: Cyber threat intelligence in industrial IoT. IEEE Access. https://doi.org/10.1109/ACCESS.2024.3371996
SID396	Springer	2024	Maamar, Z., Faci, N., Al-Khafajiy, M., & Dohan, M. (2024). Thing Artifact-based Design of IoT Ecosystems. Service Oriented Computing and Applications, 18(1), 15-31. https://doi.org/10.1007/s11761-023-00379-3
SID397	Springer	2024	Shen, T., Zhang, L., Geng, R., Li, S., & Sun, B. (2024). Traffic prediction for diverse edge IoT data using graph network. Journal of Cloud Computing, 13(1), 84. https://doi.org/10.1186/s13677-023-00543-2
SID398	Springer	2024	Humayun, M., Alsirhani, A., Alserhani, F., Shaheen, M., & Alwakid, G. (2024). Transformative synergy: SSEHCET—bridging mobile edge computing and AI for enhanced eHealth security and efficiency. Journal of Cloud Computing, 13(1), 37. https://doi.org/10.1186/s13677-024-00602-2
SID399	Scopus / WoS	2024	Drăgulinescu, A. M., Zamfirescu, C., Halunga, S., Marcu, I., Li, F. Y., & Dobre, O. A. (2024). Understanding LoRaWAN transmissions in harsh environments: A measurement-based campaign through unmanned aerial/surface vehicles. IEEE Transactions on Instrumentation and Measurement, 73, 1-14. https://doi.org/10.1109/TIM.2024.3351262
SID400	Springer	2024	Vranić, V., Lang, J., Nores, M. L., Arias, J. J. P., Solano, J., & Laseca, G. (2024). Use case modeling in a research setting of developing an innovative pilgrimage support system. Universal Access in the Information Society, 23(4), 1543-1560. https://doi.org/10.1007/s10209-023-01047-1
SID401	IEEE	2019a	Wang, Q., Jia, Z., Wang, T., Shen, Z., Zhao, M., Chen, R., & Shao, Z. (2020). A highly parallelized PIM-based accelerator for transaction-based blockchain in IoT environment. IEEE Internet of Things Journal, 7(5), 4072–4083. https://doi.org/10.1109/JIOT.2019.2963245
SID402	IEEE	2019a	Krishna, A., Le Pallec, M., Mateescu, R., Noirie, L., & Salaün, G. (2019a, May). IoT composer: Composition and deployment of IoT applications. In 2019 IEEE/ACM 41st International Conference on Software Engineering: Companion

			Proceedings (ICSE-Companion) (pp. 19-22). IEEE. https://doi.org/10.1109/ICSE-Companion.2019.00028
SID403	IEEE	2019b	Krishna, A., Le Pallec, M., Mateescu, R., Noirie, L., & Salaün, G. (2019b, May). Rigorous design and deployment of IoT applications. In 2019 IEEE/ACM 7th International Conference on Formal Methods in Software Engineering (FormaliSE) (pp. 11-20). IEEE. https://doi.org/10.1109/FormaliSE.2019.00011
SID404	IEEE	2019b	Wang, G., Nixon, M., & Boudreaux, M. (2019b). Toward cloud-assisted industrial IoT platform for large-scale continuous condition monitoring. Proceedings of the IEEE, 107(6), 1193-1205. https://doi.org/10.1109/JPROC.2019.2914021
SID405	Springer	2020a	Fan, P., Liu, J., Yin, W. et al. 2PC*: a distributed transaction concurrency control protocol of multi-microservice based on cloud computing platform. J Cloud Comp 9, 40 (2020). https://doi.org/10.1186/s13677-020-00183-w
SID406	Springer	2020a	Javed, A. R., Sarwar, M. U., Beg, M. O., Asim, M., Baker, T., & Tawfik, H. (2020). A collaborative healthcare framework for shared healthcare plan with ambient intelligence. Human-centric Computing and Information Sciences, 10, 40. https://doi.org/10.1186/s13673-020-00245-7
SID407	Scopus	2020a	Sun, C., Zheng, F., Zhou, G., & Guo, K. (2020a, July). Design and implementation of cloud-based single-channel LoRa IIoT gateway using raspberry pi. In 2020 39th Chinese Control Conference (CCC) (pp. 5259-5263). IEEE. https://doi.org/10.23919/CCC50068.2020.9189480
SID408	IEEE	2020a	Abbas, S., Khan, M. A., Falcon-Morales, L. E., Rehman, A., Saeed, Y., Zareei, M., ... & Mohamed, E. M. (2020a). Modeling, simulation and optimization of power plant energy sustainability for IoT enabled smart cities empowered with deep extreme learning machine. IEEE Access, 8, 39982-39997. https://doi.org/10.1109/ACCESS.2020.2976452
SID409	IEEE / Scopus	2020b	Fan, J., Zhu, H., & Wang, X. (2020b, November). Classification Method of Indoor Environmental Data based on Internet of Things. In 2020 IEEE 9th Data Driven Control and Learning Systems Conference (DDCLS) (pp. 325-330). IEEE. https://doi.org/10.1109/DDCLS49620.2020.9275275
SID410	Springer	2020b	Javed, A., Robert, J., Heljanko, K., & Främling, K. (2020b). IoTEF: A federated edge-cloud architecture for fault-tolerant IoT applications. Journal of Grid Computing, 18(1), 57-80. https://doi.org/10.1007/s10723-019-09498-8
SID411	IEEE/ Scopus	2020b	Abbas, A. M., Zekry, A., Youssef, K. Y., & Mahmoud, I. I. (2020b, December). Simulink based modeling and performance analysis of NB-IoT uplink scheduler. In 2020 8th International Japan-Africa Conference on Electronics, Communications, and Computations (JAC-ECC) (pp. 11-17). IEEE. https://doi.org/10.1109/JAC-ECC51597.2020.9355921
SID412	IEEE / Scopus	2020b	Sun, H., Li, S., Yu, F. R., Qi, Q., Wang, J., & Liao, J. (2020b). Toward communication-efficient federated learning in the Internet of Things with edge computing. IEEE Internet of Things Journal, 7(11), 11053-11067. https://doi.org/10.1109/JIOT.2020.2994596
SID413	IEEE	2021a	Wang, X., Hu, J., Lin, H., Garg, S., Kaddoum, G., Piran, M. J., & Hossain, M. S. (2021a). QoS and privacy-aware routing for 5G-enabled industrial Internet of Things: A federated reinforcement learning approach. IEEE Transactions on Industrial Informatics, 18(6), 4189-4197. https://doi.org/10.1109/TII.2021.3124848
SID414	IEEE	2021b	Wang, X., Garg, S., Lin, H., Hu, J., Kaddoum, G., Piran, M. J., & Hossain, M. S. (2021b). Toward accurate anomaly detection in industrial internet of things using hierarchical federated learning. IEEE Internet of Things Journal, 9(10), 7110-7119. https://doi.org/10.1109/JIOT.2021.3074382
SID415	Springer	2022a	Moin, A., Challenger, M., Badii, A., & Günnemann, S. (2022a). A model-driven approach to machine learning and software modeling for the IoT: Generating full source code for smart Internet of Things (IoT) services and cyber-physical systems (CPS). Software and Systems Modeling, 21(3), 987-1014. https://doi.org/10.1007/s10270-021-00967-x
SID416	ACM	2022a	Wang, M. B., Manesh, D., Hu, R., & Lee, S. W. (2022a, October). iThem: Programming Internet of Things Beyond Trigger-Action Pattern. In Adjunct Proceedings of the 35th Annual ACM Symposium on User Interface Software and Technology (pp. 1-5). https://doi.org/10.1145/3526114.3558776
SID417	IEEE	2022b	Wang, Y., Liu, S., Shao, Z., & Li, Z. (2022b, December). Research and Application of Edge Computing Technology for Power Smart Internet of Things. In 2022 4th International Academic Exchange Conference on Science and Technology Innovation (IAECST) (pp. 41-45). IEEE. https://doi.org/10.1109/IAECST57965.2022.10062161
SID418	IEEE	2022b	Moin, A., Challenger, M., Badii, A., & Günnemann, S. (2022b, June). Supporting AI engineering on the IoT edge through model-driven TinyML. In 2022 IEEE 46th Annual Computers, Software, and Applications Conference (COMPSAC) (pp. 884-893). IEEE. https://doi.org/10.1109/COMPSAC54236.2022.00140
SID419	IEEE / Scopus	2022c	Wang, T., Kara, D., Li, J., Liu, S., Abdelzaher, T., & Jalaian, B. (2022c, November). The methodological pitfall of dataset-driven research on deep learning: An iot example. In MILCOM 2022-2022 IEEE Military Communications Conference (MILCOM) (pp. 1082-1087). IEEE. https://doi.org/10.1109/MILCOM55135.2022.10017612
SID420	Scopus	2023a	Bao, H., Zhao, Y., Zhang, X., Wang, G., Duan, J., Tian, R., ... & Zhang, M. (2023a). A Probabilistic and Distributed Validation Framework Based on Blockchain for Artificial Intelligence of Things. IEEE Internet of Things Journal, 11(1), 17-28. https://doi.org/10.1109/JIOT.2023.3279849
SID421	IEEE	2023a	Wang, T., Zheng, X., Yang, L., & Xiang, R. (2023a, November). An Adaptive Sampling Strategy for Federal Graph Neural Networks in Internet of Things. In 2023 IEEE International Performance, Computing, and Communications Conference (IPCCC) (pp. 249-258). IEEE. https://doi.org/10.1109/IPCCC59175.2023.10253854
SID422	IEEE	2023a	Putra, M. A. P., Hermawan, A. P., Kim, D. S., & Lee, J. M. (2023a). Data prediction-based energy-efficient architecture for industrial iot. IEEE Sensors Journal, 23(14), 15856-15866. https://doi.org/10.1109/JSEN.2023.3280485
SID423	IEEE	2023b	Putra, M. A. P., Hermawan, A. P., Nwakanma, C. I., Kim, D. S., & Lee, J. M. (2023b). FDPR: A novel fog data prediction and recovery using efficient DL in IoT networks. IEEE Internet of Things Journal, 10(19), 16895-16906. https://doi.org/10.1109/JIOT.2023.3271026
SID424	Scopus	2023b	Wang, M., Shen, K., Tai, C., Zhang, Q., Yang, Z., & Guo, C. (2023b). Research on fault diagnosis system for belt conveyor based on internet of things and the LightGBM model. Plos one, 18(3), e0277352. https://doi.org/10.1371/journal.pone.0277352
SID425	IEEE / Scopus / WoS	2023b	Bao, H., Zhang, X., Wang, G., Tian, R., Duan, J., & Zhao, Y. (2023b, May). Smart-PKI: A blockchain-based distributed identity validation scheme for IoT devices. In ICC 2023-IEEE International Conference on Communications (pp. 4749-4754). IEEE. https://doi.org/10.1109/ICC45041.2023.10279752

CAT-TODNet: A Contextual Transformer-Based Optimized Deformable Convolution Framework for Efficient ECG-Based Heart Failure Detection

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***Abstract*—Heart Failure detection using Electrocardiogram (ECG) signals is a critical clinical task, as continuous analysis of cardiac waveforms supports early diagnosis and effective intervention. Despite advancements in machine learning and deep learning techniques, existing approaches often suffer from limited contextual representation, sensitivity to noise, and inadequate handling of non-stationary temporal deformations in ECG signals, which restrict diagnostic reliability. To address these challenges, this study introduces a novel deep learning framework termed Contextual Auxiliary Transformer with Triple Stacked Optimized Deformable Convolution Network (CAT-TODNet) for accurate heart failure detection from ECG signals. ECG recordings acquired from the MIT-BIH Arrhythmia Database are initially subjected to three-stage preprocessing, including denoising, signal smoothing, and Power Line Interference (PLI) removal, to enhance signal quality. The Contextual Auxiliary Transformer (CAT) module explicitly captures both static and dynamic contextual dependencies, enabling robust contextual feature extraction. These context-aware features are subsequently processed through triple stacked deformable convolution layers with adaptive receptive fields. To ensure stable offset estimation under non-stationary ECG conditions, the Al-Biruni Earth Radius (ABER) optimization algorithm is employed to optimize deformable convolution offsets, overcoming the limitations of gradient-based learning. Experimental results demonstrate that CAT-TODNet achieves an accuracy of 98.88.**

***Keywords*—Heart Failure (HF); Electrocardiogram (ECG); Artificial Intelligence (AI); Contextual Auxiliary Transformer (CAT); deformable convolution; optimization algorithm**

I. Introduction

Heart Failure (HF) is better understood as a complicated condition with a range of clinical indications rather than just one illness [1]. Heart failure is caused by a variety of circumstances, such as structural heart disease as well as functional changes in the heart. Poor circulation is the result of the heart's inability to pump blood efficiently throughout the body, which causes this ailment. People who have heart failure usually have a number of obvious symptoms, including exhaustion, edema in the ankles, and dyspneal [2]. In addition, patients could show symptoms from abnormalities in cardiac or noncardiac tissues, such as peripheral edema, lung fissure, and increased jugular vein pressure. Researchers have been looking into a variety of strategies for predicting cardiac conditions [3]. However, it has proven difficult to anticipate these conditions precisely in their early phases due to a number of factors, including complexity, implementation time, and the precision of the selected method. It is crucial to stress that early diagnosis and appropriate treatment can make a substantial difference in saving lives [4]. According to an international survey conducted by the European Society of Cardiology (ESC), 4.2 million new instances of heart failure were identified globally every year on top of the 30 million people who currently have the condition. Regretfully, a substantial proportion of patients among one fifth and half do not live past the first year following the onset of heart failure, and almost all patients experience a mortality rate within the period of five years [5].

Concerning the diagnosis of heart failure (HF), the electrocardiogram (ECG) is the non-invasive test that is most frequently used in the medical industry to record and capture a patient's cardiac activity [6]. However, the lack of sensitivity and specificity of classic manual analysis approaches employed to diagnose HF through the examination of ECG signals is frequently observed. ECG is a widely used diagnostic instrument that measures changes in the electrical activity of the heart to determine the condition of the heart [7]. It provides physicians with a clear-cut and simple-to-understand clinical signal. Although people with and without heart failure exhibit discernible differences in their ECG patterns, these differences are not very specific [8]. Moreover, it's critical to recognize that individual variations may be significant while manually examining ECG readings in order to diagnose heart failure. To be clearer, Cardiologists use visual analysis of ECG recordings to identify abnormalities [9]. However, this approach can take a long time, particularly when evaluating multiple ECG readings from different patients [10], [11]. Furthermore, the consistency of manual ECG signal interpretation might be affected by differences in interpretation between observers. Because of this unpredictability and time-consuming nature, developing and implementing Computer-Aided Diagnosis (CAD) systems becomes essential to improving the reliability of diagnosing heart failure using ECG records [12], [13].

There are numerous computer-assisted approaches for diagnosing heart failure have been developed as a result of the development of machine learning techniques [14]. These systems use automated feature extraction to determine heart problems with high accuracy. The most sophisticated instrument in the realm of biomedical engineering applications is Deep Learning (DL), a cutting-edge subset of Machine Learning (ML) [15]. It demonstrates its efficacy in this field by integrating hierarchical neural networks. The common ML models utilized are Naïve Bayes (NB), Gradient Boosting Classifier (GBC), Support Vector Machine (SVM), Random Forest (RF), Adaptive Boosting model (AdaBoost), and Stochastic Gradient Descent (SGD)

[16], [17]. Those ML classifiers are utilized for classification purpose of HF. The common DL models utilized are Long Short-Term Memory (LSTM), Convolution Neural Network (CNN), Gated Recurrent Unit (GRU), Deep Neural Network (DNN)., Auto Encoder (AE) etc.., [18]. Those DL models are utilized for feature extraction and feature analysis. Nonetheless, conventional ML/DL techniques necessitate manually designed features, which demand a trial-and-error approach to attain the highest classification accuracy [19]. To achieve effective and precise classification, it's essential to identify the most suitable visual characteristics for extracting ECG signals. Consequently, there's a need for further exploration into ECG signal classification without the need for feature extraction [20].

Despite recent advances in machine learning, deep learning, and transformer-based approaches for ECG-based heart failure detection, several critical limitations remain unresolved. Existing convolutional and recurrent models primarily focus on local temporal patterns and often fail to capture long-range contextual dependencies inherent in ECG signals. Although transformer-based models improve global representation, most rely on implicit self-attention mechanisms that lack explicit contextual supervision and remain sensitive to signal noise and inter-patient variability. In addition, conventional deformable convolution networks estimate offset parameters using gradient-based learning, which leads to unstable receptive field adaptation under non-stationary ECG deformations. These limitations reveal a clear research gap in developing a unified framework that explicitly models contextual information while enabling robust, optimized receptive field learning for reliable heart failure detection. This work introduces a tightly coupled framework that jointly integrates contextual transformer learning, deformable convolution, and metaheuristic offset optimization for ECG-based heart failure detection. Unlike existing transformer-based ECG models that rely on implicit self-attention or token-wise context aggregation, the Contextual Auxiliary Transformer (CAT) explicitly models static contextual dependencies prior to self-attention and enforces contextual consistency using auxiliary supervision. Furthermore, conventional deformable convolution layers estimate offsets through local gradient-based learning, which becomes unstable for ECG signals exhibiting non-stationary temporal deformations. To address this limitation, the offset estimation process is formulated as an optimization problem and solved using the Al-Biruni Earth Radius (ABER) algorithm, enabling robust exploration-exploitation balance for offset refinement. The unified interaction between CAT-derived contextual features and ABER-optimized deformable convolution distinguishes the proposed framework from existing transformer or deformable CNN architectures applied independently.

II. Related Works

In study [21] authors combine a variety of data mining approaches in conjunction with the SMOTE to improve the accuracy of forecasting the survival of patients with heart failure. In this study authors uses sophisticated data mining techniques to increase prediction accuracy and emphasizes to address class imbalance concerns in the dataset. In study [22], authors investigate the use of LSTM and CNN for automated congestive heart failure detection based on ECG readings. It emphasizes how well deep learning methods handle ECG data and produce precise diagnostic findings. A method that uses ECG signals to automatically diagnose heart failure was presented in study [23]. With an emphasis on facilitating prompt and accurate diagnostics, it probably involves techniques for feature extraction and classification to identify heart failure disorders. In order to improve the identification of cardiac disorders from ECG data, this work highlights the application of deep learning techniques in the form of ensemble models [24].

It draws attention to the possibility of enhancing overall detection performance by mixing several deep learning models. In [25], this research emphasizes the use of ECG readings in a time-adaptive manner to identify cardiovascular illnesses. It probably discusses the dynamic nature of ECG data and looks into techniques for adaptive or real-time detection, which could offer insightful information about how a disease develops. Authors in [26], designs a novel lightweight deep learning framework that uses heart sound recordings to classify cardiovascular illnesses. The special characteristics and architecture while emphasizing its potential for use in medical applications. In [27] authors provide an end-to-end deep learning system for improving the identification of cardiac illness by denoising heart sounds in real time.

It probably investigates how deep learning might improve the accuracy of disease identification by managing noise and variability in heart sound recordings. Authors in study [28], explores the creation of an explainable deep learning method for multi-label ECG data classification. It probably looks on techniques that enhance comprehension and openness by classifying ECG signals and offering comprehensible insights into the classification process. Authors in this work [29] focuses on using machine learning and deep learning techniques to analyze ECG images in order to diagnose cardiovascular disorders. It could go over feature extraction, image processing, and classification techniques, highlighting the importance of visual information in diagnosis. In study [30], authors investigate the use of deep learning neural networks for categorizing ECG signals in order to identify congestive heart failure and arrhythmia. It emphasizes how crucial it is to classify data accurately and effectively in order to recognize these serious cardiac problems.

In study [31], authors study probably presents an ECG-convolution-vision transformer network for inter-patient congestive heart failure identification. It emphasizes the creation of specialized networks for difficult jobs like diagnosing heart failure in various people. In study [32], explores a thorough method for the multilevel categorization and identification of cardiac arrhythmias. In order to increase the precision of arrhythmia diagnosis, it most likely blends deep convolutional neural networks with signal processing methods such as the superlet transform. Authors focuses on creating a wearable electrocardiogram device that leverages deep learning methods to identify cardiovascular illness in real time [33]. It emphasizes how important wearable technology is for ongoing surveillance and early detection.

The use of hybrid CNN-SVM deep neural networks in conjunction with Long Short-Term Memory (LSTM) networks to classify ECG signals into normal sinus rhythm, aberrant arrhythmia, and congestive heart failure [34]. It probably shows how useful it is to combine various deep learning architectures

to achieve precise classification. In study [35], authors draw attention to the effective use of machine learning algorithms in the prediction of cardiovascular illness. It probably highlights how crucial feature selection methods like Relief and LASSO are to raising the precision and effectiveness of prediction models. In study [36], this research presents a novel model that uses ECG signals to categorize heartbeats in order to diagnose heart illness.

The GOA in conjunction with the hybrid convolutional neural network presents a novel strategy that holds potential to improve the efficiency and accuracy of heart disease detection. Authors in study [37], centered on the use of ECG data in a multimodal fusion strategy for the diagnosis of cardiovascular illnesses. It most likely looks at ways to combine several information streams and enhance the accuracy of disease diagnosis by integrating multiple data sources or modalities. In study [38], authors discuss a DL method that uses empirical mode decomposition to extract ECG features in order to categorize cardiovascular illnesses. This approach is probably going to emphasize how crucial signal processing methods are to improving the data that is taken from ECG recordings in order to classify diseases. Authors in [39] highlight the creation and implementation of an autonomous heart failure prediction machine learning model. It might go over the usefulness of applying machine learning models in actual healthcare settings and show how they could be used to detect heart failure early on. In study [40], authors introduce a low-power ensemble network that uses ECG data to identify heart illness. It might concentrate on the effectiveness and computational viability of ensemble models, offering a method for detecting cardiac disease that is accurate and resource-efficient. Recent advances in transformer-based object detection have significantly improved contextual modeling, convergence efficiency, and real-time performance. Grounding DINO 1.5 [41] extends the DETR framework to open-set object detection by incorporating grounded representations and large-scale pretraining, enabling strong generalization to unseen categories. Relation-DETR [42] introduces explicit positional relation priors within the attention mechanism to enhance spatial reasoning and accelerate convergence. RT-DETR [43] focuses on real-time detection by eliminating non-maximum suppression and employing a hybrid encoder with optimized query selection, achieving superior speed–accuracy trade-offs compared to YOLO-based detectors. Despite these advancements, most existing DETR variants primarily target visual object localization and lack explicit contextual supervision or optimization-driven adaptive feature learning, motivating the development of more robust and context-aware detection frameworks.

III. Proposed Model

This section explains the proposed model with suitable mathematical and diagrammatic explanations. Fig. 1 represents the architectural pipeline of the proposed CAT-TODNet. The proposed research model is composed of three major stages: 1) Triple-Way Pre-Processing, 2) Transformer-based Feature Extraction, and 3) Optimized Heart Failure Detection. The overall pipeline of the proposed model is illustrated in Fig. 1. A detailed explanation of each stage is provided below.

A. Triple-Way Pre-Processing

In the Triple-Way Pre-Processing stage, the acquired ECG signals from the MIT-BIH database are pre-processed through three distinct operations: 1) denoising, 2) signal smoothing, and 3) removal of power-line interferences. The primary objective of this stage is to minimize the computational burden on subsequent Transformer and convolutional layers used for feature extraction and feature processing.

Formally, let the acquired ECG signal be represented as $s(t)$. The pre-processed signal $s'(t)$ can be defined as:

$$s'(t) = f_3(f_2(f_1(s(t)))) \tag{1}$$

where $f_1(\cdot)$, $f_2(\cdot)$, and $f_3(\cdot)$ represent the denoising, smoothing, and power-line interference removal functions, respectively.

This triple-stage processing enhances the quality of the input signal by suppressing noise components that are irrelevant to heart failure detection. Consequently, the removal of signal distortions improves both the feature representation and the overall performance of the Transformer and convolution operations in identifying the rate and severity of heart failures.

For denoising the acquired ECG signals, the Discrete Wavelet Transform (DWT) is employed since it effectively captures the signal information in both time and frequency domains. Let the original signal be represented as $s(t)$; it can be decomposed for denoising as follows:

$$s(t) = \sum_{k} c_{j_0}(k)\, \phi_{j_0,k}(t) + \sum_{j=j_0}^{J} \sum_{k} d_j(k)\, \psi_{j,k}(t) \tag{2}$$

In the above equation, $c_{j_0}(k)$ and $d_j(k)$ denote the approximation (scaling) and detail (wavelet) coefficients, respectively. The functions $\phi_{j_0,k}(t)$ and $\psi_{j,k}(t)$ represent the scaling and wavelet functions. The first term represents the coarse approximation of the signal, while the second term captures the detailed variations and noise components across different scales.

The Daubechies wavelet (DB) with a selected scale number is used as the mother wavelet to perform decomposition up to level five. The resulting coefficients—denoted as WC1–WC5 and WAC5—represent the wavelet and approximating coefficients, respectively. The noise components are eliminated by thresholding small-magnitude coefficients (setting them to zero), resulting in a denoised version of the ECG signal, $s_d(t)$, free from redundant and fluctuating artifacts.

1) Signal smoothing: After denoising, the ECG signal undergoes a smoothing process to further eliminate low-bit noise fluctuations. Let the denoised signal be $s_d(t)$. The signal length is computed and divided into N equal segments to evaluate local variations between neighboring peaks. The smoothing operation determines the local maxima deviations and removes minimal fluctuations as noise, resulting in the smoothed signal $s_s(t)$. The process can be expressed as:

$$s_s(t) = s_d(t) - \Delta n(t) \tag{3}$$

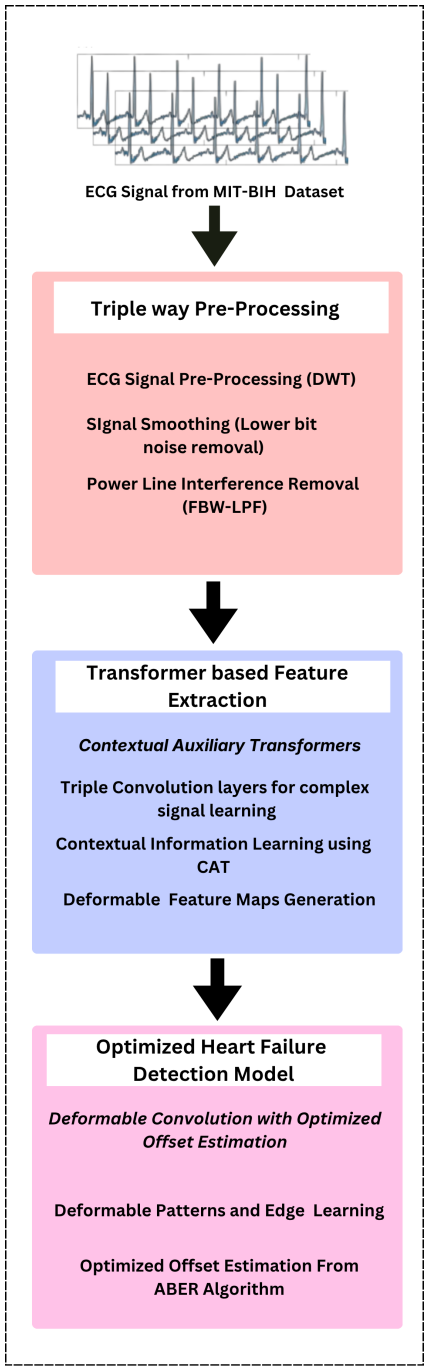


Fig. 1. Pipeline of the proposed work.

where $\Delta n(t)$ denotes the estimated low-bit noise component. This step refines the ECG waveform by preserving essential physiological characteristics while suppressing high-frequency artifacts.

2) Removal of power line interferences: To eliminate power line interference (PLI), typically occurring at 50 Hz, a Fractional Butterworth Low-Pass Filter (FBW-LPF) is adopted. The magnitude response of the FBW-LPF is mathematically formulated as:

$$|H(j\omega)| = \frac{1}{\sqrt{1 + \left(\frac{j\omega}{\omega_c}\right)^{2\alpha}}} \tag{4}$$

where ω represents the analog angular frequency (in rad/s), ω_c is the cutoff frequency (set at 50 Hz), and α defines the fractional order of the filter. This filter efficiently suppresses frequency components below the 50 Hz range, resulting in a clean waveform $s_f(t)$ suitable for the subsequent Transformer-based feature extraction stage.

B. Transformer-Based Feature Extraction

To address the limitations of conventional self-head attention Transformers in handling complex contextual dependencies, a Contextual Auxiliary Transformer (CAT) is adopted to enhance feature extraction and contextual representation. The CAT model extends the standard Transformer by integrating contextual learning within the self-attention mechanism, thereby reducing computational redundancy and improving discriminative representation of the ECG signals.

The pre-processed ECG signal $s_f(t)$ is given as the input to the CAT module, which operates based on the query (Q), key (K), and value (V) matrices. These matrices encode relationships across temporal and spatial contexts of the signal sequences. The CAT model reformulates these parameters into contextual groups and grids to efficiently capture cross-key dependencies. The contextual input y is derived from the feature representations, and the contextual interaction is modeled as the combination of keys and local attention matrices through three convolutional layers:

$$B = \text{Conv}_3(K \otimes y) \tag{5}$$

where, $\text{Conv}_3(\cdot)$ denotes a three-layer convolutional operation, $\otimes$ represents element-wise multiplication, and B refers to the local attention matrix incorporating contextual relationships. The matrix B assists in describing localized dependencies at each spatial position based on neighboring queries and keys, avoiding isolated query-key evaluations common in traditional Transformer-based models.

The resulting contextual attention allows the generation of a feature map F by integrating the value matrix V with the attention weights as follows:

$$F = B \cdot V \tag{6}$$

Here, F captures both static and dynamic feature interactions, making it highly capable of representing signal contexts with varying temporal behavior. The final CAT module output, denoted by X, integrates both static and dynamic contextual representations through the attention mechanism:

$$X = F_{static} \oplus F_{dynamic} \tag{7}$$

where, $\oplus$ denotes the element-wise summation of feature maps arising from static and dynamic contexts. The inclusion of deformable contextual maps enables the CAT network to

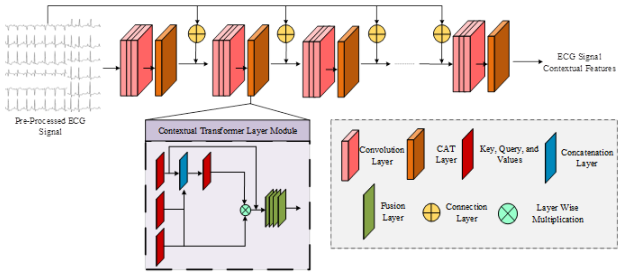


Fig. 2. Contextual Auxiliary Transformer (CAT) based feature extraction module.

model fine-grained local variations essential for accurate heart failure detection.

Finally, the CAT module is trained using a combined loss function that incorporates both the primary and auxiliary objectives, expressed as:

$$\mathcal{L}_{total} = \mathcal{L}_{main} + \lambda \mathcal{L}_{aux} \tag{8}$$

where, $\mathcal{L}_{main}$ and $\mathcal{L}_{aux}$ denote the general and auxiliary losses, respectively, and λ is the weighting coefficient controlling the contribution of the auxiliary task. Fig. 2 illustrates the architectural layout of the proposed Transformer-based feature extraction stage.

Conventional transformer architectures model contextual relationships implicitly through query-key similarity, treating each token independently during attention computation. In contrast, the Contextual Auxiliary Transformer employed in this work introduces a dual-context mechanism that combines static contextual representations with dynamic self-attention. The static context is extracted through grouped contextual convolutions applied to neighboring signal segments, enabling explicit modelling of local temporal dependencies prior to attention calculation. This contextual guidance stabilizes attention responses for ECG signals affected by noise, baseline drift, and waveform deformation. Moreover, the auxiliary loss enforces consistency between contextual and attention-driven representations, which is absent in standard self-attention or auxiliary attention models. As a result, CAT produces deformable-aware feature maps that are more suitable for subsequent offset-adaptive convolution.

The output feature map X obtained from the Transformer-based feature extraction module is provided to the optimized heart failure detection network, which comprises a sequence of deformable convolutional layers integrated with an optimized offset estimator. The deformable convolution is used to accurately capture complex and subtle ECG feature variations that are often missed by standard convolution operations.

1) Deformable convolution operation: The conventional convolution operation on a feature map x with kernel weights w and sampling locations p_n can be formulated as:

$$y(p_0) = \sum_{p_n \in R} w(p_n) \cdot x(p_0 + p_n) \tag{9}$$

where p_0 denotes the reference location on the output feature map, and R represents the regular grid kernel (e.g., 3×3).

In a deformable convolution layer, additional offsets Δp_n are introduced to adaptively sample feature locations, resulting in enhanced modeling of geometric variations in ECG waveforms. The deformable convolution operation is expressed as:

$$y(p_0) = \sum_{p_n \in R} w(p_n) \cdot x(p_0 + p_n + \Delta p_n) \tag{10}$$

Here, Δp_n represents the learnable offset parameters, dynamically adjusted during training. These offsets are computed using bilinear interpolation to ensure differentiability. Although deformable convolutions enhance adaptability, they may also produce redundant or noisy features. To alleviate this, a weighted coefficient sampling method ω is employed to selectively suppress irrelevant responses as:

$$x'(p) = \omega(p) \cdot x(p) \tag{11}$$

This weighting scheme ensures that only informative local features contribute to the heart failure classification, thereby improving detection precision and generalization.

In deformable convolution networks, offset parameters are commonly learned using back-propagation alongside convolution weights. While effective for spatial image data, this strategy becomes sub-optimal for ECG signals due to irregular temporal deformations, inter-patient variability, and sensitivity to noise. Gradient-based offset learning is prone to local minima and unstable convergence under such conditions. To overcome this limitation, offset estimation is reformulated as a global optimization problem, where the objective is to maximize feature similarity alignment across deformable receptive fields. The Al-Biruni Earth Radius (ABER) algorithm is employed to optimize offset vectors due to its balanced exploration and exploitation capability, enabling robust search in highly non-convex offset spaces. Unlike conventional optimizers such as PSO or gradient descent, ABER maintains adaptive search radius control, which improves convergence stability and prevents premature stagnation in offset learning.

2) Optimized offset estimation using ABER algorithm: To further enhance the offset estimation, the Al-Biruni Earth Radius (ABER) optimization algorithm is integrated as an intelligent offset estimator. The ABER algorithm finds optimal offsets by maximizing similarity between reference and input ECG feature maps. Let the inputs to the estimator be denoted as F_r (reference features) and F_i (input features); the optimization problem can be defined as:

$$\min_{\Delta p} f(F_r, F_i, \Delta p) \tag{12}$$

where, $f(\cdot)$ represents the fitness function evaluating the similarity between input and reference features. The search space dimension is denoted as D, and the candidate solution at iteration t is expressed as X_t.

The ABER algorithm consists of two primary phases:

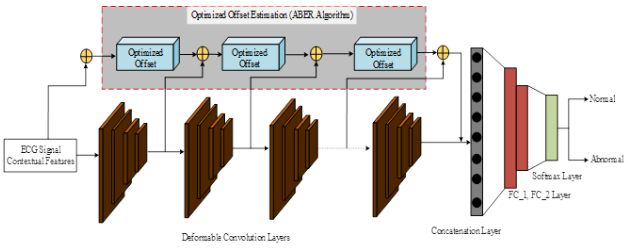


Fig. 3. Illustration of optimized heart failure detection model.

3) Non-Local feature enhancement: To capture long-range dependencies within the ECG features, non-local operations are employed after offset optimization. This operation enhances the model's capacity to represent both global and local characteristics. Mathematically, the non-local operation between an input feature f_i and an output position f_o is defined as:

$$f_o(i) = \frac{1}{C(i)} \sum_{\forall j} \theta(f_i(i)) \cdot \phi(f_i(j)) \cdot g(f_i(j)) \tag{13}$$

where, $\theta(\cdot)$, $\phi(\cdot)$, and $g(\cdot)$ denote embedding, pairwise, and transformation functions, respectively, and $C(i)$ is a normalization factor. The combined use of deformable convolution, ABER-optimized offset estimation, and non-local contextual modeling effectively refines the heart failure detection mechanism.

Fig. 3 illustrates the architecture of the proposed Optimized Heart Failure Detection Model.

a) Exploitation phase: In this phase, the primary objective is to enhance the performance of the previously explored candidate solutions by refining them toward the optimal offset estimator. The formulation for the exploitation-based ABER can be expressed as:

$$X_t^{\text{new}} = X_{\text{best}} + \gamma \cdot (R_d \cdot \text{rand}()) \tag{14}$$

where, X_t^{new} represents the updated offset vector at iteration t, X_{best} is the best solution obtained from the exploration phase, R_d is the search area diameter [from Eq. (13)], and γ is the adaptive learning rate controlling step-size toward the best candidate.

To further refine the best offset estimator within the exploitation region, the updated position is evaluated using:

$$X_{t+1} = X_t + \phi \cdot (X_{\text{best}} - X_t) + \delta \cdot \text{rand}() \tag{15}$$

where, ϕ and δ denote adaptation coefficients balancing exploitation intensity and stochastic perturbation, respectively. The random vector $\text{rand}() \in [0, 1]$ introduces controlled randomness to avoid premature convergence and improve the stability of offset estimation.

Finally, the best candidate solution during dual iteration is updated as:

Algorithm 1 ABER-Based Optimized Offset Estimation for Deformable Convolution

Require: Reference feature F_r, Input feature F_i, Parameters R_d, β, ϕ, δ
Initialize candidate solutions X_i randomly within the search space.
for $t = 1$ to $T_{\max}$ **do**
  Evaluate fitness $f(X_i)$ for all candidates.
  Update best solution: $X_{\text{best}} = \arg\min f(X_i)$.
  {Exploration Phase}
  Compute: $R_d = 2E_r \cdot \text{rand}() - E_r$.
  Update candidate position: $X_t^{\text{new}} = X_t + \beta \cdot R_d$.
  {Exploitation Phase}
  Update position:

$$X_{t+1} = X_t + \phi(X_{\text{best}} - X_t) + \delta \cdot \text{rand}()$$

  if $f(X_{t+1}) < f(X_{\text{best}})$ **then**
    $X_{\text{best}} = X_{t+1}$.
  end if
  Gradually reduce R_d to ensure convergence.
end for
return Optimized offset vector: $X_{\text{optimal}} = X_{\text{best}}$.

$$X_{\text{optimal}}^{t+1} = \begin{cases} X_{t+1}, & \text{if } f(X_{t+1}) < f(X_{\text{best}}) \\ X_{\text{best}}, & \text{otherwise} \end{cases} \tag{16}$$

where, $f(\cdot)$ denotes the fitness function evaluating the similarity and feature matching accuracy between the reference and input ECG signals.

C. Experimental Evaluation

This section extensively details the results achieved through our novel approach, considering both quantitative and qualitative evaluations in contrast to established methodologies. Furthermore, it thoroughly assesses how our method performs across three separate datasets when compared to existing approaches. It initiates by outlining the dataset characteristics, proceeds with an in-depth analysis of results under various conditions, and concludes with a meaningful discussion, providing valuable insights based on the findings.

The electrocardiogram (ECG) signals used in this study are obtained from the MIT-BIH Arrhythmia Database, which is publicly available through PhysioNet. The database consists of annotated ECG recordings collected from 48 subjects, with each record sampled at 360 Hz and containing two leads. The signals are segmented into fixed-length windows to facilitate uniform analysis and model training.

For experimental evaluation, ECG segments are categorized into heart failure and non–heart failure classes based on the provided annotations. A patient-wise data split strategy is employed to avoid data leakage, ensuring that samples from the same subject do not appear in more than one subset. The dataset is divided into training, validation, and testing sets using a fixed ratio.

The heart failure detection model, referred to as CATTODNet, is implemented using MATLAB. The model is trained for 100 epochs with a batch size of 32 and a learning rate of 0.001, using the Adam optimization algorithm. All

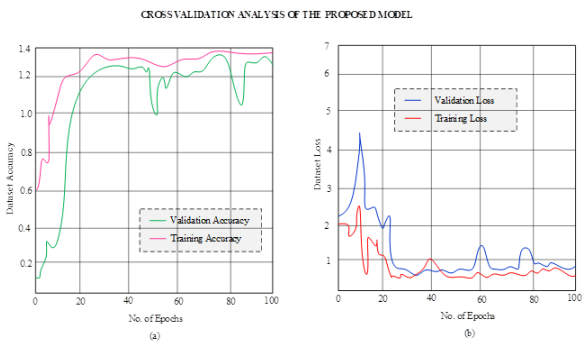


Fig. 4. (a) Shows the training and validation accuracy, (b) shows the training and validation loss.

experiments are conducted on an HP Pavilion laptop equipped with an AMD Ryzen 5 5600H processor with Radeon Graphics operating at 3.30 GHz, 8 GB of Random-Access Memory (RAM), and the Windows 11 Operating System. The same training configuration is maintained across all experiments to ensure reproducibility and fair performance evaluation.

The performance metrics utilized for validating the proposed work can be formulated as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{17}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{18}$$

$$\text{Recall (Sensitivity)} = \frac{TP}{TP + FN} \tag{19}$$

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{20}$$

where, TP, TN, FP, and FN denote the true positive, true negative, false positive, and false negative rates, respectively. The AUC-ROC curve offers a comprehensive assessment of the classifier's performance across a range of possible thresholds. A higher AUC signifies superior performance by the classifier.

Fig. 4(a) and (b) represent the training and validation accuracy, and training and validation loss of the proposed work, respectively.

The following state-of-the-art models were selected for comparison against the proposed CAT-TODNet architecture:

- SMOTE-HF [21]: This study adopts ECG data for analysing the heart failure by comparing the nine benchmark machine learning algorithms.
- DeepCNN-LSTM [6]: This study also utilized ECG signals for diagnosing the heart disease using combine deep learning algorithm.

TABLE I. Quantitative Evaluation of Pre-Processing Across Methods

Model	Accuracy	Precision	Recall	F1-Score
CAT-TODNet (w/ Pre-processing)	**0.9899**	**0.9903**	**0.9800**	**0.9876**
CAT-TODNet (w/o Pre-processing)	0.9435	0.9323	0.9326	0.9300
DeepCNN-LSTM [22]	0.9267	0.9309	0.9215	0.9276
CHF-CVTN [31]	0.9154	0.9149	0.9184	0.9126

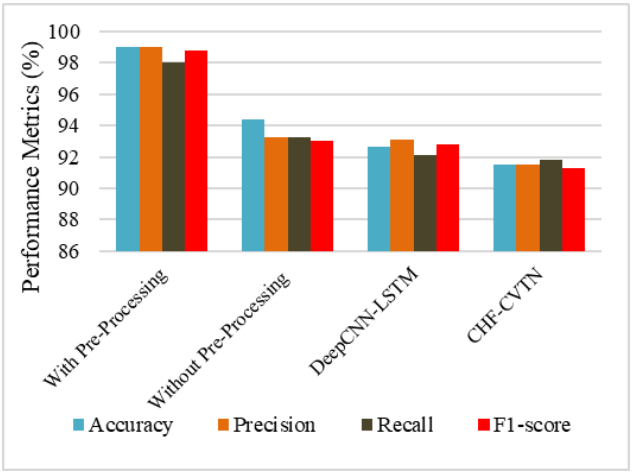


Fig. 5. Evaluation of pre-processing process.

- Ensemble-DL [24]: In this research, an ensemble of DL models is utilized for detecting the heart disease from two benchmark ECG database.
- Heart-CVDD [25]: This research adopts two stage classification algorithms for cardiovascular disease detection from ECG signals.
- CHF-CVTN [31]: In this study the heart failure disease are diagnosed by adopting convolution based transformer network using ECG signals.
- CHF-DL-ML [34]: The diagnosis of congenital heart failure disease gets diagnosed by adopting combined DL and ML algorithms named LSTM-CNN-SVM from ECG signals.

IV. Experimental Evaluation

Fig. 5 represents the comparison of the proposed pre-processing process and its impacts with the existing works. In order to employ the better pre-processing examination process, we also split the proposed CAT-TODNet into two scenarios such as with and without pre-processing respectively. In addition to that, we have compared the proposed CAT-TODNet with two existing works that adopts pre-processing such as DeepCNN-LSTM [22], and CHF-CVTN [31] respectively. The quantitative results of the pre-processing are shown in Table I below.

From Fig. 5 and Table I, it is seen that the proposed scenario with pre-processing achieves higher results whereas the proposed scenario without pre-processing lesser than the with pre-processing scenario. On the other hand, the existing works which uses pre-processing in which the DeepCNN-LSTM

TABLE II. COMPARISON OF CONVENTIONAL MODELS AND PROPOSED FEATURE EXTRACTION MODEL

Model	Accuracy	Precision	Recall	F1-Score	AUC
RF	0.8478	0.8598	0.8502	0.8487	–
DT	0.8646	0.8734	0.8615	0.8711	–
SVM	0.9156	0.9110	0.9199	0.9197	–
DNN	0.9465	0.9451	0.9595	0.9537	–
AEs	0.9552	0.9509	0.9698	0.9689	–
Proposed (CAT-TODNet)	**0.9777**	**0.9888**	**0.9810**	**0.9836**	**–**

TABLE III. COMPARISON OF EXISTING METHODS AND PROPOSED FEATURE EXTRACTION MODEL

Model	Accuracy	Precision	Recall	F1-Score	AUC
SMOTE-HF [21]	0.8889	0.8809	0.8813	0.8898	–
DeepCNN-LSTM [22]	0.9046	0.9045	0.9026	0.9022	–
Ensemble-DL [24]	0.9367	0.9321	0.9300	0.9308	–
Heart-CVDD [25]	0.9576	0.9562	0.9698	0.9648	–
CHF-CVTN [31]	0.9763	0.9720	0.9708	0.9790	–
Proposed (CAT-TODNet)	**0.9988**	**0.9999**	**0.9921**	**0.9948**	**–**

utilizes only normalization procedure whereas the CHF-CVTN resampling, normalization, and segmentation respectively. The quantitative results of the existing works are significantly lower than the proposed scenarios. The reason for such higher results of the proposed work is that, we perform signal denoising, signal smoothing, and powerline interference removal which effectively suppress noise components in the ECG signal thereby providing denoised signal for further processing that also improve the performance results. Whereas the existing works are not focused on resolving noises whereas they only normalize them to certain limit which resolves the complexity but reduces the performance of the overall model. In detailed manner, the proposed with pre-processing scenario achieves higher accuracy, precision, recall, and F1-score rate of (4.64%–7.45%), (5.8%–7.54%), (4.74%–6.16%), and (5.76%–7.5%) than the existing works.

A. Evaluation of Feature Extraction

The validation of proposed feature extraction model named Contextual Auxiliary Transformer (CAT) to the conventional model and existing works are detailed in this section. The conventional models includes Machine Learning (ML) and Deep Learning (DL) models such as Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), Deep Neural Network (DNN), Auto Encoders (AEs) whereas the existing feature extraction models includes SMOTE-HF [21] which uses ML algorithms, DeepCNN-LSTM [22] which uses CNN for feature extraction, Ensemble-DL [24] uses self-organizing maps for feature extraction, Heart-CVDD [25] uses time based dynamic CNN for feature extraction, and CHF-CVTN [31] uses transformer based convolution model for feature extraction. The quantitative results of the feature extraction in terms of conventional models and existing research works are shown in Table II and Table III below.

The graphical representation depicted in Fig. 6(a) and 6(b), and Fig. 7(a) and 7(b) compares the proposed Feature Extraction (FE) approach with both traditional models and previous studies, evaluating their performance metrics and AUC-ROC values. Specifically, Fig. 6(a) and 6(b) analyse the performance metrics of conventional models and prior works, respectively. The illustration indicates that the proposed model outperforms both the traditional models and existing works. Regarding the quantitative outcomes, the accuracy, precision, recall, and F1-score achieved by the proposed FE are 2.55%–12.99%, 3.79%–2.9%, 1.12%–13.08%, and 1.47%–13.49% higher than the conventional ML/DL models, whereas for existing works the proposed work achieved are 2.25%–10.99%, 2.79%–11.9%, 2.13%–8.95%, and 1.58%–10.5% higher. Similarly, Fig. 7(a) and 7(b) present the AUC-ROC evaluation for conventional models and existing works, respectively. The AUC-ROC is higher for the conventional models compared to existing works. This superior performance of the proposed FE stems from its utilization of an attention-based transformer model, enabling robust extraction of signal context features by analysing intricate signal patterns. Conversely, the shortcomings in conventional and existing models include higher tendencies toward overfitting, training complexity, adaptability issues, and respectively lower accuracy in feature extraction.

TABLE IV. COMPARISON OF EXISTING WORKS AND PROPOSED OPTIMIZED CLASSIFICATION MODEL

Model	Accuracy	Precision	Recall	F1-score	AUC
SMOTE-HF [21]	0.8555	0.8500	0.8526	0.8523	–
DeepCNN-LSTM [22]	0.8857	0.8845	0.8816	0.8812	–
Ensemble-DL [24]	0.9078	0.9032	0.9022	0.9019	–
Heart-CVDD [25]	0.9387	0.9373	0.9317	0.9359	–
CHF-DL-ML [34]	0.9663	0.9610	0.9609	0.9690	–
DeepECG-Net [44]	0.9820	0.9820	0.9680	0.9750	–
Proposed (CAT-TODNet)	**0.9888**	**0.9899**	**0.9821**	**0.9847**	**–**

B. Evaluation of Heart Disease Classification Model

This section thoroughly outlines the validation process for the proposed optimized heart failure detection model concerning existing methods. The current classification models under scrutiny encompass diverse approaches: SMOTE-HF [21], employing nine ML algorithms; DeepCNN-LSTM [22], utilizing LSTM; Ensemble-DL [24], employing autoencoders; Heart-CVDD [25], utilizing Bi-directional LSTM; and CHF-DL-ML [34], utilizing support vector machines. The quantitative outcomes derived from these models concerning heart disease classification are tabulated below in Table IV for a comprehensive comparison (also see, Fig. 8 and 9).

V. DISCUSSION AND LIMITATIONS

This section explores the overall summary of the proposed work with its implementation results. From the implementation summary, the results achieved demonstrate superior performance than the existing works. We also compare the proposed implementation model with the conventional ML and DL models respectively. It is clearly depicted that in the above tables and figures that the results of the proposed work are within 97%–100%. The near-saturation accuracy is achieved under a strict patient-wise evaluation protocol, which mitigates overfitting and ensures reliable performance estimation. The major difference among the proposed and existing works are that, most of the existing works utilized CNN and ML algorithms as their FE and classification model

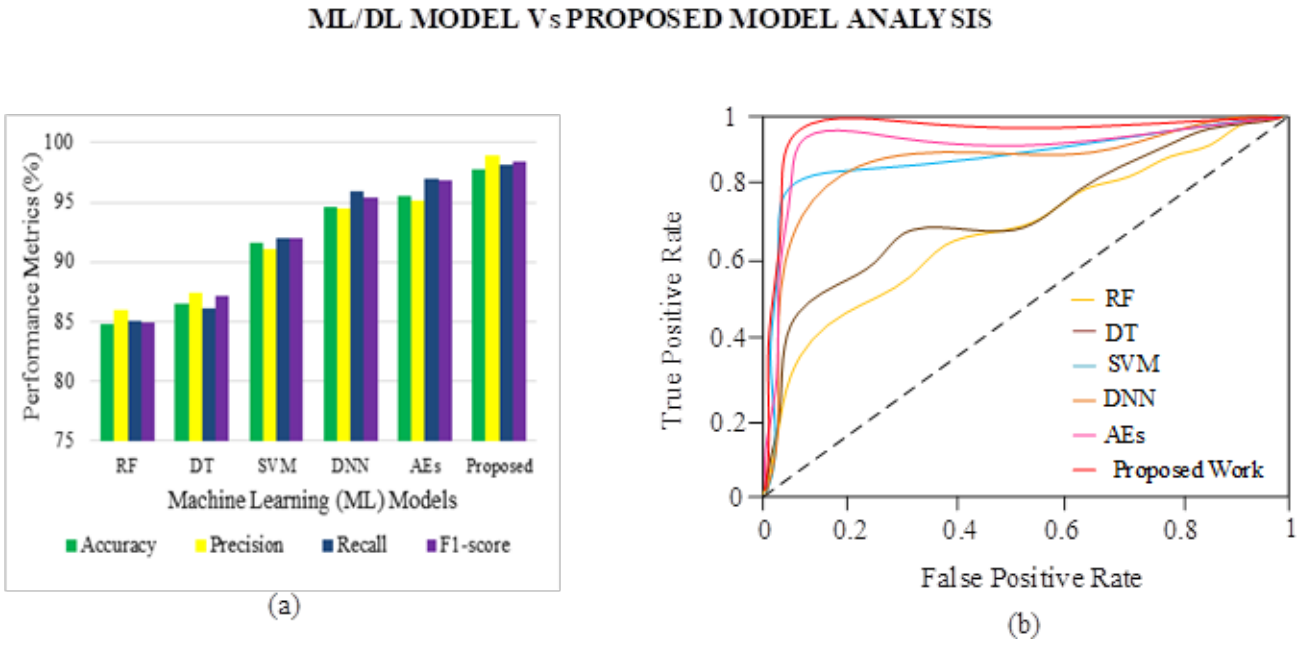


Fig. 6. (a) Performance metrics analysis of proposed work vs. ML/DL Models, (b) AUC comparison of proposed vs. ML/DL models.

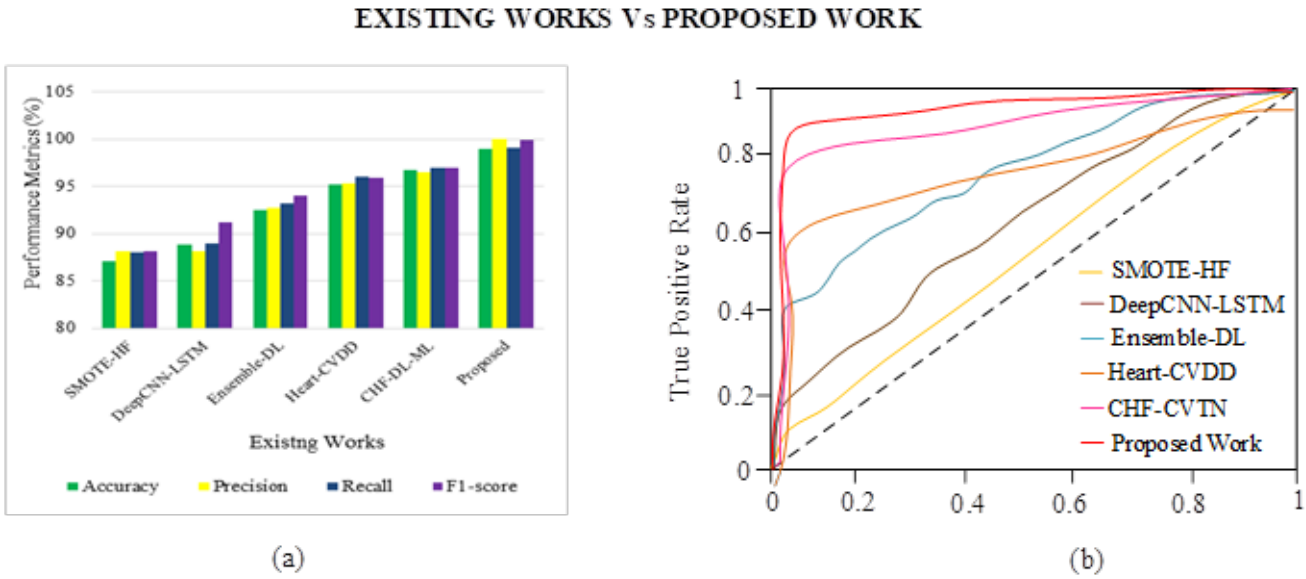


Fig. 7. (a) Performance metrics analysis of proposed vs. Existing models, (b) AUC comparison of proposed vs. Existing models.

and there were no improvements over that models which leads to higher complexity, time consumption, and poor accuracy in detecting heart disease respectively. On the whole, the major contribution of the proposed CAT-TODNet is that we utilize the attention based contextual transformer model for feature extraction which extracts the signal contextual features with the signal characteristics. Furthermore, those contextual features are provided to the optimized offset estimator which dynamically set the offset value to the deformable convolution layers to capture the feature interdependencies and provide the accurate output.

On the other hand, one of the major limitations of our study is that, the proposed research is not suitable for remote detection/prediction of heart disease detection. To be clearer, the designed model is centralized and did not adopt for distributed remote diagnosis for heart disease detection. On the other hand, we utilize only limited data to train the proposed model which make it to provide only limited results.

VI. Conclusion

The detection of Heart Failure (HF) through continuous monitoring of heart wave patterns is pivotal in reducing mortality rates. Utilizing Electrocardiogram (ECG) alongside Artificial Intelligence (AI) has been explored in previous

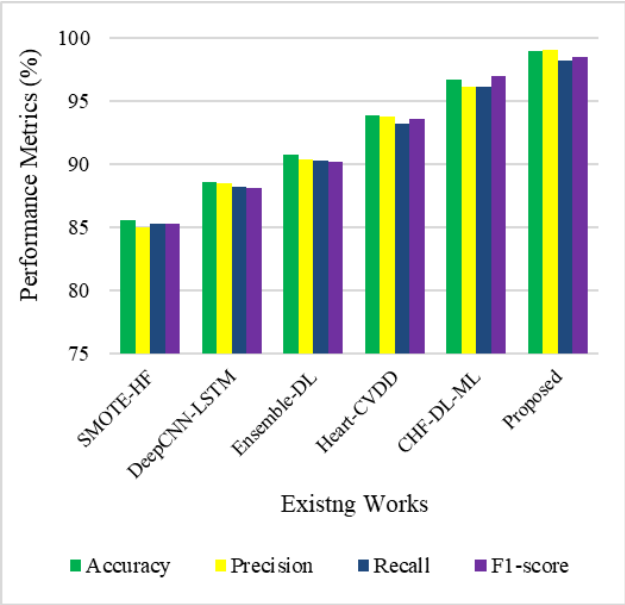


Fig. 8. Evaluation of heart failure detection model for proposed vs. Existing works.

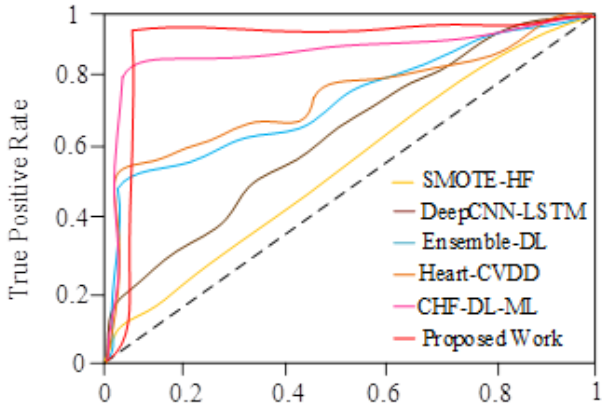


Fig. 9. AUC analysis of proposed heart failure detection model.

research, albeit with issues of accuracy and complexity. To address these shortcomings, our innovation, CAT-TODNet, integrates a stacked and optimized deformable convolution with a Contextual Attention Transformer (CAT) for HF detection from ECG signals. By preprocessing data from the MIT-BIH dataset through denoising, signal smoothing, and power line interference removal, we optimize feature extraction through CAT. This model learns contextual features and generates deformable feature maps crucial for HF detection. Our optimized HF model incorporates dynamic offset estimation in deformable convolution layers, enhancing the interpretation of contextual features. The integration of the Al-Biruni Earth Radius (ABER) optimization algorithm dynamically adjusts the offset estimator, improving feature similarities and ensuring precise and reliable outputs.

MATLAB simulations validate our approach, exhibiting superior performance compared to existing methods across multiple evaluation metrics such as accuracy, recall, precision, F1-score, and AUC. This research underscores the potential of CAT-TODNet in significantly enhancing HF detection accuracy, thereby contributing to reducing HF-related mortality rates. Future work could delve deeper into real-time implementation and explore the scalability of the proposed model across diverse datasets for robust and widespread applicability in clinical settings.

REFERENCES

[1] M. R. Maurya, N. U. S. Riyaz, M. S. B. Reddy, H. C. Yalcin, H. M. Ouakad, I. Bahadur, and K. K. Sadasivuni, "A review of smart sensors coupled with Internet of Things and Artificial Intelligence approach for heart failure monitoring," *Medical & Biological Engineering & Computing*, pp. 1–19, 2021.

[2] M. Kavitha, G. Gnaneswar, R. Dinesh, Y. R. Sai, and R. S. Suraj, "Heart disease prediction using hybrid machine learning model," in *2021 6th International Conference on Inventive Computation Technologies (ICICT)*, 2021, pp. 1329–1333.

[3] A. Gahane and C. Kotadi, "An Analytical Review of Heart Failure Detection based on IoT and Machine Learning," in *2022 Second International Conference on Artificial Intelligence and Smart Energy (ICAIS)*, 2022, pp. 1308–1314.

[4] M. O. Butt, A. U. Rehman, S. Javaid, T. M. Ali, and A. Nawaz, "An Application of Artificial Intelligence for an Early and Effective Prediction of Heart Failure," in *2022 Third International Conference on Latest trends in Electrical Engineering and Computing Technologies (INTELLECT)*, 2022, pp. 1–6.

[5] A. Newaz, F. S. Haq, and N. Ahmed, "A case study on risk prediction in heart failure patients using random survival forest," in *2021 5th International Conference on Electrical Engineering and Information Communication Technology (ICEEICT)*, 2021, pp. 1–6.

[6] A. Kumar, K. Rathor, S. Vaddi, D. Patel, P. Vanjarapu, and M. Maddi, "ECG Based Early Heart Attack Prediction Using Neural Networks," in *2022 3rd International Conference on Electronics and Sustainable Communication Systems (ICESC)*, 2022, pp. 1080–1083.

[7] R. K. Mahendran, P. Velusamy, and P. Pandian, "An efficient priority-based convolutional auto-encoder approach for electrocardiogram signal compression in Internet of Things based healthcare system," *Transactions on Emerging Telecommunications Technologies*, vol. 32, no. 1, p. e4115, 2021.

[8] R. Avanzato and F. Beritelli, "Heart disease recognition based on extended ECG sequence database and deep learning techniques," in *2022 IEEE International Conference on Internet of Things and Intelligence Systems (IoTaIS)*, 2022, pp. 117–121.

[9] S. N. Singh and M. Bhushan, "Smart ECG monitoring and analysis system using machine learning," in *2022 IEEE VLSI Device Circuit and System (VLSI DCS)*, 2022, pp. 304–309.

[10] I. H. Tsai and B. I. Morshed, "Beat-by-beat Classification of ECG Signals with Machine Learning Algorithm for Cardiac Episodes," in *2022 IEEE International Conference on Electro Information Technology (eIT)*, 2022, pp. 311–314.

[11] R. R. Lopes *et al.*, "Improving electrocardiogram-based detection of rare genetic heart disease using transfer learning: An application to phospholamban p.Arg14del mutation carriers," *Computers in Biology and Medicine*, vol. 131, p. 104262, 2021.

[12] D. R. Krithika and K. Rohini, "Ensemble Based Prediction of Cardiovascular Disease Using Bigdata analytics," in *2021 International Conference on Computing Sciences (ICCS)*, 2021, pp. 42–46.

[13] A. Al Ahdal, M. Rakhra, S. Badotra, and T. Fadhaeel, "An integrated machine learning techniques for accurate heart disease prediction," in *2022 International Mobile and Embedded Technology Conference (MECON)*, 2022, pp. 594–598.

[14] Z. Sun *et al.*, "Comparing machine learning models and statistical models for predicting heart failure events: a systematic review and meta-analysis," *Frontiers in Cardiovascular Medicine*, vol. 9, p. 812276, 2022.

[15] M. A. M. Hasan, J. Shin, U. Das, and A. Srizon, "Identifying prognostic features for predicting heart failure by using machine learning algorithm," in *2021 11th International Conference on Biomedical Engineering and Technology*, 2021, pp. 40–46.

[16] J. Botros, F. Mourad-Chehade, and D. Laplanche, "CNN and SVM-Based Models for the Detection of Heart Failure Using Electrocardiogram Signals," *Sensors*, vol. 22, no. 23, p. 9190, 2022.

[17] H. R. Al-Absi *et al.*, "Risk factors and comorbidities associated to cardiovascular disease in Qatar: A machine learning based case-control study," *IEEE Access*, vol. 9, pp. 29929–29941, 2021.

[18] M. F. Aslan, K. Sabanci, and A. Durdu, "A CNN-based novel solution for determining the survival status of heart failure patients with clinical record data: numeric to image," *Biomedical Signal Processing and Control*, vol. 68, p. 102716, 2021.

[19] S. Hussain *et al.*, "Novel deep learning architecture for predicting heart disease using CNN," in *2021 19th OITS international conference on information technology (OCIT)*, 2021, pp. 353–357.

[20] V. Jahmunah *et al.*, "Automated detection of coronary artery disease, myocardial infarction and congestive heart failure using GaborCNN model with ECG signals," *Computers in Biology and Medicine*, vol. 134, p. 104457, 2021.

[21] A. Ishaq *et al.*, "Improving the Prediction of Heart Failure Patients' Survival Using SMOTE and Effective Data Mining Techniques," *IEEE Access*, vol. 9, pp. 39707–39716, 2021.

[22] S. Kusuma and K. R. Jothi, "ECG signals-based automated diagnosis of congestive heart failure using Deep CNN and LSTM architecture," *Biocybernetics and Biomedical Engineering*, 2022.

[23] L. Chen, H. Yu, Y. Huang, and H. Jin, "ECG Signal-Enabled Automatic Diagnosis Technology of Heart Failure," *Journal of Healthcare Engineering*, 2021.

[24] A. Rath, D. Mishra, G. Panda, S. C. Satapathy, and K. Xia, "Improved heart disease detection from ECG signal using deep learning-based ensemble model," *Sustainable Computing: Informatics and Systems*, vol. 35, p. 100732, 2022.

[25] M. S. Haleem *et al.*, "Time adaptive ECG driven cardiovascular disease detector," *Biomedical Signal Processing and Control*, vol. 70, p. 102968, 2021.

[26] S. B. Shuvo *et al.*, "CardioXNet: A Novel Lightweight Deep Learning Framework for Cardiovascular Disease Classification Using Heart Sound Recordings," *IEEE Access*, vol. 9, pp. 36955–36967, 2021.

[27] S. N. Ali *et al.*, "An End-to-End Deep Learning Framework for Real-Time Denoising of Heart Sounds for Cardiac Disease Detection in Unseen Noise," *IEEE Access*, vol. 11, pp. 87887–87901, 2023.

[28] E. Sala and S. Ursprung, "Artificial Intelligence in Radiology: The Computer's Helping Hand Needs Guidance," *Radiology: Artificial Intelligence*, vol. 2, no. 6, p. e200207, 2020.

[29] M. Abubaker and B. Babayiğit, "Detection of Cardiovascular Diseases in ECG Images Using Machine Learning and Deep Learning Methods," *IEEE Transactions on Artificial Intelligence*, vol. 4, pp. 373–382, 2023.

[30] S. Krishnakumar *et al.*, "Detection of Arrhythmia and Congestive Heart Failure Through Classification of ECG Signals Using Deep Learning Neural Network," in *2021 International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA)*, 2021, pp. 1–7.

[31] T. Liu *et al.*, "Inter-Patient Congestive Heart Failure Detection Using ECG-Convolution-Vision Transformer Network," *Sensors*, vol. 22, 2022.

[32] P. M. Tripathi, A. Kumar, M. Kumar, and R. S. Komaragiri, "Multi-level Classification and Detection of Cardiac Arrhythmias With High-Resolution Superlet Transform and Deep Convolution Neural Network," *IEEE Transactions on Instrumentation and Measurement*, vol. 71, pp. 1–13, 2022.

[33] P. Wang *et al.*, "A Wearable ECG Monitor for Deep Learning Based Real-Time Cardiovascular Disease Detection," 2022.

[34] A. C. Cinar and S. A. Tuncer, "Classification of normal sinus rhythm, abnormal arrhythmia and congestive heart failure ECG signals using LSTM and hybrid CNN-SVM deep neural networks," *Computer Methods in Biomechanics and Biomedical Engineering*, vol. 24, pp. 203–214, 2020.

[35] P. Ghosh *et al.*, "Efficient Prediction of Cardiovascular Disease Using Machine Learning Algorithms With Relief and LASSO Feature Selection Techniques," *IEEE Access*, vol. 9, pp. 19304–19326, 2021.

[36] A. Tyagi and R. Mehra, "Intellectual heartbeats classification model for diagnosis of heart disease from ECG signal using hybrid convolutional neural network with GOA," *SN Applied Sciences*, vol. 3, 2021.

[37] G. Song *et al.*, "A Multimodel Fusion Method for Cardiovascular Disease Detection Using ECG," *Emergency Medicine International*, vol. 2022.

[38] Y. Li *et al.*, "A deep learning approach to cardiovascular disease classification using empirical mode decomposition for ECG feature extraction," *Biomedical Signal Processing and Control*, vol. 79, p. 104188, 2023.

[39] K. A. Pandian, T. S. Sai Kumar, S. P. Dhandare, and S. Thabasum Aara, "Development and Deployment of a Machine Learning Model for Automatic Heart Failure Prediction," in *2021 Asian Conference on Innovation in Technology (ASIANCON)*, 2021, pp. 1–6.

[40] S. Shin *et al.*, "Lightweight Ensemble Network for Detecting Heart Disease Using ECG Signals," *Applied Sciences*, vol. 12, no. 20, p. 10562, 2022.

[41] T. Ren *et al.*, "Grounding DINO 1.5: Advancing the edge of open-set object detection," *arXiv preprint arXiv:2405.10300*, 2024.

[42] X. Hou *et al.*, "Relation DETR: Exploring explicit position relation prior for object detection," in *European Conference on Computer Vision (ECCV)*, pp. 89–105, Springer Nature Switzerland, 2024.

[43] Y. Zhao *et al.*, "DETRs beat YOLOs on real-time object detection," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 16965–16974, 2024.

[44] M. Alghieth, "DeepECG-Net: A hybrid transformer-based deep learning model for real-time ECG anomaly detection," *Scientific Reports*, vol. 15, no. 1, p. 20714, 2025.

Application of Improved YOLO-LSTM with Combined MQTT-LoRaWAN for AI Surveillance in Tea Plantations to Prevent Elephant Intrusion

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***Abstract*—Elephant-human conflict is a growing problem in tea garden areas of Dooars in North Bengal, resulting in massive cost for crops, infrastructures and sometimes human life as well. Each year, these mild-mannered giants destroy crops, destroy fences and even threaten the locals, which raises the costs of repairs and endangering lives. The conventional deterring methods, such as fences, firecrackers, and patrols are mostly ineffective, unsustainable or cruel to the animals. As a way of addressing this predicament, scholars have designed a non-invasive, intelligent surveillance system named HIS-Hexagonal Intelligent Surveillance. HIS integrates state-of-the-art machine learning with artificial intelligence by combining an improved YOLO-LSTM and MQTT-LoRaWAN, which combines the capabilities of distributed-based agents with predictive analytics and hex-grid mapping scheme. HIS is an effective solution for elephant intrusions detection and deterrence for ecological balance. The system sends specific warnings before the elephants can cause havoc when an intrusion is detected. The hex-grid mapping enables the operators to have accurate spatial knowledge and the predictive analytics forecasts the time and location where the elephants could roam. The virtual simulation of the proposed work shows 98% accuracy on designed-custom dataset of elephants. The paper offers a background of the architecture, theoretical framework, algorithm models, and expected benefits of the proposed framework.**

***Keywords*—Tea garden; machine learning; artificial intelligence**

I. Introduction

It is the source of livelihood of millions of workers besides being a key economic activity in some areas of Dooars in the North Bengal region of India. These plantations are however, mostly located in or near the elephant habitats. For this reason, human-elephant conflict in the form of elephant crop raiding is a repeated calamity in these areas. Elephants invade plantations for food or migratory movement and cause economic loss, infrastructural damage and casualties.

Reinforcing mahouts using traditional barriers such as electric fencing and manual surveillance for a number of years has not provided the hoped-for relief from elephant pressure. These techniques suffer from little flexibility, laborious nature, and acting in an ecologically or morally questionable manner. There is an urgent need for a smart, non-invasive and autonomous system for dynamic prediction, monitoring and prevention of elephant intrusions.

This study offers a new hybrid strategy to combine different advanced technologies for better tracking and monitoring of elephant movements. It uses Machine Learning (ML) for real-time prediction of the movement pattern of elephants, making a timely and accurate prediction possible. In addition, it adds Intelligence (SI) to autonomously detect and react to changes in the environment and to animal behavior. In order to guarantee a thorough coverage and an efficient zone-based surveillance, the method also utilizes Hexagonal Surveillance (HS) which allows for an efficient spatial surveillance using a structured hexagon-based grid system.

The organization of the present study is as follows: Section II is the review of the related literature, and Section III is the description of the proposed methodology. Section IV identifies the mathematical model. The algorithm appears in Section V, and other Sections provide virtual simulation results, concluding statements and possible research directions.

II. Related Works

Current means of controlling the elephant movement are based on traditional ways, lacking significant limitations. A YOLO-LSTM framework that builds upon the benefit of rapid spatial detection and time modeling and thus delivers very high accuracy in human action recognition in video sequences [1]. Another YOLO-LSTM-based motorway surveillance model, capable of deriving real-time traffic features and forecasting congestion to control effective use of emergency lanes [2, 3]. Rivera-Acosta et al. create the American Sign Language alphabet translator in real time, which puts together a YOLO detector, LSTM module, and a developed spelling correction system [4, 5]. A comparative study of communication protocols in the IoT in CoAP, MQTT, and HTTP in their architecture, performance, and application-suitability [6]. A module-oriented over-the-air firmware update system was proposed on LoRaWAN, which allows flexible, efficient, and reliable distribution of software parts to IoT devices with limited capabilities [7]. Although electric fences are expensive to install and maintain and may be very detrimental to wildlife [8]. Noise-based deterrents like firecrackers are also likely to become ineffective over time as the elephants soon become accustomed to them [9, 10]. Human patrolling though useful is very laborious and unreliable as it is not always available [11].

The recent research indicates that there is the potential of transforming the way machine learning is used to complement various next-generation surveillance systems, such as grid-based approach to guard crop [12]. Cloud-based detection is another research [13]. Among others, one study identifies

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the necessity of a communication-aware coverage strategy due to the need to adapt to dynamic environments through monitoring using UAV [14, 15]. Moreover, distributed machine learning has been known to increase capabilities. As a result, as mentioned in a recent open-access archive preprint, UAVs have the capability of providing robust and intelligent surveillance and communication, even in the presence of failures and/or varying conditions through distributed learning [16]. Another study also reported that a hybrid AI with deep reinforcement learning architecture can help in efficient surveillance that increases scalability and autonomy [17]. Collectively, these innovations demonstrate the transformative power of machine learning in driving the frontiers of intelligence for modern surveillance systems.

Swarm-based surveillance has seen a significant advancement in distributed monitoring and intelligent decision making. An instance is the project Eye that offers an integrated platform of intelligence, emergent behavior, and computer graphics. This system permits trying new image processing methods in order to enhance the decision making abilities. It is able to process and capture imagery in parallel via highly developed collaboratively functioning visual units able to view, capture and process imagery simultaneously to create information of great value in real time. Remarkably, the platform is used to provide autonomous and distributed reconfiguration to the UAV formations according to the situational changes in tactical domain, thus exhibiting flexibility as well as adaptability to changing scenarios [18].

Likewise, the DIANA structure solves several important problems in the safety of the motion and effectiveness of operations during -based missions. It presents a new parallel mission planning algorithm that combines evolutionary computation, machine learning, and deterministic solutions to guarantee robust and reliable coordination [19].

Collectively, these innovations demonstrate the potential of networked smart cameras and autonomous agents with machine learning capabilities to serve as intelligent and adaptive components in the advanced surveillance architecture.

Emerging new technologies for wildlife monitoring such as camera traps combined with AI-based image-recognition based on animal tracking, and smart cameras for unending vigil have come into existence but there are serious constraints like shorter battery life, being prone to the environment etc. However, as promising as these technologies are, they are often deployed in silos and are rarely embedded in a convergent methodology or system, almost never with enough real-time agility to adapt for speedy, effective wildlife management.

III. Methodology

The proposed HIS (Hexagonal Intelligent Surveillance) System — a fully integrated, intelligent framework designed to enhance elephant monitoring and deterrence by combining advanced computational methods and spatial strategies. The schematic overview of the system is shown in Fig. 1. The proposed methodology is shown in Fig. 2. The proposed hexagonal surveillance system is pictured in Fig. 3. The work flow progress of the proposed system is described in Fig. 4. It shows that the proposed system will help to focus the accuracy and speed of the object detection by combining YOLOv8 with Long Short-Term Memory (LSTM) and using MQTT and LoRaWAN to exchange data. The process has three obvious steps, the first step is to deploy a cloud environment to host the computation, the second step is to carefully label and annotate a separate dataset (named elephant) and turn the raw images to a fully ready-to-train model, and, lastly, the combined YOLOv8-LSTM-MQTT-LoRaWAN model is deployed on that dataset, trained, validated and tested its performance to make sure that the improvements are actual. The system is built upon the following core components:

1) Hexagonal / Hex-Grid Area Coverage:

a) Purpose: The surveillance area is divided into hexagons for efficient, non-overlapping coverage.

b) Deployment: Smart cameras are placed at or near each hexagon vertex, ensuring comprehensive monitoring [20].

2) intelligence - Smart Cameras (Agents):

A smart camera can act as an autonomous agent within a surveillance system, using collaborative intelligence to enhance monitoring and situational awareness. Research shows that in distributed surveillance, s function as interconnected units that coordinate flexibly to perform tasks. Smart cameras, as advanced visual agents, capture and process data in parallel, providing valuable insights for collective decision-making [21]. In multi-camera systems, coordinated spatial alignment enables cameras to adjust their positions dynamically for optimal coverage, functioning as intelligent nodes within a broader network [22].

a) Role: Each smart camera acts as an autonomous or semi-autonomous node, capable of local processing and peer-to-peer communication.

b) Collaboration: Cameras share detection results, adaptively adjust focus or coverage as needed [23].

c) Examples: IP (Intenet Protocol) cameras with onboard AI(Artificial Intelligence) (e.g., Reolink Duo 3, TP-Link Tapo C230, or custom smart cameras with edge processing).

3) Onboard Edge Processing (YOLOv8+LSTM): Hybrid YOLOv8-LSTM.

To process this complex data, the system employs a hybrid neural network combining two powerful deep learning models:

a) YOLOv8: The YOLOv8 component plays a key role in spatial feature extraction within the system. It processes image data to identify critical features such as the shape of elephants, movement patterns, and distinct auditory signals. By recognizing these spatial patterns, the YOLOv8 aids in accurately determining the position and behavior of elephants in specific zones, enhancing real-time monitoring and response capabilities.

b) LSTM – Long Short-Term Memory Network: The Long Short-Term Memory (LSTM) network component is responsible for recognizing temporal patterns in elephant behavior. By analyzing sequential data—such as movement trajectories over hours or days—the LSTM learns how elephant activity evolves over time. Its memory units allow it to capture long-term dependencies, enabling the identification of preferred migration routes or seasonal movement trends. This temporal

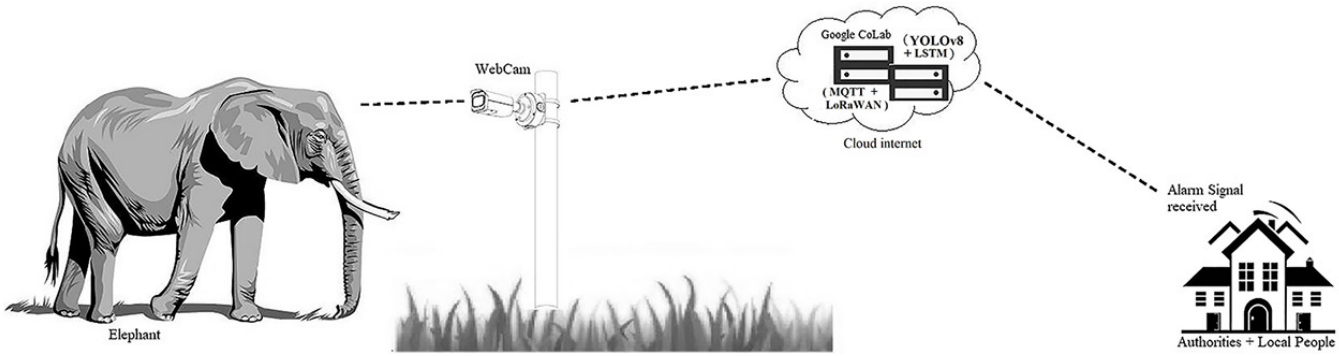


Fig. 1. Schematic diagram overview of the system.

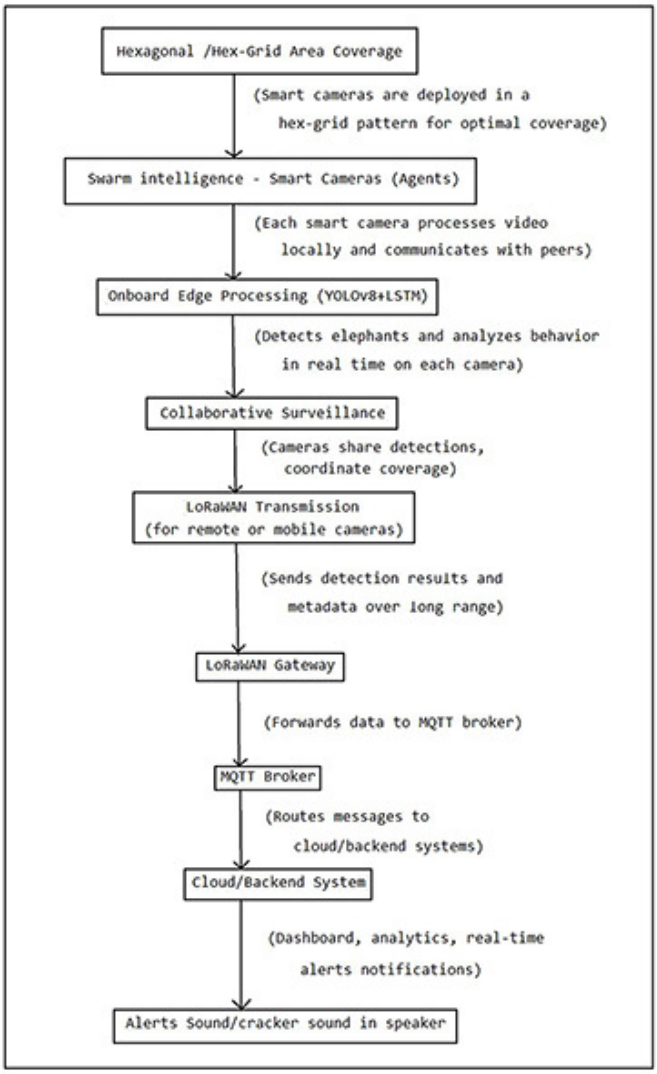


Fig. 2. System architecture: Step-by-step explanation.

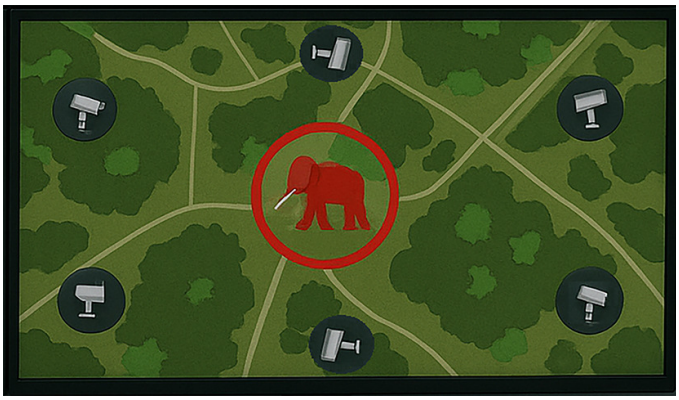


Fig. 3. Hexagonal surveillance system.

insight is crucial for accurately forecasting future elephant movements and enhancing proactive monitoring strategies.

Together, the YOLOv8 detects objects in each frame, while the LSTM models temporal patterns in detection data—enabling the system to predict where elephants are likely to move next, that is, the output it predicts are actions, anomalies, or behaviors.

c) Function: Each camera runs YOLOv8 for real-time elephant detection and LSTM for temporal behavior analysis.

d) Output: Generates detection results (e.g., "elephant detected," "anomaly detected") and metadata.

4) Collaborative Surveillance:

a) Function: Cameras communicate with each other to share detection information, optimize tracking, and ensure continuous coverage.

b) Hand-off: When an object moves from one camera's field of view to another, tracking is seamlessly transferred [24].

5) LoRaWAN Transmission (for remote/mobile cameras):

a) Function: For cameras in remote or hard-to-reach locations, detection results and metadata are transmitted wirelessly via LoRaWAN to a central gateway.

b) Advantage: Long-range, low-power communication suitable for large areas.

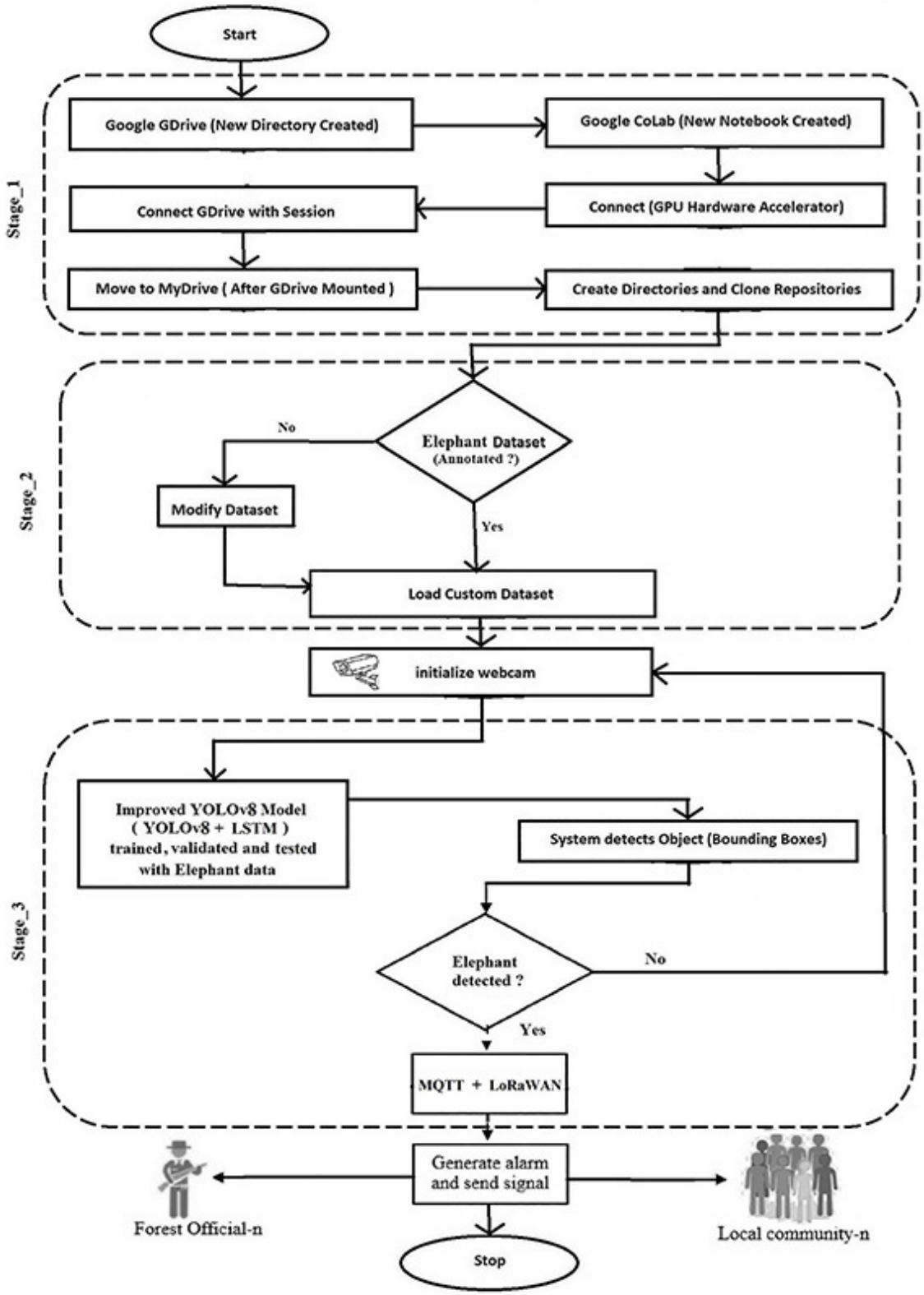


Fig. 4. Work flow progress of the system.

6) LoRaWAN Gateway:

a) Role: Receives data from multiple cameras and forwards it to an MQTT broker.

7) MQTT Broker:

a) Role: Efficiently routes messages to cloud/backend systems for further processing and visualization [25].

8) Backend System:

a) Function: Aggregates data, provides dashboards, analytics, and real-time alerts.

b) User Interface: Authorities or rangers receive notifications and can monitor the area in real time.

9) Alerts sound/ cracker sound in speaker:

a) Purpose: Immediate alerts for elephant detection and deter, enabling rapid response.

10) Key Features:

a) Intelligence: Smart cameras collaborate for adaptive, robust surveillance.

b) Edge AI: YOLOv8+LSTM enable real-time, on-device detection and behavior analysis.

c) Hexagonal Grid: Ensures efficient area coverage and minimal blind spots[26].

d) LoRaWAN & MQTT: Support reliable, scalable communication for remote monitoring [27].

e) Cloud Integration: Provides analytics, dashboards, and real-time alerts.

IV. Mathematical Model for Surveillance System

A. Notations

a) n: Number of smart camera agents in the system.

b) t: Time step (frame index).

c) $C_i(t)$: State of agent i at time t, including its position, battery, and current task.

d) $I_i(t)$: Video frame captured by agent i at time t.

e) $D_i(t)$: Set of detections from agent i at time t, where each detection is a tuple (x, y, w, h, c, p) representing bounding box coordinates, class, and confidence.

f) $\varepsilon_i(t)$: Set of elephant detections (filtered from $D_i(t)$ for class "elephant").

g) $\mathcal{S}_e^{(i)}(t)$: Sequence of features (bounding boxes, confidences) for elephant e tracked by agent i across recent frames.

h) $\mathrm{LSTM}(\cdot)$: LSTM model function.

i) $\mathcal{P}_e^{(i)}(t)$: Temporal prediction (e.g., movement, behavior) for elephant e by agent i at time t.

j) $M_i(t)$: MQTT message published by agent i at time t, containing local predictions and alerts.

k) $G(t)$: Gateway/edge node aggregating MQTT messages from all agents.

l) $M(t)$: Set of all MQTT messages received by the gateway at time t.

m) $A(t)$: Aggregated alert or summary sent via LoRaWAN to control center at time t.

B. Object Detection (YOLOv8)

For each agent i and time t, detections are given by Eq. (1):

$$D_i(t) = \mathrm{YOLOv8}(I_i(t)) \tag{1}$$

Filter for elephant detections, shown in Eq. (2):

$$\varepsilon_i(t) = \{(x, y, w, h, c, p) \in D_i(t) \mid c = \text{“elephant”}\} \tag{2}$$

C. Feature Preparation and Tracking

For each elephant e detected by agent i:

- Track elephant identity across frames (e.g., using a tracking algorithm).
- Build feature sequence for each tracked elephant given in Eq. (3):

$$\mathcal{S}_e^{(i)}(t) = [(x, y, w, h, p)_{t-k}, \ldots, (x, y, w, h, p)_t] \tag{3}$$

where k is the sequence length.

D. Temporal Analysis (LSTM)

The Eq. (4) shows the temporal prediction using LSTM:

$$\mathcal{P}_e^{(i)}(t) = \mathrm{LSTM}(\mathcal{S}_e^{(i)}(t)) \tag{4}$$

E. Coordination (MQTT)

Each agent publishes its predictions and alerts, as shown in Eq. (5):

$$M_i(t) = \{(\mathcal{P}_e^{(i)}(t), \text{agent_id}, \text{timestamp}) \mid e \in \varepsilon_i(t)\} \tag{5}$$

Gateway collects messages from all agents, shown in Eq. (6):

$$M(t) = \bigcup_i M_i(t) \tag{6}$$

F. Data Aggregation and Transmission (LoRaWAN)

Gateway aggregates and compresses messages for transmission shown in Eq. (7):

$$A(t) = \mathrm{Aggregate}(M(t)) \tag{7}$$

G. Summary Equation

Overall surveillance system model is shown in Eq. (8):

$$A(t) = \mathrm{Aggregate}\Big(\{\mathrm{LSTM}(\mathrm{Track}(\mathrm{YOLOv8}(I_i(t))))\}\Big) \tag{8}$$

V. Proposed Algorithm

The proposed work has been described in the below Algorithm 1:

Algorithm 1 Hexagonal Surveillance System with YOLOv8, LSTM, MQTT and LoRaWAN integration

Initialize
Deploy η smart camera agents across the surveillance area
Set up MQTT broker and LoRaWAN gateway
Initialize YOLOv8 and LSTM models on each agent
Define sequence length κ for LSTM input
Initialize tracking for elephant identity maintenance
Compute
For each agent i, capture initial video frame $I_i(0)$
while surveillance is active **do**
    for every agent i **do**
        Capture current video frame $I_i(t)$
        Detect objects using YOLOv8: $D_i(t) = \text{YOLOv8}(I_i(t))$
        Filter for elephant detections:

$$\varepsilon_i(t) = \{(x, y, w, h, c, p) \in D_i(t) \mid c = \text{“elephant”}\}$$

        Track each elephant $e \in \varepsilon_i(t)$ across frames
        Build feature sequence for each tracked elephant
        Compute temporal prediction: $\mathcal{P}_e^{(i)}(t) = \text{LSTM}(\cdot)$
        Publish prediction and alert via MQTT:

$$M_i(t) = \{(\mathcal{P}_e^{(i)}(t), \text{agent_id}, \text{timestamp}) \mid e \in \varepsilon_i(t)\}$$

        if unusual behavior or critical alert **then**
            Search for optimal agent coverage or notify control center
        end if
    end for
    Gateway collects all MQTT messages: $M(t) = \bigcup_i M_i(t)$
    Gateway aggregates and transmits via LoRaWAN: $A(t) = \text{Aggregate}(M(t))$
end while

VI. Virtual Simulation

The proposed work has been performed in Google Colab with designed-custom dataset. The virtual simulation of the proposed methodology has been shown in following sections:

A. Construction of Dataset

In this research, we compiled a dedicated dataset, which we obtained through the web by gathering the images of elephants. The range of poses, lighting circumstances, and backgrounds covered by these photographs is quite extensive, thus allowing the model to learn how to see elephants in many real-life situations. We additionally used a basic Python script to cut still frames out of video footage thus further increasing the data pool. After compilation, the images may be enhanced using a number of deep-learning algorithms to enhance quality and consistency then to train the detection system.

B. Data Annotation

The open-source tool of labeling named as LabelImg redefines the labeling process in such a way that it does not feel like a tedious experience but instead a creative and simplified one. The user can easily outline bounding boxes on parts of an image that are of interest, apply class labels to them, and save that information in a one-step process. Internally, the tool creates a plain-text document where the first integer is the identifier of the class, then there is the coordinates of the centre of the box and the width and height of the box. Since LabelImg can also export annotations in both YOLO and PAScal VOC XML formats, as well as CreateML, the cost of an additional conversion step is eliminated, especially with systems that operate on the YOLO framework. The software also offers easy key board shortcuts to drawing and saving and viewing images and allows remote server annotation. , therefore, regardless of the intended goal, be it detection, segmentation, or classification, the intuitive workflow and predefined system of classes provided by LabelImg allows the user to focus on the underlying data, instead of focusing on the underlying mechanics of labeling.

C. Dataset Preparation

The present project created a strong and detailed dataset when the real-world observations were integrated with the synthetic information to improve the predictive model in the real-time applications. The real-world data were obtained by the means of the open-access datasets of the elephant movements.

The models are trained using the custom dataset using 8,608 number of original elephant images and 1,592 number of non-elephant images. Table I has presented the information in the image dataset used to evaluate the models.

TABLE I. Designed-Custom Dataset

Image	Training	Validation	Test	Total
Positive (Elephant)	6,458	2,150	2,150	10,758
Negative (Non_elephant)	1,192	400	400	1,992
Total	7,650	2,550	2,550	12,750

D. Google CoLab

Google is a cloud based, no cost Jupyter notebook bearing the name Google Colab designed to engage a group of coders in a game. It also provides free and immediate access to strong GPUs and TPUs, ideal when training machine-learning models, and also allows to share a notebook with teammates as with a Google Doc. Everything on Google works in Google Drive, and it includes the possibility to open, edit, and share files everywhere. and since all notebooks are already pre-equipped with popular data science libraries such as TensorFlow, PyTorch, and pandas amongst others, one can immediately get started on data science instead of wasting time installing on own environment.

E. Model Training

The hybrid YOLOv8-LSTM architecture, i.e., the spatial feature extraction of YOLOv8 and the temporal sequence modeling of Long Short-Term Memory (LSTM) networks, was trained to create the predictive model. This architecture was chosen to be good at retrieving both spatial patterns (e.g., movement paths over terrain), and temporal dynamics (e.g., repeat entry times, or repeat behavior sequences) related to the activity of elephants. To balance the evaluation, an 60-20-20 (train-validate-test split) was used to divide the dataset in order to allow the model to generalize well to unknown data.

When trained, the model was very impressive and detected the entry patterns of the elephants with a high level of accuracy of about 98 percent. The findings support the strength of the model in practice, and it is highly suitable when applying to the proactive wildlife surveillance and early-warning systems.

VII. Simulated Results

The model evaluation was developed in controlled simulation conditions to determine the effectiveness of the system, responsiveness and efficiency of the system.

The confusion matrix for proposed ML model is shown in Fig. 5.

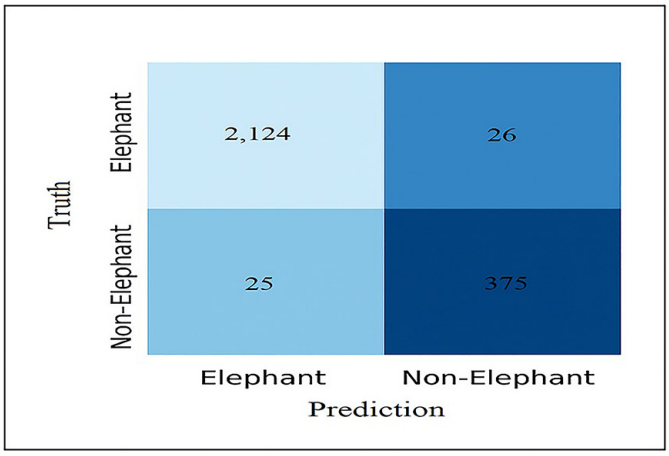


Fig. 5. Confusion matrix for proposed ML model.

The Fig. 6 shows confusion matrix for YOLOv8 model for elephant detection.

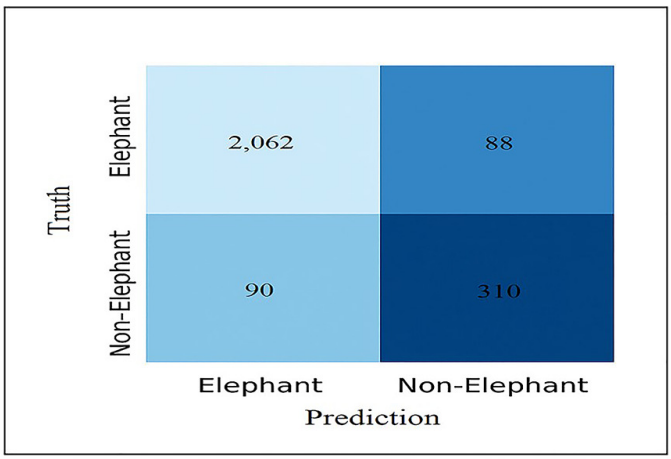


Fig. 6. Confusion matrix for YOLOv8 model for elephant detection.

Table II presents the results Machine Learning(ML) of proposed model.

The Fig. 7 shows the elephant detected by the proposed system.

The prediction model had a high accuracy of 98.0 percent in detecting the patterns of elephant movement and low false positive of 1.0 percent that guaranteed reliability of the detection with minimal false alarms.

TABLE II. ML Results for Proposed Model

Parameter (/ Measure)	Proposed ML	YOLOv8
Total predicted	2,550	2,550
True positive	2,124	2,062
False positive	26	88
False negative	25	90
True negative	375	310
Accuracy	0.98	0.93

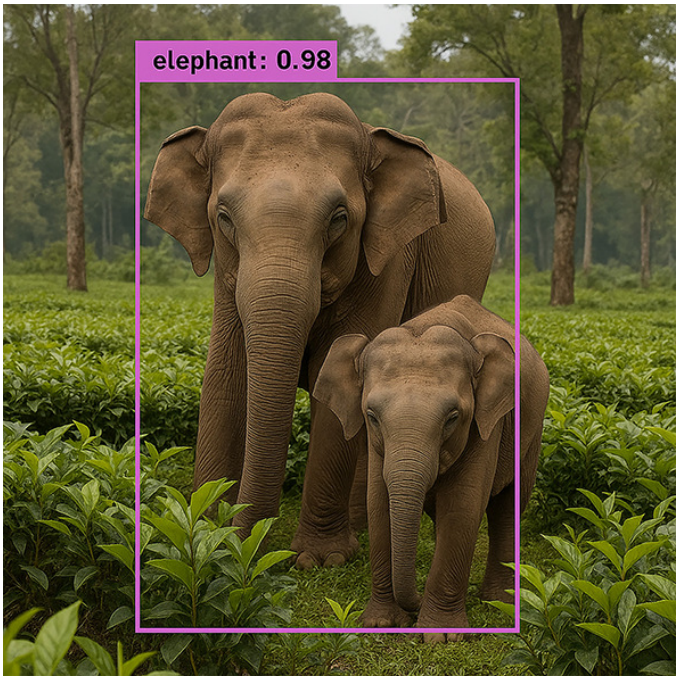


Fig. 7. Elephant detected.

VIII. Discussion

With MQTT on top of LoRaWAN, it is possible to make AI-based surveillance systems both practical and large-scale. LoRaWAN oxygen incapacity has some sweeping advantages of IoT links to hundreds of inactive, long-range sensors in a town, villa, or off-grid locations that maintain their operation with minimal roadwork studies. MQTT then manages the light, latency constrained communications between those edge devices and the cloud, cuts down bandwidth wastage and allows the network to scale to any topography; be it a smart village or a microgrid [28]. It is a combination of feeds live to YOLO-LSTM models providing video and sensor data in real time reliably even when in dense forests or during busy city times, therefore object detection and sequence analysis remains keen in high-traffic surges. Collectively, MQTT and LoRaWAN reduce power consumption and data rates that enable cameras and sensors detached in the distant areas to extend their lifespan on a limited battery and yet still provide the real time information that current AI surveillance relies upon [29, 30].

Table III presents the key advantages of proposed model.

TABLE III. SUMMARY TABLE: KEY ADVANTAGES

Parameter (/ Feature)	LoRaWAN Contribution	MQTT Contribution	Combined with YOLO-LSTM for Benefiting AI Surveillance
Coverage	Long-range	Not fixed	Flexible deployment
Power Consumption	Minimal	Reduces unnecessary transfer	Sustainable, low-maintenance operation
Scalability	Supports many devices	Flexible brokering	Easily expandable networks
Latency	Low (with MQTT integration)	Efficient message handling	Real-time data for AI models
Data Congestion	Avoids with hybrid protocol	Manages high-frequency data	Reliable, up-to-date AI inference

Overall, the integration of MQTT and LoRaWAN with an YOLO-LSTM model to create AI surveillance systems has major scalability, power consumption, low-latency communications, environmental flexibility benefits which are essential to advanced and efficient real-time surveillance systems.

IX. FUTURE PROPOSAL

The current simulation-based system shows a satisfactory initial result, which can be further developed in future work for a wider scope of practical application and technology robustness. Finally, field trials should be executed in cooperation with the forest departments and conservation authorities to ensure the performance of the system in real conditions and to improve its behavior under natural environmental conditions. These trials are expected to give important feedback regarding agent coordination, detection accuracy, and system robustness in various terrain types. Additionally, blockchain technology is suggested to be implemented to provide transparency and security of the data, enabling tamper-proof and decentralized data sharing between, for example, tea estate owners, conservationists, or local administration. This would provide confidence and accountability of system warning and movement records. In addition, thermal imaging sensors will be integrated for intelligences through enhanced detection capabilities particularly at night, when the elephant's skin color is barely noticeable by agents, irrespective of the lighting conditions. Additionally, the capabilities to create mobile applications that can provide localized parties (planting workers and local communities) with real-time alerts will allow localized response initiatives, enabling even more human-autonomous system collaboration. Together, these improvements will bring the system closer to full-scale deployment, and bring about a robust, ethical, community-driven elephant conflict mitigation solution.

X. CONCLUSION

This paper introduces a new, holistic and interdisciplinary way of looking at the increasingly challenging issue of elephant-human conflict, especially in tea plantation areas. The proposed autonomous Hexagonal Intelligent Surveillance (HIS) entails the non-separate, combined application of machine learning-based prediction models, intelligence, and a hexagonal spatial grid to constitute a cohesive, responsive, and ethically-grounded system. The virtual simulation of the proposed work shows 98% accuracy on designed-custom dataset of elephants. In addition, in order to reduce the need for human intervention, the system detects potential elephant intrusions ahead of time and provides coordinated adjuvant decentralized reaction through autonomous agents in a non-lethal and animal safe way. The hexagonal cell topology improves the coverage and flexibility of the system by enabling it to adapt to changing levels of risk over large geographical areas. Apart from its scalability, this combination of technologies puts both the safety of humans and the conservation of wildlife at the forefront. With further field testing and real-world implementation, the HIS framework has the potential of revolutionizing current strategies for wildlife conflict mitigation by providing a smarter, more efficient, and more humane solution for preserving livelihood and ecosystems on agricultural frontiers worldwide.

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DISCLOSURE OF INTERESTS

The authors have no competing interests to declare that are relevant to the content of this article.

REFERENCES

[1] Elnady, Mahmoud, and Hossam E. Abdelmunim. "A novel YOLO LSTM approach for enhanced human action recognition in video sequences." Scientific Reports 15.1 (2025): 17036.

[2] Tong, Xing, et al. "Efficient Utilization Method of Motorway Lanes Based on YOLO-LSTM Model." Sensors 25.21 (2025): 6699.

[3] Reis, Dillon, et al. "Real-time flying object detection with YOLOv8." arXiv preprint arXiv:2305.09972 (2023).

[4] Rivera-Acosta, Miguel, et al. "Spelling correction real-time american sign language alphabet translation system based on yolo network and LSTM." Electronics 10.9 (2021): 1035.

[5] Lu, Yongyi, Cewu Lu, and Chi-Keung Tang. "Online video object detection using association LSTM." Proceedings of the IEEE international conference on computer vision. 2017.

[6] Ruchi, Lalhriatpuii, and Vikas Wasson. "Comprehensive Exploration of IoT Communication Protocol: CoAP, MQTT, HTTP." Machine Learning Algorithms: First International Conference, ICMLA 2024, Himachal Pradesh, India, February 23–24, 2024, Proceedings. Vol. 2238. Springer Nature, 2024.

[7] Nguyen, Huy Dat, Nicolas Le Sommer, and Yves Mahéo. "Over-the-Air Firmware Update in LoRaWAN Networks: A New Module-based Approach." Procedia Computer Science 241 (2024): 154-161.

[8] Kioko, John, et al. "The performance of electric fences as elephant barriers in Amboseli, Kenya." South African Journal of Wildlife Research-24-month delayed open access 38.1 (2008): 52-58.

[9] Sivakumar, V., et al. "Decibel level of firecrackers and its possible impact on the hearing of marauding elephants in Sri Lanka." Int. J. Sci. Environ. Technol. 2.4 (2013): 593-600.

[10] King, Lucy E., Iain Douglas-Hamilton, and Fritz Vollrath. "African elephants run from the sound of disturbed bees." Current Biology 17.19 (2007): R832-R833.

[11] Montgomery, Robert A., et al. "The efficacy of interventions to protect crops from raiding elephants." Ambio 51.3 (2022): 716-727.

[12] Mullick, Rabin Kumar, and Rakesh Kumar Mandal. "A Proposed Grid-Based Elephant Detection Model Using Artificial Intelligence (AI) to Prevent Crop Damage in Farming Fields." Doctoral Symposium on Intelligence Enabled Research. Singapore: Springer Nature Singapore, 2023.

[13] Mullick, Rabin Kumar, and Rakesh Kumar Mandal. "An Efficient Elephant Detection Strategy using Visual Attention Network (VAN) in Custom Dataset improved YOLOv7 Model." (2025).

[14] Tahir, Anam, et al. " s of unmanned aerial vehicles—A survey." Journal of Industrial Information Integration 16 (2019): 100106.

[15] Xu, Chengtao, et al. "Communication aware UAV surveillance based on hierarchical architecture." Drones 5.2 (2021): 33.

[16] Ding, Yahao, et al. "Distributed machine learning for uav s: Computing, sensing, and semantics." IEEE Internet of Things Journal 11.5 (2023): 7447-7473.

[17] Arranz, Raul, et al. "Application of deep reinforcement learning to UAV ing for ground surveillance." Sensors 23.21 (2023): 8766.

[18] Khan, Faisal, et al. "Eye: A Distributed Autonomous Surveillance System."International Journal of Advanced Computer Science and Applications (IJACSA), 9.12 (2018): 591-600.

[19] Majd, Amin. "DIANA: Distributed and Safe Autonomous Navigation for a of Autonomous Vehicles." (2021).

[20] A. Kumar, S. Patel, R. Singh. "Elephant recognition using deep learning: A comparative study." Data in Brief, 2024. https://www.sciencedirect.com/science/article/abs/pii/S2352710223014377.

[21] Tian, Wei, et al. "A Review of Smart Camera Sensor Placement in Construction." Buildings 14.12 (2024): 3930.

[22] Li, Congcong, et al. "Multi-camera joint spatial self-organization for intelligent interconnection surveillance." Engineering Applications of Artificial Intelligence 107 (2022): 104533.

[23] B. Rinner. "Distributed Smart Cameras." Technische Universität Graz, 2008. https://www.ece.rice.edu/ av21/Documents/pre2011/Distributed%20 Smart%20Cameras.pdf.

[24] T. Menteş, H. Artuner, C. Baransel. "A Distributed Surveillance Camera Network Architecture for Public Security Applications in Metropolitan Area." Hacettepe University, 2010.

[25] Amazon Web Services. "Design considerations for cost-effective video surveillance platforms with AWS IoT for Smart Homes." AWS IoT Blog, 2023. https://aws.amazon.com/blogs/iot/design-considerations-for-cost-effective-video-surveillance-platforms-with-aws-iot-for-smart-homes.

[26] An, Zehua, Xiaoping Rui, and Chaojie Gao. "Improved A* navigation path-planning algorithm based on hexagonal grid." ISPRS International Journal of Geo-Information 13.5 (2024): 166.

[27] L. Valentín, S.A. Serrano, R. Oves García, A. Andrade, M.A. Palacios-Alonso, L.E. Sucar. "A Cloud-Based Architecture for Smart Video Surveillance." The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLII-4/W3, 2017. https://d-nb.info/1143989678/34.

[28] Shuaib M., Alam S. (2025). A secure and energy-efficient IoT-blockchain framework for decentralized renewable energy trading. Sustainable Computing: Informatics and Systems, 48. https://doi.org/10.1016/j.suscom.2025.101252.

[29] Changazi S., Bakhshi A., Yousaf M., Mohsin S., Akber S., Abazeed M., Ali M. (2024). Optimization of network topology robustness in IoTs: A systematic review. Computer Networks, 250. https://doi.org/10.1016/j.comnet.2024.110568.

[30] Hadji O., Maimour M., Benyahia A., Kadri O., Rondeau E. (2025). EcoWatch: Region of interest-based multi-quantization resource-efficient framework for migratory bird surveillance using wireless sensor networks and environmental context awareness. Computers and Electrical Engineering, 123. https://doi.org/10.1016/j.compeleceng.2025.110076.

Creative Guidance of Intelligent Emotion Recognition in Video Art

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***Abstract*—This study optimizes the existing emotion recognition model to improve the application effect of emotion recognition technology in the guidance of video art creation. It also compares the performances of Multimodal Sentiment Analysis (MMSA), Multimodal Sequence Encoder (MuSE), and the optimized model through a series of simulation experiments. In the fine-grained accuracy of emotion recognition, the optimized model performs well in micro-expression recognition accuracy and multimodal fusion effect, and scores 4.17 and 4.96, respectively. In the robustness test under a complex background, the background interference resistance score of the optimized model is 4.30, and the modal mismatch processing score is 4.38. In the experiment on the effectiveness of emotion recognition in creative guidance, the optimized model scores 4.40 and 3.66 in terms of artistic expression enhancement and creative feedback accuracy, respectively. The experimental results show that the optimized model is superior to the existing models in several key dimensions of emotion recognition, especially in enhancing the emotional expression of artistic works and providing creative guidance. Therefore, this study provides some reference for the application and development of emotion recognition technology in video art creation.**

***Keywords*—Emotional recognition; image art; artistic expressiveness; creative feedback**

I. Introduction

With the rapid development of artificial intelligence (AI) technology, affective computing has gradually gained widespread attention as a crucial research direction in human-computer interaction. Affective computing aims to endow computers with the ability to recognize, understand, and express emotions, thereby enabling more natural and intelligent human-computer interaction [1]. In recent years, emotion recognition technology has developed rapidly in multimedia, entertainment, healthcare, and education. It has also demonstrated enormous potential in enhancing user experience and interaction quality [2]. As an artistic form that conveys emotions and ideas through visual language, audio-visual art creation relies heavily on emotional expression and audience emotional resonance [3]. However, traditional audio-visual art creation mainly depends on artists' experience and intuition. This hinders its ability to accurately capture the emotional feedback of different audiences and systematically integrate such emotional information into creative decisions [4, 5].

Despite the significant progress of existing emotion recognition technology in various scenarios, obvious research gaps remain in the field of audio-visual art creation. Firstly, current models mostly focus on single-modal or coarse-grained emotion classification, lacking effective recognition of fine-grained emotional information such as microexpressions and subtle emotional changes—details that are particularly critical for artistic expression. Secondly, the diverse visual styles and complex scene changes in audio-visual art result in insufficient robustness and real-time performance of existing models, which fail to meet the needs of creative practice. Thirdly, existing literature rarely explores how emotion recognition results can be linked to specific creative behaviors, such as shooting, editing, color scheduling, and narrative rhythm. Thus, a clear disconnect persists between "technology and artistic creation".

To address the above research gaps, this study optimizes existing multimodal emotion recognition models and proposes an intelligent emotion recognition framework for guiding audio-visual art creation. Through an improved multimodal fusion mechanism, the model significantly enhances microexpression recognition capabilities and robustness in complex backgrounds. Its structural design also improves the usability of converting emotional information into creative decisions. In addition, this study constructs a comprehensive evaluation system that includes both technical and art creation-related indicators, verifying the model's effectiveness from both technical performance and practical creation perspectives. The main innovative contributions of this study are as follows:

1) Explicitly propose the task requirements of emotion recognition "for guiding audio-visual art creation", bridging the disconnect between technology and artistic creation in existing research.

2) Design an optimized multimodal fusion architecture to improve the accuracy of fine-grained emotion recognition and robustness in complex backgrounds.

3) Establish a new evaluation system that balances technical performance and creative value, providing an operable evaluation paradigm for the application of emotion recognition technology in artistic creation.

The subsequent structure of this study is arranged as follows: Section II reviews relevant research on affective computing and emotion recognition, and sorts out their application status in artistic creation. Section III elaborates on the theoretical basis of affective computing and introduces the overall design and optimized architecture of the intelligent emotion recognition model. Section IV presents the experimental design, including datasets, experimental processes, simulation experiments, and ablation experiments, along with analysis and discussion of results. Section V summarizes the research findings, points out limitations, and proposes future research directions.

*Corresponding author.

II. Literature Review

In the field of affective computing and emotion recognition, existing studies have systematically explored emotion modeling from diverse modalities and application scenarios. Lian et al. (2023) found that deep learning-based text emotion recognition algorithms achieved high accuracy in sentiment polarity and fine-grained emotion analysis. However, when extending from text emotions to multimodal contexts such as speech and images, models still faced significant challenges in cross-modal alignment and feature fusion, especially lacking robustness in complex scenarios [6]. Kopalidis et al. (2024) proposed a facial expression recognition model based on a convolutional neural network (CNN). Its recognition accuracy exceeded 90% on standard datasets, proving the effectiveness of the visual modality in static or regularized scenarios. Yet, the method focused primarily on single-modal visual inputs and lacked targeted handling of typical artistic scenarios such as background interference and stylized visual elements [7]. Liu and Li (2023) discovered that fusing multiple physiological signals—such as heart rate and skin conductance responses—into affective computing models significantly improved emotion recognition accuracy. This indicated that multimodal physiological signals played a complementary and corrective role in emotional states. However, most related works remained confined to laboratory or medical contexts, with relatively limited discussions on adaptability to open and complex environments like video art creation [8].

Regarding multimodal emotion recognition and its applications in creative fields, Dash and Agre (2024) pointed out that music generation systems incorporating emotion recognition technology could dynamically adjust rhythm and melody based on audience emotional feedback. Thus, it can enhance the emotional appeal of musical works. Nevertheless, their multimodal modeling focused mainly on audio and simple interaction signals, lacking comprehensive modeling of complex information such as visual content and contextual semantics [9]. Monser and Fadel (2023) found that intelligent emotion recognition technology helped visual art creators understand audience emotional responses and adjust expression techniques accordingly. However, their research mainly proceeded from the perspective of "emotion analysis-assisted evaluation". Meanwhile, they did not deeply construct a systematic mapping mechanism from emotion recognition results to specific creative decisions (e.g., shot language, color configuration, narrative rhythm) [10]. Li (2024) proposed a method combining emotion recognition with film production, using real-time audience emotional responses to optimize editing rhythm and sound effect design, thereby improving the viewing experience. However, the model design emphasized the control of overall emotional curves, with relatively superficial discussions on microexpressions, fine-grained emotional transitions, and multimodal fusion strategies [11]. Wang (2024) discovered that applying emotion recognition to film character emotion analysis helped directors and screenwriters shape character images and narrative tension more accurately. Yet, most related works focused on character-level emotion label prediction, with little consideration of how to feed recognition results back into real-time adjustments and iterative optimization in the creative process [12].

In the direction of optimizing the rhythm and structure of audio-visual works, Zhang et al. (2024) proposed a film editing method based on emotion recognition. By analyzing changes in audience emotions, the method optimized editing rhythm, making the film's emotional expression more coherent and concentrated. However, the approach remained mostly at the rule-driven or experience-driven level of rhythm regulation, failing to fully leverage multimodal deep features and robust modeling in complex contexts [13]. Zhang and Pu (2024) showed that introducing emotion recognition technology in animation production enabled more delicate character expression and movement design, significantly enhancing audience emotional resonance. Nevertheless, most related systems centered on "character image shaping" and lacked systematic support for "emotional structure control and creative guidance of the entire audio-visual work" [14].

Synthesizing the aforementioned studies, it is evident that multimodal emotion recognition technology has achieved significant progress in fields such as text, speech, facial expressions, physiological signals, music, film, and animation. However, obvious gaps remain in systematic research oriented toward guiding audio-visual art creation. Firstly, most studies focus on improving "recognition accuracy" but lack systematic evaluation and targeted optimization of model robustness, real-time performance, and generalization ability in complex audio-visual contexts. Secondly, existing works apply emotion recognition to scenarios like music generation, film editing, or character shaping. However, they generally lack interpretable mapping and creative guidance mechanisms from "emotion recognition results to specific creative decision parameters (e.g., shot editing, color style, narrative rhythm)". Thirdly, multimodal fusion strategies mostly remain at relatively fixed early/late fusion or simple weight superposition; they lack targeted structural designs and training strategies to address issues such as complex backgrounds, modal mismatches, and fine-grained emotional changes.

Based on this, this study builds on previous research and further focuses on audio-visual art creation scenarios. The fusion mechanism and robustness design of multimodal emotion recognition models are optimized, and evaluation dimensions closely related to artistic expression and creative feedback are introduced. Thus, it constructs a tighter bridge between "technical performance improvement" and "artistic creation usability". This fills the key gap in existing research regarding the guidance of video art creation.

III. Emotion Recognition Based on AI

A. Affective Computing and Emotion Recognition Technology

Affective computing is an important branch of computer science and AI, making computers have the ability to perceive, understand, explain, and simulate human emotions [15]. The research content of affective computing includes the identification, expression, and generation of emotion and the construction of emotional intelligence [16]. With the development of technology, affective computing has gradually expanded from the initial theoretical exploration to a wide range of applications, such as HCI, intelligent education, mental health, entertainment, and so on [17]. Emotion recognition technology is one of the core tasks of affective

computing, which aims to identify human emotional state from various data sources through computer algorithms [18]. At present, emotion recognition technology is mainly divided into two categories: single-mode emotion recognition and multi-mode emotion recognition [19], as shown in Table I:

TABLE I. EMOTION RECOGNITION TECHNOLOGY

Technology	Application	Description
Single-mode emotion recognition technology	Facial expression recognition	Emotion recognition based on facial expressions is the most common method in emotion recognition technology. Early research usually relies on artificial feature extraction, such as local binary pattern and scale-invariant feature transformation. However, with the rise of deep learning, the model based on a CNN has become mainstream.
	Speech emotion recognition	The speech signal contains rich emotional information, such as intonation, speech speed, volume and so on. Speech emotion recognition usually judges the emotional state of the speaker by extracting these features. Traditional methods include the hidden Markov model and the support vector machine.
	Text sentiment analysis	Text sentiment analysis mainly analyzes the emotional tendency in the text through natural language processing technology. Traditional methods include the sentiment dictionary method and machine learning classifiers, such as support vector machines and naive Bayes.
Multi-mode emotion recognition	Feature extraction	Representative features are extracted from different modal data, such as geometric and texture features from facial expressions, frequency and energy features from speech, word vectors, and emotional vocabulary from texts.
	Feature fusion	Feature fusion is a key step in multimodal emotion recognition. Common methods include early fusion and late fusion. Early fusion combines features from different modes directly in the feature extraction stage, while late fusion is decision-level fusion based on the emotion classification results of each mode.
	Emotional classification	The fused features or classification results are input into the emotion classifier to identify the final emotion state. Commonly used classifiers include support vector machine, random forest and deep neural network.

To sum up, emotion calculation and emotion recognition technology have laid an important foundation for the application of intelligent emotion recognition in video art [20]. With the continuous progress of technology, emotion recognition plays an increasingly important role in the creation of video art, providing a new channel for emotional communication between artists and audiences [21].

B. The Combination of Intelligent Emotion Recognition and Artistic Creation

With the continuous development of AI technology, emotion recognition technology is not limited to traditional application fields such as HCI and mental health, and its potential is gradually explored and applied in artistic creation [22]. Artistic creation, as an important way for human beings to express emotions, thoughts, and concepts, usually depends on the creator's deep understanding of emotions and the audience's emotional resonance [23]. The introduction of intelligent emotion recognition technology can inject new vitality into the artistic creation process. By capturing and analyzing the emotional reaction of the audience, it can help artists to make more accurate emotional expression and adjustment in their creation, thus enhancing the emotional appeal of their works. In artistic creation, emotion recognition technology can help creators from many aspects, including real-time feedback of creative effects, personalized customization of artistic content, and optimization of emotional communication methods of works [24]. Through intelligent emotion recognition technology, the creator can better understand the emotional needs and reactions of the audience, provide a scientific basis for the creative process, and thus realize the deep integration of artistic creation and emotion recognition.

As an intuitive and infectious art form, visual art has long been used to express complex emotions and thoughts. The application of intelligent emotion recognition technology in visual arts can help artists capture and express emotions more accurately and optimize the audience's viewing experience. Music, as an art form with sound as the medium, has a strong emotional expression ability [25]. The application of intelligent emotion recognition technology in music creation is mainly reflected in music generation driven by emotion recognition, music creation with real-time emotion feedback, and the combination of emotion recognition and music recommendation systems. Image art includes many art forms such as movies, animations, and videos, and has strong emotional expression and narrative ability [26]. The application of intelligent emotion recognition technology in video art can help the creator to better understand the emotional reaction of the audience and optimize the emotional expression of video works [27].

In short, the combination of intelligent emotion recognition technology and artistic creation expands the means and forms of artistic creation, while providing the audience with a more personalized and interactive artistic experience [28]. With the continuous progress of technology, emotion recognition plays an increasingly important role in artistic creation and builds a closer bridge for emotional communication between artists and audiences [29].

C. Model Construction of Intelligent Emotion Recognition Technology in Video Art

The application of intelligent emotion recognition technology in video art depends on the complex model construction process, which includes multiple stages from data collection to model training, optimization, and application. The construction of an emotion recognition model requires a deep understanding of the basic theories of affective computing and AI, such as machine learning, deep learning, and multimodal data processing. Meanwhile, it is necessary to combine the relevant theories of psychology, cognitive science, and art to ensure that the model not only has accurate emotional

recognition ability, but also can be effectively applied to artistic creation to enhance the emotional expression of works. In the process of model construction, it is important to consider the characteristics of image art, such as diverse visual elements, dynamic scenes, and complex interaction with audience emotions. Based on these characteristics, to build an emotion recognition model suitable for video art, it is usually necessary to integrate multi-modal emotion recognition technology, an emotion calculation model, and an artistic expression model to accurately capture and express emotions. The designed optimized model is shown in Fig. 1:

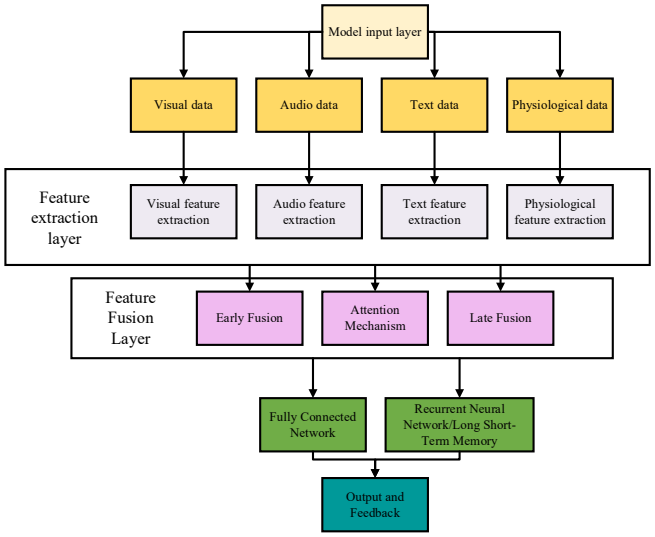


Fig. 1. Intelligent emotion recognition model architecture.

Through the above model framework, intelligent emotion recognition technology can accurately capture and feedback the audience's emotions in video art, thus enhancing the emotional expression and interactive experience of video works.

IV. Comparison between the Performance of Intelligent Emotion Recognition Model and Simulation Results

A. Performance Analysis of an Intelligent Emotion Recognition Model

The Interactive Emotional Motion Capture (IEMOCAP) dataset is selected in the experiment. It is especially suitable for the study of emotion recognition because it contains multimodal records designed for emotion recognition. The IEMOCAP dataset includes 302 video conversations, which are recorded in five sessions, and each session contains two speakers. The dataset labels nine different emotions: anger, excitement, fear, sadness, surprise, depression, happiness, disappointment, and neutrality. In addition, it also provides continuous labeling about pleasure, arousal, and dominance. The computer used in the experiment is equipped with an Intel Xeon Gold 6230 processor, which has up to 20 cores /40 threads, provides powerful multi-thread processing ability, and can process a large amount of data efficiently. In order to speed up the training of a deep learning model, NVIDIA Tesla V100 is selected in the experiment, which has 32 GB of HBm2 memory and supports the parallel computing of deep learning frameworks such as TensorFlow and PyTorch, which significantly improves the training speed of the model. The experimental system is equipped with 128GB DDR4 ECC memory to ensure the stability and performance of the system when dealing with large data sets. The experimental data is stored on a 2TB NVMe SSD, which provides fast data reading and writing speed, reduces the I/O bottleneck, and ensures efficient data processing in the experimental process. Multimodal Sentiment Analysis (MMSA) and Multimodal Sequence Encoder (MuSE) are selected as the contrast models in the experiment. The experimental parameters are set as follows: the image input dimension is 2242243, and the audio input is the feature matrix of 128128. CNN layer, using 32 convolution kernels of 33, the activation function is ReLU, followed by the maximum pool layer of 22. In the deep convolution layer, 64 convolution kernels of 33 are used, and the activation function is ReLU, followed by the maximum pool layer of 22. In the fully connected layer, the number of neurons is 256, and the activation function is ReLU. Dropout is used to prevent over-fitting, and the discard rate is set to 0.5. The indicators of experimental comparison are accuracy, Area Under the Receiver Operating Characteristic Curve (AUC-ROC), Kappa coefficient, and Mean Squared Error (MSE). The experimental results are shown in Fig. 2:

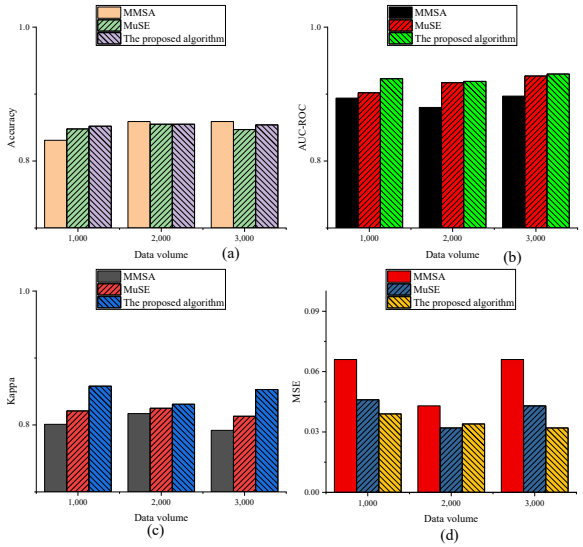


Fig. 2. Performance comparison results: (a) Accuracy, (b) AUC-ROC, (c) Kappa coefficient, (d) MSE.

In Fig. 2, in terms of accuracy, when the data volume is 1000, the MMSA, MuSE, and optimized models' accuracy are 0.831, 0.848, and 0.852. It can be found that the performance of the optimized model is slightly better than that of MMSA and MuSE models in the case of less data, especially when the accuracy of MuSE is close, the optimized model still has certain advantages. When the data volume is 2000, the accuracy of MMSA rises to 0.859, MuSE is 0.855, and the optimized model is 0.855. With the increase in data volume, the performance of the MMSA and optimized models is very close, and the MuSE model is slightly inferior. This shows that with the increase in data volume, the accuracy of the MMSA and optimized models has been improved, but the gap between them has narrowed. When the data volume is 3000, the accuracy of MMSA is maintained at 0.859, while that of MuSE

is slightly reduced to 0.847, and that of the optimized model is 0.854. When the data volume reaches 3000, the accuracy of the MMSA and optimized models shows good stability, while the accuracy of MuSE decreases slightly. This may indicate that MuSE is more sensitive to data under a larger data volume, which leads to the fluctuation of model accuracy.

In terms of AUC-ROC, under different data sets, the AUC-ROC values of the optimized model reach 0.923, 0.919, and 0.93, respectively, which shows significant advantages when the data volume is small. With the increase of data volume, the AUC-ROC performance of MuSE is gradually improved, and it tends to be close to that of the optimized model, which shows that MuSE has good scalability when dealing with large-scale data. However, MMSA is relatively stable when the data volume increases, but it fails to show significant improvement.

In terms of the Kappa coefficient, when the data volume is 1000, the Kappa coefficients of the MMSA and MuSE models are 0.801 and 0.821, and that of the optimized model is 0.858. When the data volume is 2000, the Kappa coefficient of MMSA rises to 0.817, that of MuSE is 0.825, and that of the optimized model is 0.831. When the data volume is 3000, the Kappa coefficient of MMSA drops slightly to 0.782, that of MuSE is 0.813, and that of the optimized model rises to 0.853. With a larger amount of data, the Kappa coefficient of the optimized model remains at a high level, while the MuSE model shows stability, but it fails to surpass the optimized model. The Kappa coefficient of the MMSA model decreases slightly, which may be affected by the complexity increase when the data volume increases.

In terms of MSE, when the data amount is 1000, the MSE of the MMSA, MuSE, and optimized models are 0.066, 0.046, and 0.039. In the case of small data, the MSE of the optimized model is the lowest, which shows that its prediction error is the smallest and it has better precision. MuSE is also better than MMSA. When the data volume is 2000, the MSE of the MMSA and MuSE models is significantly reduced to 0.043 and 0.032, and the MSE of the optimized model is 0.034. With the increase in data volume, the MSE of MMSA has been significantly improved, but the MuSE performs better, reaching the lowest MSE value. The MSE of the optimized model is slightly higher than that of MuSE, but it still remains at a low level. When the data volume is 3000, the MSE of MMSA rises to 0.066, that of MuSE is 0.043, and that of the optimized model is further reduced to 0.032. Under a larger data volume, the optimized model once again showed its advantages, reaching the lowest MSE value, indicating that it can still maintain a low prediction error when dealing with large-scale data. The MSE of MMSA fluctuates, while the MuSE maintains a relatively stable performance.

B. Simulation Experiment Comparison of Intelligent Emotion Recognition Model

The experiment adopts a scoring system of 1-5 points. The higher the score, the higher the representative satisfaction. This study selects four indicators, namely, fine-grained accuracy of emotion recognition, response speed, robustness in complex background, and effectiveness of creative guidance. For each indicator, it is divided into three dimensions, and the results are shown in Fig. 3:

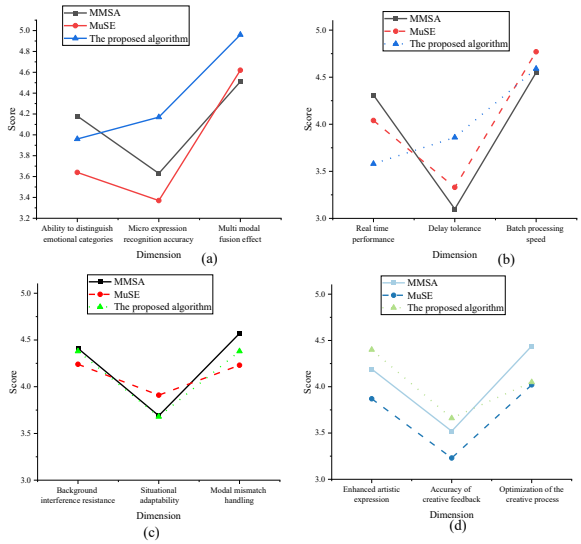


Fig. 3. Comparison results of simulation experiments: (a) Fine-grained accuracy of emotion recognition; (b) Response speed of emotion recognition; (c) Robustness of emotion recognition in complex backgrounds; (d) Effectiveness of emotion recognition in creative guidance.

In Fig. 3, in the comparison of the fine-grained accuracy of emotion recognition, the MMSA model scored 4.18, the MuSE model scored 3.64, and the optimized model scored 3.96 in terms of the ability to distinguish emotion categories. In terms of micro-expression recognition accuracy, the MMSA model scored 3.63, the MuSE model scored 3.37, and the optimized model scored 4.17. In the aspect of multimodal fusion effect, the MMSA, MuSE, and optimized models score 4.51, 4.62, and 4.96. The optimized model shows excellent performance in all dimensions of fine-grained emotion recognition, especially in micro-expression recognition accuracy and multimodal fusion effect, and the score of the optimized model is significantly higher than other models. This shows that the optimized model has higher accuracy and robustness when dealing with complex and diverse emotional data.

In the comparison of response speed, the scores of the optimized model are 3.58, 3.86, and 4.59 in different dimensions, and the MMSA model is the best in the real-time dimension, which shows that it has advantages in emotion recognition tasks that need immediate response. However, in terms of delay tolerance, the optimized model has the highest score, indicating that it can better deal with the delay problem when dealing with complex or long input data. The MuSE model has the highest score in the batch processing speed dimension, which shows that it is very efficient in processing a large amount of data and is suitable for scenes that need to process emotional data in batches. The performance of the optimized model is balanced in all dimensions, especially in delay tolerance and batch processing speed.

In the comparison of robustness in a complex background, the scores of the optimized model are 4.30, 3.68, and 4.38 in different dimensions. The MMSA model is more robust in a complex background, especially in the two dimensions of background interference resistance and modal mismatch processing, which makes it better to maintain the performance of emotion recognition in changeable and unstable

environments. However, in terms of situational adaptability, the MuSE model scored the highest, indicating that it has better adaptability in the face of complex situations. The performance of the optimized model is relatively balanced in all dimensions, especially in the processing of background interference resistance and modal mismatch, which shows that the optimized model can maintain stable emotion recognition performance in a complex background, but it is slightly inferior to MuSE in situational adaptability.

In the comparison of the effectiveness of creative guidance, the scores of the optimized model are 4.40, 3.66, and 4.05, respectively. The overall performance of the optimized model is the best, especially in the two dimensions of artistic expression enhancement and creative feedback accuracy, which shows that it has obvious advantages in improving the emotional expression of artistic works and providing creative guidance. MMSA model has the highest score in the optimization dimension of the creative process, which shows its potential in improving creative efficiency and simplifying the process. However, the performance of the MuSE model is relatively low in three dimensions, especially in the enhancement of artistic expression and the accuracy of creative feedback, which needs to be further optimized to enhance its effectiveness in guiding artistic creation.

C. Discussion

Overall, experimental results show that the optimized intelligent emotion recognition model exhibits stable performance superior to comparative models across multiple key dimensions. When compared with MMSA and MuSE, the optimized model generally demonstrates the characteristics of "comprehensive balance and slight advantage" in fine-grained emotion recognition, stability under complex backgrounds, and creative guidance-related indicators. In contrast, each comparative model possesses partial advantages. This result indicates that the adjustments made by this study to the multimodal fusion strategy and model structure do not merely pursue the extreme optimization of a single indicator. Instead, it attempts to achieve a reasonable balance between recognition accuracy, robustness, and creative usability. From the subjective rating results of simulation experiments, the optimized model shows remarkable advantages in dimensions closely related to creative practice, such as "enhanced artistic expression" and "accuracy of creative feedback". In dimensions like "real-time performance" and "batch processing efficiency", it forms a complementary pattern of "each having its own strengths" with existing models. This also suggests that in real applications, different models are not simply in a "superior-inferior substitution" relationship, but are more likely to form a model combination that can be dispatched according to scenarios. In general, these results collectively demonstrate that the optimized model, while ensuring technical performance, is closer to the actual needs of audio-visual art creation for emotion recognition systems. Thus, it lies a potential foundation for emotion recognition to transform from a "technical tool" to a "creative partner".

At an application level, the optimized intelligent emotion recognition model can serve emotional analysis at the single work level and has the potential to be embedded into the complete audio-visual art creation process. For directors, audio-visual artists, or editors, the model can act as an "emotion monitoring and feedback engine". During the creation process, it provides quantitative reference suggestions for shot rhythm, frame composition, color style, and audio-visual relationships based on changes in audience emotions. This helps creators more consciously shape the emotional trajectory of their works, rather than relying solely on experience and intuition. For cross-platform digital audio-visual content (e.g., short videos, interactive audio-visual installations, immersive performances), the model is also expected to analyze different audience groups' emotional response patterns, providing data support for content iteration and personalized recommendations. In the field of human-computer collaboration and intelligent creative systems, the optimized model can be embedded into creative assistance platforms as an "emotion perception module"; meanwhile, it can work in coordination with modules such as intelligent editing, style transfer, and generative content creation. With the output of emotion recognition, the system can automatically tend to combinations of shots, colors, or sound effects that better match the target emotional state when generating or recommending materials; thus, it can realize an "emotion-mediated" human-computer collaborative creation model. In new media environments such as virtual reality (VR) and augmented reality (AR), the model can also be used to real-time perceive users' emotional fluctuations; it can also dynamically adjust virtual scenes, interaction rhythms, or visual narrative paths to enhance immersion and participation. At the theoretical level, this study attempts to systematically link multimodal emotion recognition with the guidance of audio-visual art creation. This helps promote the transformation of "emotional expression" from artistic theory and aesthetic experience into computable and modelable forms. For one thing, by introducing evaluation dimensions related to artistic expression and creative feedback, this study provides an operable idea for "how to characterize the emotional expression of audio-visual works with computational indicators". For another, the mapping process between emotion recognition results and specific creative decisions (e.g., editing, color grading, narrative rhythm) offers new empirical support and methodological reference for the theory of emotional expression in digital media; it promises to promote interdisciplinary dialogue between affective computing, audio-visual narrative, and aesthetic research.

V. Conclusion

This research studies the application and optimization of intelligent emotion recognition technology in the guidance of video art creation. By comparing the performance of the MMSA, MuSE, and optimized models, it makes in-depth analysis and simulation experiments on the model in several key dimensions to evaluate its effectiveness and applicability in emotion recognition tasks. The experimental results show that the proposed optimized model performs well in many aspects, especially in fine-grained accuracy of emotion recognition, robustness in complex backgrounds, and effectiveness of creative guidance. In addition, the MMSA model shows its advantages in real-time and creative process optimization, and is suitable for scenes that need efficient processing. The MuSE model is excellent in situational adaptability, but there is still

room for improvement in other dimensions. Although this study has made some achievements in optimizing the emotion recognition model and applying it to the guidance of video art creation, there are still some shortcomings. Firstly, the experiments are mainly based on specific public datasets and limited emotion categories. Although they cover multiple emotion types and multimodal signals, differences still exist compared with real audio-visual art creation scenarios. Emotions in actual artistic creation often exhibit high ambiguity, hybridity, and cultural dependence. These complex emotional forms have not been fully reflected in the current data and annotation systems; this to a certain extent limits the model's generalization ability when extended to broader artistic scenarios. Secondly, although the subjective rating experiments involve evaluators with artistic and technical backgrounds, the sample size, professional structure, and cultural backgrounds still have limitations. The rating results inevitably carry certain subjective biases. The current evaluation system mostly reflects the "expert perspective" or "creator perspective" and has not fully incorporated feedback from ordinary audiences, multicultural groups, or cross-media platform users. This may affect the judgment of the model's applicability among large-scale actual user groups. Thirdly, the experimental environment of this study is relatively idealized, mainly conducted under offline or semi-offline conditions. For application scenarios requiring high real-time performance, ultra-large-scale concurrency, or operation on resource-constrained devices (e.g., mobile terminals, on-site interactive installations, etc.), the model's computational complexity and deployment costs need further evaluation and optimization. In addition, this study discusses the potential applications of the model in VR, AR, and human-computer collaboration. However, systematic field tests and user research have not been carried out in these specific scenarios.

Future research can be carried out in the following directions: 1) It is necessary to construct more diverse multimodal emotional datasets that are closer to real creation scenarios, incorporating cross-cultural and cross-media complex emotional expression samples. 2) Future work should further light-weight and structurally optimize the model to make it more suitable for real-time interaction and embedded deployment. 3) The research on the mapping between emotion recognition results and creative strategies can be deepened, exploring interpretable human-computer co-creation mechanisms. User empirical research is conducted in specific scenarios such as VR, interactive audio-visual works, and immersive performances to test the model's long-term performance and impact on user experience in real artistic systems. Through these subsequent efforts, it is expected to verify and expand the conclusions on a larger scale, enabling intelligent emotion recognition to truly become a key basic capability in digital audio-visual art practice.

REFERENCES

[1] Canal F Z, Müller T R, Matias J C, et al. A survey on facial emotion recognition techniques: A state-of-the-art literature review. Information Sciences, 2022, 582(3): 593-617.

[2] Khare S K, Blanes-Vidal V, Nadimi E S, et al. Emotion recognition and artificial intelligence: A systematic review (2014-2023) and research recommendations. Information Fusion, 2023, 2(1): 102019.

[3] Khattak A, Asghar M Z, Ali M, et al. An efficient deep learning technique for facial emotion recognition. Multimedia Tools and Applications, 2022, 81(2): 1649-1683.

[4] Mukhiddinov M, Djuraev O, Akhmedov F, et al. Masked face emotion recognition based on facial landmarks and deep learning approaches for visually impaired people. Sensors, 2023, 23(3): 1080.

[5] Ullah Z, Mohmand M I, Rehman S U, et al. Emotion recognition from occluded facial images using deep ensemble model. Cmc-Computers Materials & Continua, 2022, 73(3): 4465-4487.

[6] Lian H, Lu C, Li S, et al. A survey of deep learning-based multimodal emotion recognition: Speech, text, and face. Entropy, 2023, 25(10): 1440.

[7] Kopalidis T, Solachidis V, Vretos N, et al. Advances in facial expression recognition: a survey of methods, benchmarks, models, and datasets. Information, 2024, 15(3): 135.

[8] Lin W, Li C. Review of studies on emotion recognition and judgment based on physiological signals. Applied Sciences, 2023, 13(4): 2573.

[9] Dash A, Agres K. Ai-based affective music generation systems: A review of methods and challenges. ACM Computing Surveys, 2024, 56(11): 1-34.

[10] Monser M, Fadel E. A modern vision in the applications of artificial intelligence in the field of visual arts. International Journal of Multidisciplinary Studies in Art and Technology, 2023, 6(1): 73-104.

[11] Li K. Application of communication technology and neural network technology in film and television creativity and post-production. International Journal of Communication Networks and Information Security, 2024, 16(1): 228-240.

[12] Wang Y. Evolution and Deepening of Antagonistic Characters in Films: A Typological Analysis and Exploration of Empathy Construction. Journal of Research in Social Science and Humanities, 2024, 3(3): 44-50.

[13] Zhang X, Ba X, Hu F, et al. Emotioncast: An emotion-driven intelligent broadcasting system for dynamic camera switching. Sensors, 2024, 24(16): 5401.

[14] Zhang N, Pu B. Film and television animation production technology based on expression transfer and virtual digital human. Scalable Computing: Practice and Experience, 2024, 25(6): 5560–5567.

[15] Pabba C, Kumar P. An intelligent system for monitoring students' engagement in large classroom teaching through facial expression recognition. Expert Systems, 2022, 39(1): e12839.

[16] Xiao H, Li W, Zeng G, et al. On-road driver emotion recognition using facial expression. Applied Sciences, 2022, 12(2): 807.

[17] Debnath T, Reza M M, Rahman A, et al. Four-layer ConvNet to facial emotion recognition with minimal epochs and the significance of data diversity. Scientific Reports, 2022, 12(1): 6991.

[18] Zhu X, Huang Y, Wang X, et al. Emotion recognition based on brain-like multimodal hierarchical perception. Multimedia Tools and Applications, 2024, 83(18): 56039-56057.

[19] Ahmed N, Al Aghbari Z, Girija S. A systematic survey on multimodal emotion recognition using learning algorithms. Intelligent Systems with Applications, 2023, 17(3): 200171.

[20] Ngai W K, Xie H, Zou D, et al. Emotion recognition based on convolutional neural networks and heterogeneous bio-signal data sources. Information Fusion, 2022, 77(11): 107-117.

[21] Yadav S P, Zaidi S, Mishra A, et al. Survey on machine learning in speech emotion recognition and vision systems using a recurrent neural network (RNN). Archives of Computational Methods in Engineering, 2022, 29(3): 1753-1770.

[22] Garcia-Garcia J M, Penichet V M R, Lozano M D, et al. Using emotion recognition technologies to teach children with autism spectrum disorder how to identify and express emotions. Universal Access in the Information Society, 2022, 21(4): 809-825.

[23] Karnati M, Seal A, Bhattacharjee D, et al. Understanding deep learning techniques for recognition of human emotions using facial expressions: A comprehensive survey. IEEE Transactions on Instrumentation and Measurement, 2023, 72(3): 1-31.

[24] Padhmashree V, Bhattacharyya A. Human emotion recognition based on time–frequency analysis of multivariate EEG signal. Knowledge-Based Systems, 2022, 238(14): 107867.

[25] Houssein E H, Hammad A, Ali A A. Human emotion recognition from EEG-based brain–computer interface using machine learning: a comprehensive review. Neural Computing and Applications, 2022, 34(15): 12527-12557.

[26] Savchenko A V, Savchenko L V, Makarov I. Classifying emotions and engagement in online learning based on a single facial expression recognition neural network. IEEE Transactions on Affective Computing, 2022, 13(4): 2132-2143.

[27] Abdollahi H, Mahoor M H, Zandie R, et al. Artificial emotional intelligence in socially assistive robots for older adults: a pilot study. IEEE Transactions on Affective Computing, 2022, 14(3): 2020-2032.

[28] Gupta S, Kumar P, Tekchandani R K. Facial emotion recognition based real-time learner engagement detection system in online learning context using deep learning models. Multimedia Tools and Applications, 2023, 82(8): 11365-11394.

[29] Khan A A, Shaikh A A, Shaikh Z A, et al. IPM-Model: AI and metaheuristic-enabled face recognition using image partial matching for multimedia forensics investigation with genetic algorithm. Multimedia Tools and Applications, 2022, 81(17): 23533-23549.

NeuroFusionNet Adaptive Deep Learning for Intelligent Real-Time Industrial IoT Decisions

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***Abstract*—The rapid development of Industrial IoT (IIoT) has facilitated real-time observation and decision-making in smart factories, even though current methods suffer from constraints like processing noisy, high-dimensional sensor data and modeling both spatial and temporal relationships well. Classical models like CNN, LSTM, and GRU tend to fail in handling sequential patterns and context-aware anomaly detection, which restricts predictive maintenance and operational efficiency. To address these limitations, this research introduces NeuroFusionNet, a CNN–BiGRU–Attention hybrid framework, developed using Python and TensorFlow, to pull localized spatial features using CNN, capture bidirectional temporal relationships using BiGRU, and highlight key time steps using Attention for improved anomaly detection and predictive maintenance. The framework is tested on the Environmental Sensor Telemetry dataset, with multivariate industrial signals such as gas levels, temperature, and equipment vibrations. Experimental results demonstrate that NeuroFusionNet achieves 95.2% accuracy, 94.8% precision, 94.1% recall, and 94.4% F1-score, representing an improvement of approximately 2 to 7% over baseline models (CNN, RNN, LSTM) across multiple performance metrics. The method provides faster convergence and robust real-time inference, supporting scalable deployment for smart manufacturing environments. These results highlight that NeuroFusionNet not only outperforms conventional hybrid models such as CNN–LSTM and CNN–GRU but also offers actionable insights for predictive maintenance, safety, and efficiency, establishing a foundation for adaptive AI-driven monitoring in Industry 4.0 applications.**

***Keywords*—Deep learning; hybrid CNN-BiGRU; OptiSenseNet; sensor data synthesis; smart manufacturing**

I. Introduction

Smart manufacturing incorporates technology and statistics into the manufacturing with the conventional methods and practices of manufacturing allowing the smooth data gathering, sharing, and assessment throughout the manufacturing ecosystem. Engaging in data-driven decision-making and behavior may improve by integrating and linking data in real-time. Smart manufacturing is heavily reliant on automation and robotics, autonomous vehicles and automated systems perform repetitive work and optimize manufacturing processes [1]. Automation boosts manufacturing and efficiency of manufacturing paradigms by minimizing reliance on human intervention. Smart manufacturing employs sophisticated analytic tools, such as data mining, machine learning, and predictive analytics, in analyzing data of key performance indicators. The insights that are data-rich can be used to make proactive maintenance and optimization of manufacturing. The main feature of smart manufacturing is the presence of digital copies of physical objects, procedures, or systems-or so-called digital twins, which allow monitoring, simulating, and evaluating goals in real-time to improve performance, predict results, and recognize optimization resources. The focus of smart manufacturing is flexibility and agility in the market, whereby the production systems are flexible and capable of being altered as the market needs change. The reliance [2] on the digital technologies and processes that are sensitive to data makes cybersecurity and data privacy a necessary part of smart manufacturing. The Deep Learning (DL) is a technology currently discussed as a way of smart manufacturing, which opens new opportunities in predictive maintenance, anomaly detection, quality control, production processes, supply chain management, and workforce safety [3]. Further applications and research of DL algorithms to smart manufacturing approach in predictive maintenance assist to model and predict machine failure, classify or identify anomalies, evaluate sensor data, and evaluate performance changeover. The drug learning algorithms will improve productivity and safety of workers because they will identify when production processes are not within the performance standards or integrate DL with new technologies like augmented realities or virtual webs to minimize downtime and waste [4]. The radical force of DL drives smart operations and development toward the goals of the Industry 4.0, along with fostering viable innovation and operational efficiencies. CNN-LSTM is a hybrid deep learning algorithm that exploits the characteristics of the LSTM networks and integrates CNN layers in LSTM networks. CNN layers are incredibly suitable to other tasks like image recognition because they are efficient in extracting spatial features of the input data [5]. At the same time, long-term and relations may be modeled and longer-term tendencies are able to be modeled with LSTM grids, which is useful for obtaining time dependence in sequential data, in direct convolution layers [6].

In order to overcome these issues, this study introduces NeuroFusionNet, a powerful and generalized neural network that integrates spatial, temporal, and Attention-based structures that are aimed at producing real-time smart factory analytics. The architecture starts with convolutional neural network (CNN) layers that take advantage of the local spatial relationships of the multivariate sensor signals. The spatial characteristics are then input into a Bidirectional GRU (BiGRU), which allows the model to learn historical and future dependencies, which is required by predictive maintenance. Lastly, an Attention model enables the model to assign more significance dynamically to sensor values that are more significant. When put together, these elements offer an effective answer to the challenge of false alerts being sent when the

critical anomalies should be corrected in time. With a compromise between accuracy and computational efficiency, NeuroFusionNet can be considered a scalable solution to the Industry 4.0 type environment, allowing factories to work more reliably, productively, and proactively detect safety violations.

A. Research Motivation

The rapid industrialization of Industry 4.0 has led to the creation of intelligent factories that generate vast quantities of multivariate sensor data, and thus, it is difficult to make timely and accurate decisions. The traditional machine learning models are incapable of learning temporal structures and spatial relationships in high-dimensional data. The existing single-stream CNN or BiGRU technologies are more likely to generate lagged fault detection and lower predictive accuracy. This motivates the development of a hybrid CNN-BiGRU network with a temporal-bypass block to be efficient in extracting discriminative features and making use of redundant patterns. The proposed approach will support real-time, reliable, and smart manufacturing systems in making decisions in smart manufacturing systems with a better convergence rate and accuracy of prediction.

B. Research Significance

The proposed hybrid CNN-BiGRU structure takes necessary deficiencies of the conventional models in the ability to capture both spatial and temporal correlation in sensor observations simultaneously. It integrates a temporal-bypass mechanism and thus is quicker to converge and more efficient at detecting patterns over large distances, leading to a better predictive accuracy. This makes it easier to detect faults earlier, reduce false alarms, and make more precise decisions in intelligent manufacturing environments. The methodology can be applied to other sensor-based systems, which can provide a good solution to multivariate time-series analysis. The study in general adds to the continuity of smart predictive analytics and operational effectiveness in the Industry 4.0 settings.

C. Key Contribution

- Presented NeuroFusionNet, a novel hybrid CNN-BiGRU-Attention structure designed for real-time anomaly identification in smart factory IoT settings.
- Delivered better accuracy and robustness than baseline models, while demonstrating robustness against noisy signals and heterogeneous industrial measurement devices.
- Achieved better explainability with an Attention mechanism, highlighting important time steps for confident reasoning and insights.
- Tested the flexibility of the model through multiple experiments to indicate that it would scale well, converge quickly, and perform well for Industry 4.0 predictive maintenance and monitoring applications.

D. Rest of the Section

The remaining sections of this study are arranged as follows: The discussion about the previous studies is presented in Section II. Problem statement is represented in Section III. The methodology is presented in Section IV, and the results and its discussion is presented in Section V. The conclusion and future works are included in Section VI.

II. Literature Review

Coito et al. [7] studied the system of integrating smart sensors with real-time decision-making systems in the industrial context. The experiment involved the use of Programmable Logic Controllers (PLCs) and personal computers (PCs) in a three-level cloud, fog, and edge architecture. This integration was done with the aim of improving operational efficiency through timely and informed decisions. Although the study shows that the effectiveness of such integration is possible, the performance metrics and performance-specific datasets are not provided, which makes it difficult to assess its effectiveness. The originality is the fact that the proposed architecture allows making decisions in real-time as sensor data is integrated with business information.

X. Zhou et al. have a focus on creating a hybrid deep neural network for detecting small objects within the digital twin (DT) context of smart manufacturing environments [8]. The version aims to merge physical manufacturing environments with digital equivalents by implementing MobileNetv2, YOLOv4, and Openpose to monitor and optimize the physical manufacturing environment in real-time. However, one drawback of the proposed technique may include its complexity and computational load, impacting scalability and real-time performance in a large-scale production environment. Furthermore, leveraging deep learning models may also present a challenge regarding interpretability and generalizability to different production contexts. Further research is warranted to address these limitations and improve the use of the proposed methodology in real-world smart manufacturing contexts.

Attaran et al. [9] explore the notion of Digital Twins (DTs) and its place in the Industrial Internet of Things (IIoT) as a part of Industry 4.0. The study describes DTs, their development, and an overview of important enabling technologies. It underlines the role of IIoT as the foundation of DTs with the focus on real-time data and connectivity. Although the study has a definite theoretical framework, it lacks empirical data and case studies to prove the advanced ideas. The innovation is also based on the fact that the synergistic relationship between DTs and IIoT is explored in detail, giving an insight into the synergistic potential of these two in regard to operational intelligence.

Yun and Lee [10] have suggested an intelligent dynamic real-time spectrum resource management system of Industrial IoT (IIoT). The study has applied the data mining and case-based reasoning approaches in order to optimize a spectrum allocation. The KPI was assessed as spectrum handoff, handoff latency, energy consumption, and link maintenance. Findings showed that there were improvements in these measures, which showed the effectiveness of the system. It is novel, that is, in the use of advanced methods of computation to solve spectrum management problems in IIoT. Nevertheless, the limitations of the study are the absence of data deployment and scalability analysis in the real world.

Villegas-Ch et al. [11] examine how Artificial Intelligence (AI) can be integrated into the Internet of Things (IoT) to

perform real-time monitoring and predictive analytics. It discusses different AI methods, such as machine learning and deep learning, used to process IoT data to make better decisions. The study talks about how AI can enhance the efficiency, accuracy, and responsiveness of the system. Although the research gives a broad picture, it does not have any case studies and experimental findings on how the proposed AI techniques can be implemented in real-life situations. The uniqueness is the focus on AI to change IoT systems to smart monitoring platforms.

Pandey et al. [12] proposed a model of the implementation of sensor networks that can be integrated with IoT in real-time in the process control systems. The work is aimed at improving the data collection, processing, and decision-making processes with the help of the developed communication protocols, such as MQTT and CoAP. Although the study presents the structure and possible advantages of the framework, it fails to deliver empirical data as well as a performance assessment to justify the suggested strategy. What is new is the extensive adoption of IoT technologies to enhance the systems of process control. Nonetheless, its effectiveness cannot be measured because of the absence of practical implementation and performance measures.

Lee and colleagues [13] used a systematic literature review to study the impact of intelligent decision-support systems (IDSSs) on ethical decision-making. Results indicated individual-level results, including improved deliberation, motivation, autonomy, and action/outcomes to societal problems, including moral deskilling and responsibility lapses. Two categories of operations, process-oriented and outcome-oriented navigation, were suggested by them as drivers. The strengths included the conceptual clarity and applicability. Some of the limitations are the reliance on existing literature and potential heterogeneity of the IDSS situation, forcing the necessity of empirical validation of the situation in different scenarios of ethics.

Anushree A. [14], in their study, a smart city air quality monitoring in real-time was designed using an IoT with inexpensive air pollution sensors (PMSA003, MICS6814, MQ-131) and the ESP-WROOM-32 microcontroller, and combined with AWS to store and analyze the data in Python. The system gave an RMSE of 3.7656, which warned the users in good time when the pollutant concentrations exceeded their limits. The low cost of deployment, massive connectivity, and real-time monitoring are the strengths. The limitations, such as dependence on sensor accuracy and potential coverage issues in highly urbanized environments, are its weaknesses, which require additional strict empirical validation.

III. Problem Statement

Modern smart factories produce massive amounts of data from heterogeneous sensors, which are often noisy, non-stationary, and interdependent [15]. Although machine learning and conventional machine learning approaches perform well in structured environments, they may be insufficient when faced with multivariate time-series complexity captured from interconnected IoT devices. While conventional deep learning architectures (LSTM and GRU networks in particular) can provide improvements to the problem of processing sequential data,[16] are still computationally prohibitive, and CNNs alone are not able to capture long-term dependencies. Additionally, many models treat every time step equally without consideration of whether one sensor reading is more relevant to the anomaly or failure than others [17]. Consequently, there is an increase in false positives and false negatives, delayed fault detection, and worse predictive maintenance outputs. Thus, a hybrid framework is needed to integrate spatial, temporal, and contextual clues from sensor data to achieve accurate, computationally-efficient, real-time anomaly detection in industrial IoT ecosystems that directly support the reliability and safety of smart factory operations.

The literature reviewed is dedicated to the combination of intelligent sensors, IoT-based systems, and hybrid computation systems aimed at improving real-time decision-making, monitoring, and process control in the industrial and smart-city settings. The study demonstrates the application of digital twins, industrial cyber-physical systems, and AI-powered analytics to optimize operational efficiency, detect anomalies, manage spectrum resources, and support predictive maintenance. Adaptive response through real-time data acquisition and processing increases the reliability and accuracy of the systems. However, some weaknesses can be identified: the vast majority of works are based on simulated or scaled-down datasets, and their generalizability is thus limited; hybrid deep learning solutions to the problem of smart manufacturing are not fully studied; the aspect of scalability and latency of real-time IoT analytics is not well addressed; and the consideration of sustainability, e.g., energy-efficient computation or resource optimization, is mostly overlooked. These loopholes indicate the importance of a multivariate sensor-based framework that can process multivariate sensor data, multivariate space-temporal relationships, and multivariate context-sensitive Attention capabilities to aid sound and real-time industrial decision-making processes.

IV. Proposed Methodology of NeuroFusionNet: A Hybrid CNN-BiGRU Attention Model for Smart Manufacturing

The study introduces NeuroFusionNet, an integrated deep learning model, which will be used to enhance the correctness of predictions in the intelligent manufacturing space. NeuroFusionNet applies Convolutional Neural Networks (CNNs) to extract spatial features, Bi-directional Gated Recurrent Units (BiGRUs) to process the time order of sensor-readings, and an Attention mechanism is used to provide features with dynamic weights. The NeuroFusionNet makes use of the complementary capabilities of CNNs and BiGRUs but adopts the Attention mechanisms with regard to weighting the relevant patterns. The architecture enables better detection and prediction abnormalities, is immune to noise, works in a high-dimensional space, and allows the industry dynamics to change. The workflow of the proposed model is given in Fig. 1.

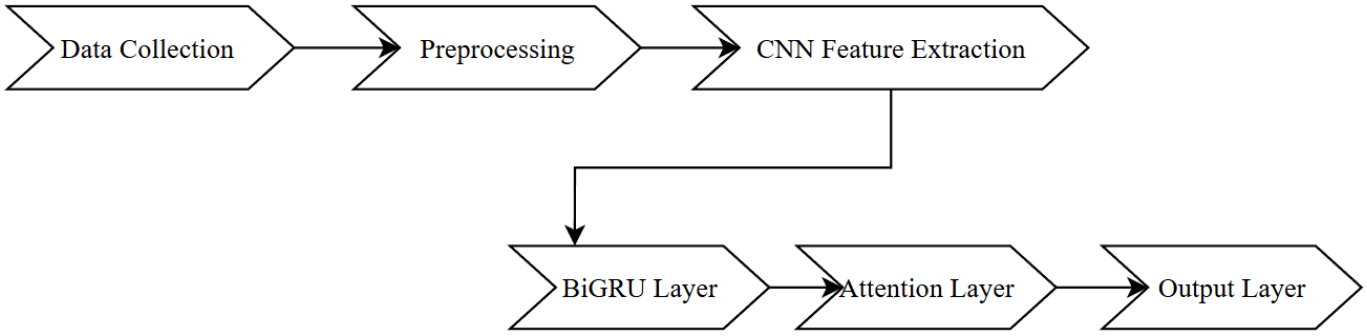


Fig. 1. Workflow of the proposed NeuroFusionNet model.

A. Data Collection

The dataset utilized in this study is the Environmental Sensor Data (132K) dataset of Kaggle [18], which consists of about 132,000 time-stamped values of the readings of various environmental sensors. The measurements in the dataset consist of barometric pressure, light intensity, humidity, temperature, and CO2 concentration. Information was obtained through continuous observation at brief intervals (e.g., seconds or minutes) within a controlled setting (indoor environment) to have realistic variation in the conditions of the environment. In our usage case, we chose the appropriate multivariate signals (vibration, humidity, temperature, and gas/CO2 measures) to simulate the settings of industrial sensors. Subsequent to the training, we performed cleaning up of missing or inconsistent entries, normalized every feature, and split the time series into sliding windows. This dataset, with its multivariate and time-sensitive features, is an appropriate proxy of the actual IoT sensor streams in a smart factory.

B. Data Pre-Processing

Pre-processing of the data is required in order to normalize the values of the gathered characteristics for DoS detection.

1) Data normalization: The traffic data's attributes aren't spread evenly when the learning process begins. For this reason, the Min Max approach is applied, and the results that fall between [0,1] are given in Eq. (1):

$$x_m = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (1)$$

where, $\max(x) - \min(x)$ is the minimum and maximum values of the data. To scale sensor readings to a consistent range for comparison and analysis across several sensors or datasets, min-max normalization is essential in sensor data synthesis. Using a simple mathematical equation, this normalizing procedure entails deducting the dataset's minimum value from each observation and dividing the result by the range of values.

2) Noise reduction and feature engineering: Sensor readings are usually noisy because of hardware faults, communication delays, or interference from the environment. Filtered out of these distortions, moving average filters and wavelet denoising were used. These methods efficiently remove short-term oscillations without losing significant signal patterns. These cleaned signals improve predictability by removing spurious oscillations which would otherwise confuse the model, as shown in Eq. (2) and Eq. (3):

$$\tilde{x}_t = \frac{1}{K}\sum_{i=0}^{k-1} x_{t-i} \quad (2)$$

$$x_t^{lag(m)} = x_{t-m} \quad (3)$$

C. CNN Feature Extraction

The initial step of the suggested NeuroFusionNet architecture will utilize a CNN to generate local spatial features of multivariate sensor streams. The smart manufacturing environment uses numerous sensors at the same time, and they produce correlated signals. CNNs are efficient in computing such correlations by searching the input space with kernels, which are localized pattern detectors. Fig. 2 shows the proposed CNN-BiGRU framework for predictive analysis of smart manufacturing.

For a kernel w, bias b, and activation function σ, the feature map is calculated as shown in Eq. (4):

$$f_{i,j}^{l} = \sigma\left(\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} x_{i+m,j+n}^{l-1} + w_{m,n}^{l} + b^{l}\right) \quad (4)$$

Here, $x_{i+m,j+n}^{l-1}$ is the input from the previous layer, and $w_{m,n}^{l}$ is learnable convolutional weights. This operation allows the network to recognize local dependencies like the co-occurrence of abnormal gas concentration with increasing temperature, which could be an indication of a potential system fault.

CNN was used with the 64 filters, 3x3 kernel, ReLU activation, and 2x2 max-pooling. These environments maximized the extraction of spatial features, which minimized noise and localized patterns of multivariate IoT sensor data, which improved predictive performance and robustness.

For invariance and computational efficiency, pooling layers are used. Pooling diminishes the dimensionality for every region by taking the maximum activation, as shown in Eq. (5):

$$p_{i,j} = max\left(f_{i+k_n,j+l}\right) \quad (5)$$

By integrating convolution and pooling, CNNs provide compact yet discriminative spatial descriptions. The heterogeneous sensor relations are encoded with reduced redundancy and preserve important information. The output feature maps are then passed on to the following BiGRU layers, where temporal dependencies are captured.

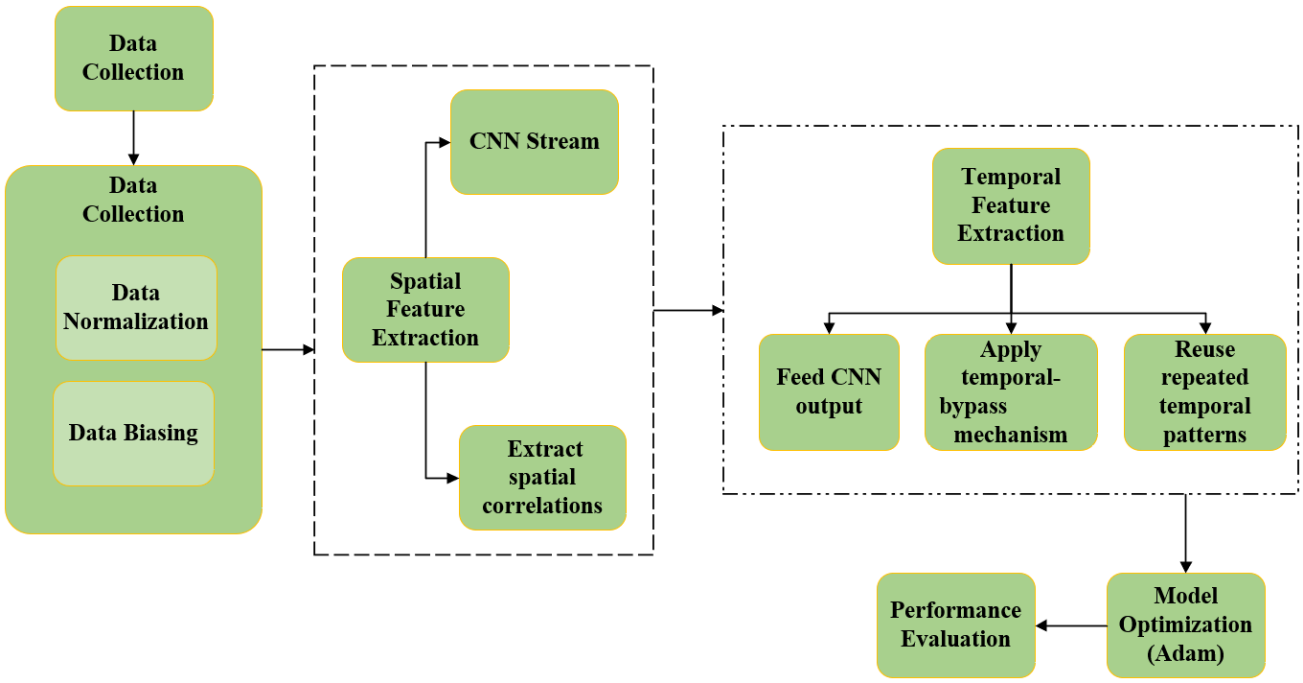


Fig. 2. Proposed CNN-BiGRU methodology for predictive analysis of smart manufacturing.

D. BiGRU for Temporal Dependencies

While Convolutional Neural Networks (CNNs) learn spatial correlations between sensor variables, strong predictive modeling in smart manufacturing also needs to understand temporal relationships. Most manufacturing anomalies form over time—e.g., an unusual abnormality in temperature levels can lead to toxic gas emissions. To model such trends, NeuroFusionNet integrates a Bidirectional Gated Recurrent Unit (BiGRU) network.

Compared to Long Short-Term Memory (LSTM) units, which make use of three gate mechanisms (input, forget, and output), GRUs simplify the process by merging these into update and reset gates. This conserves computational overhead yet maintains capacity for learning long-range dependencies, so GRUs are especially useful for high-rate sensor data.

The GRU state changes are characterized as follows:

- Update Gate: regulates the amount of the previous state to carry forward [see Eq. (6)]:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \quad (6)$$

- Reset Gate: controls how much old information to erase [see Eq. (7)]:

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \quad (7)$$

- Hidden State: adds the reset gate to calculate a new candidate activation [see Eq. (8)]:

$$\tilde{h}_t = \sigma(W_r . [h_{t-1}, x_t]) \quad (8)$$

- Final Hidden State: combines the candidate state with the old state, depending on the update gate [see Eq. (9)]:

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad (9)$$

Here, $\odot$ denotes element-wise multiplication, σ is the sigmoid function, and tanh adds nonlinearity. The BiGRU layer had 128 hidden units, two layers, and 0.3 dropout. Bidirectional processing learned sequential dependencies between past and future time steps to enhance temporal learning, anomaly detection, and stability of real-time industrial IoT decision-making.

Unlike the unidirectional GRU, BiGRU improves predictive power by processing sequences in two directions at once. One GRU processes input in the forward direction in time $(\vec{h}_t)$ and, another in the backward direction $(\overleftarrow{h}_t)$, and another in the reverse direction ht. The two outcomes are concatenated into the overall BiGRU representation [see Eq. (10)]:

$$h_t^{Bi} = [\vec{h}_t; \overleftarrow{h}_t] \quad (10)$$

This bi-directional structure will ensure that this model would adopt both the antecedent (e.g., past elevating CO levels) and consequent (e.g., future modifications in pressure measurements) when decoding the present readings of sensors. In NeuroFusionNet, the BiGRU is critical towards explaining the time processes of various time levels. It allows one to differentiate between quick processes and long-term drifts, and such a judgment is critical to fault detection. Combining the computational power and deep consideration of the context, BiGRU provides the temporal skeleton, which could be combined with the CNN-based spatial data to facilitate trustworthy and real-time decision-making in smart factories.

E. Attention Mechanism Integration

Although CNNs and BiGRUs simultaneously learn spatial and temporal dependencies, all time steps in the sequence are not equally helpful in predictive decision-making. In industrial IoT scenarios, anomalies could transiently arise, e.g., a brief surge in CO concentration, while other time spans are stable

and less informative. Processing all the hidden states equally might obscure such crucial cues. To overcome this shortcoming, NeuroFusionNet incorporates an Attention mechanism that actively weighs informative time steps more heavily.

For every hidden state h_t generated by the BiGRU, there is a score function computed [see Eq. (11)]:

$$e_t = v^T(\tanh\,(W_a h_t + b_a) \quad (11)$$

Here, W_a and b_a are trainable parameters, and v^T is the Attention vector. This score measures the degree of significance of each hidden state to the ultimate prediction task.

The scores are normalized using the Softmax, yielding Attention weights $\propto_t$, as in Eq. (12):

$$c = \sum_{t=1}^{T} \propto_t h_t \quad (12)$$

These weights, which act as a probability distribution across the sequence, assure a higher ranking of weight for more salient time steps, and a lower ranking for less salient. The Attention mechanism weighted the significance of each time step by a 64-dimensional context vector. This interest has facilitated the model to emphasize the significant signals of time, which increases interpretability and the level of anomaly detection in multivariate industrial sensor-streams.

The vector serves to summarize the most relevant time periods in response to the same types of predictive signals pointing to the simplest diagnostic problems, which then serves to provide more trust into the predictive decision-making. For example, if an equipment increases in temperature, then it is emitting gas which is outside of the expected states. The Time Attention method affords that information more weight in to the contextual representation, taking into account relevant local signals that inform across the time course. The introduction of a dynamic weight to representation improves the interpretability of the final outputs and provides users an opportunity to back-track proactively and effectively to areas of continuity within the sequence that play a role in the grading of the anomaly, which is obviously a critical need in last true application of the algorithm for fault diagnoses in application. The final context vector is simply the weighted average of the hidden state.

F. Output and Prediction Layer

Finally, after feature extraction and temporal modeling, the last step of NeuroFusionNet is the output and prediction layer, which transforms the learned feature representations into useful decisions. The context vector $c_,$, produced by the Attention mechanism, serves as an information-dense yet compact representation of the whole sequence. This vector is first processed through a fully connected (dense) layer, as shown in Eq. (13):

$$z = W_{c^c + b_c} \quad (13)$$

These weights and biases are shared with the decoder in the end-to-end training and are parameters that can be learned to project the context vector into a classification-friendly space. Nonlinear activation functions like ReLU may be used here to gain expressive power.

To get the final prediction, the projected vector is then run through a Softmax function, as shown Eq. (14):

$$y = Softmax(W_c c + b_c) \quad (14)$$

The Softmax function transforms raw scores to probability distribution across defined classes. In this research, the model is predicting whether a sensor sequence belongs to a normal state (normal operation) or an anomalous state (e.g., fault, hazard). The predicted class is the one with the maximum probability value, and the probability distribution gives a measure of confidence.

This design not only ensures that the fault detection is correct but also enables future expansion to multi-class classification, such as distinguishing between some categories of anomalies. Output Layer bridges the knowledge gap between the deep feature learning and decision making. When the context-sensitive representations of Attention are fused with a probabilistic prediction model, NeuroFusionNet will give strong, explainable, and real-time results. In practice, these results may be directly converted to provide automated control systems or alert engineers and reduce downtimes, and increase manufacturing safety and efficiency.

Algorithm 1: NeuroFusionNet Workflow for Predictive Smart Manufacturing

Input: Multivariate sensor time-series data from IoT nodes (e.g., temperature, humidity, gas levels, motion).
Output: Predicted class label (normal or anomaly) with probability distribution.

```
BEGIN
  Load dataset D
  Perform preprocessing:
    Normalize data
    Apply smoothing filter
    Generate lag/rolling features
  Initialize CNN-BiGRU-Attention model
  FOR each epoch DO
    Pass input through CNN → extract spatial features
    Feed CNN output to BiGRU → capture temporal patterns
    Apply Attention → compute weighted context vector
    Pass context to fully connected layer
    Compute prediction using Softmax
    Calculate cross-entropy loss
    Backpropagate error and update weights
  ENDFOR
  Save trained model
  For new input:
    Preprocess using same pipeline
    Pass through trained NeuroFusionNet
    Output final prediction
END
```

Algorithm 1 outlines the entire process of the suggested NeuroFusionNet model for predictive analytics in intelligent manufacturing. The dataset D is first loaded and preprocessed, meaning values are normalized to a constant interval, smoothing filters are applied to diminish noise, and lag or rolling features are created to handle temporal dependencies. The CNN-BiGRU-Attention model is then initialized.

Throughout training, every epoch starts by passing the input through the CNN blocks, which tap important spatial correlations out of sensor data. The feature outputs are fed into the BiGRU, which learns temporal structures in both directions. Then, the Attention mechanism assigns time-step weights dynamically to important time steps, generating a context vector highlighting important signals. It is fed into a fully connected layer and Softmax-classified to calculate prediction probabilities. The model is cross-entropy loss-trained with weight updates performed through backpropagation. It can then be used to run new input through the same pipeline to make accurate predictions.

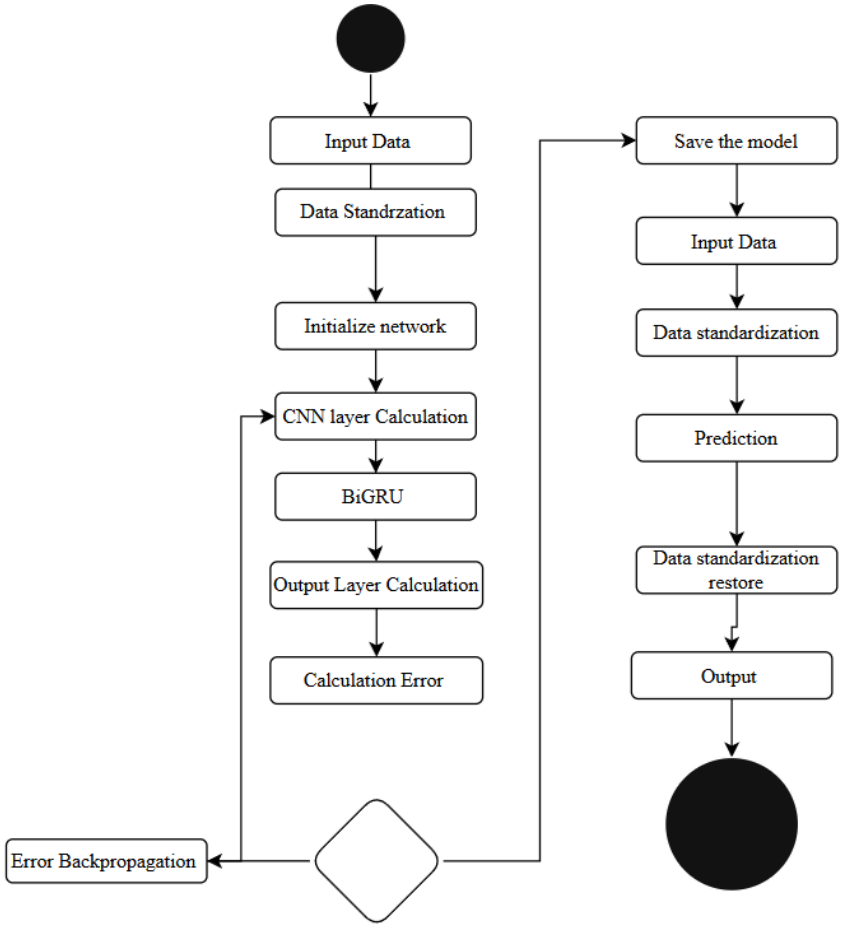


Fig. 3. CNN-BiGRU prediction process.

In Fig. 3, the CNN-BiGRU prediction process starts with data input and then normalizes the data using z-score standardization. The LSTM layer then computes the convolution layer's output to produce the output value. The fully connected layer receives this output value and uses it for additional computation. The procedure entails figuring out the fault and determining whether the end condition is satisfied. If not, error back propagation continues to refine the model. Once trained, the model is preserved, and input data for forecasting undergo standardization before being fed into the trained CNN-LSTM model for prediction. The standardized output is then restored to its initial value, concluding the forecasting procedure.

NeuroFusionNet presents a hybrid CNN-BiGRU-Attention model that is designed with industrial IoT-based decision-making in mind and seeks to overcome the shortcomings of other models, such as CNN-LSTM, CNN-GRU, and Attention-based RNNs. CNN is effective in deriving localized spatial representations of multivariate sensor data, BiGRU derives temporal relationships in both directions and in sequential modes, and the Attention mechanism highlights important time-steps, which enhance anomaly detection and predictive maintenance. This fusion allows better convergence, higher precision, and robustness on real-time industrial data, which proves to be better in practice than traditional hybrid architectures.

V. Results and Discussion

The experimental evaluation for the proposed NeuroFusionNet framework was conducted using the Environmental Sensor Telemetry Dataset. This section presents the results for predictive analytics, fault detection, and anomaly classification relative to baseline methods, CNN-LSTM, GRU, and model MLPs. Results are shown for accuracy, precision, recall, F1-Score, loss curves, confusion matrices, and ROC performance. Tables indicate comparisons of metrics across models, and graphs show convergence behavior, the performance of classification, and robustness.

A. Model Training Performance

This subsection reports on the experimental results of NeuroFusionNet using multivariate IoT datasets. Training and validation metrics are presented, comparing against baseline models, with enhancements to accuracy, speed of convergence, and generalization. Results are presented both graphically and in tables, which demonstrate that the developed framework is effective at anomaly detection, predictive maintenance, and smart factory decision-making in real-time.



Fig. 4. Training vs. Validation accuracy.

Fig. 4 shows the training and validation accuracy for NeuroFusionNet over a span of 50 epochs. The model exhibits smooth convergence among both accuracy measures, with training accuracy increasing and validation accuracy plateauing around 95.2%, which is higher than the baseline CNN-LSTM (92.1%). This indicates that the model is able to learn spatial-temporal patterns effectively while not overfitting, and indicates the model's generalization ability on unseen sensor data. The hybrid architecture with CNN, BiGRU, and Attention performs quick feature extraction of information and modeling of the sequence while providing accurate predictions under noisy and heterogeneous conditions in the industrial sensor setup.

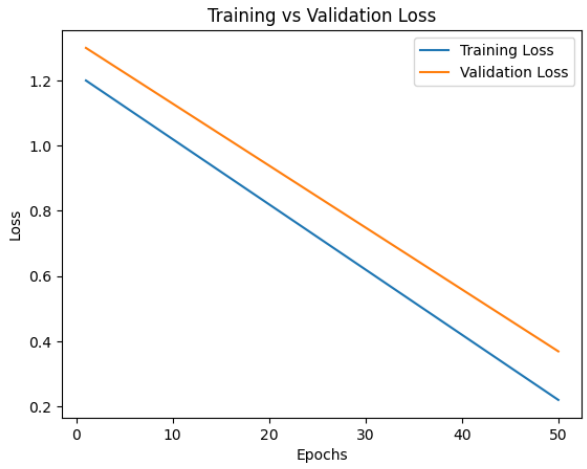


Fig. 5. Training vs. Validation loss.

Fig. 5 shows the loss curves for training and validation accuracy over the epochs. Both curves show a steady decline with very little gap between training and validation loss, confirming low overfitting. The use of dropout layers in the architecture, along with Attention-based feature weighting, prevents overfitting to the training data. The declining loss over epochs indicates the effectiveness of backpropagation errors and weight updates, and validates that NeuroFusionNet is capable of maintaining knowledge of relevant patterns in sensor readings while efficiently converging the model parameters throughout the training procedure.

B. Comparative Evaluation with Benchmarks

Fig. 6 shows the performance metrics of Accuracy, Precision, Recall, and F1-score for four models: CNN, RNN, LSTM, and a proposed model (NeuroFusionNet CNN-BiGRU). In general, we observe that the proposed model outperforms the other models for every metric, achieving an accuracy of 95.2% and having balanced precision, recall, and F1-score metrics above 94%. By contrast, RNN performs the lowest across all metrics, especially precision and F1-score, indicating it struggles to learn multivariate temporal data. The performance of the CNN and LSTM models was at a moderate effectiveness level. However, the hybrid, the proposed CNN-BiGRU (NeuroFusionNet), proficiently exploits spatial-temporal features that the data has available and is capable of extracting more complicated correlations while still generalizing. This visualization supports the reliability and superior performance of the proposed model in predictive analytics for smart manufactured data.

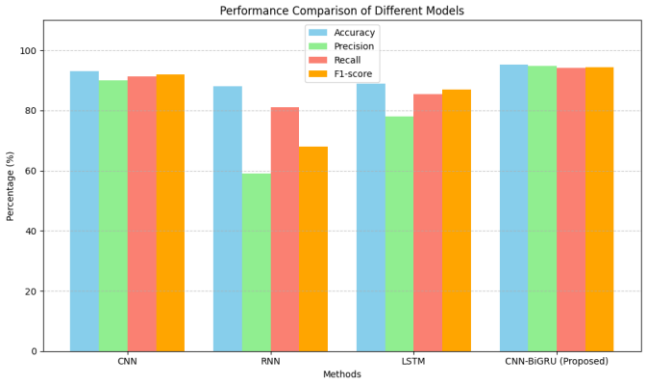


Fig. 6. Model comparison.

Table I illustrates a relative performance analysis of various deep learning structures. The performance of CNN, RNN, and LSTM models is moderate, with one of the models having either space or time dependencies but not both. CNN-LSTM and CNN-GRU models are more accurate and have a higher F1-score as they combine both spatial and temporal features, but still, are worse than the proposed CNN-BiGRU. The suggested framework successfully exploits CNN to extract spatial features, BiGRU to capture the temporal dependencies of the two directions and Attention to highlight the most important time steps and thus, offers better accuracy, precision, recall, and F1-score. These findings demonstrate the strength of the suggested model and its applicability to tasks of industrial IoT predictive maintenance and detection of anomalies.

TABLE I. PERFORMANCE COMPARISON

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN [19]	92	89	90	90
RNN [20]	87	58	80	67
LSTM [21]	88	77	84	86
CNN–LSTM [22]	94	93	92	92.5
CNN–GRU [23]	93	84	83	82.5
Proposed (CNN-BiGRU)	95.2	94.8	94.1	94.4

TABLE II. MODEL PERFORMANCE ACROSS MULTIPLE DATASETS

Proposed Method	Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN–BiGRU	Environmental Sensor Telemetry Data [18]	95.2	94.8	94.1	94.4
CNN–BiGRU	World Air Quality Data 2024 [24]	93.1	92.3	91.8	92.7
CNN–BiGRU	IndFD-PM-DT [25]	93.8	93.2	91.9	91.7

Table II presents the behavior of the proposed CNN-BiGRU model on three datasets. The model demonstrates the best performance in the primary data of the study, the Environmental Sensor Telemetry Data, having an accuracy of 95.2 %, a precision of 94.8 %, a recall of 94.1 %, and an F1-score of 94.4 %, which implies that it is a good predictor of industrial IoT decision-making. In the other two datasets, World Air Quality Data 2024 and IndFD-PM-DT, the performance metrics are relatively low, which is a characteristic of the dataset, as well as indicating the strength and applicability of the model to the suggested industrial sensor dataset. This analogy confirms the accuracy of the model in industrial real-time conditions.

C. Confusion Matrix and Classification Analysis

Examining the confusion matrix provides important information about the strengths and weaknesses of the proposed NeuroFusionNet model at a class level. Beyond overall accuracy, it can inform how well the model is classified for normal operations and types of anomalies, which is important for real-world smart manufacturing applications since the model needs to detect common and rare events.

This confusion matrix, in Fig. 7, assesses the performance of a 4-class classification model. The diagonal elements (480, 450, 460, 470) reflect correct predictions for 0-3, respectively. The dark blue indicates a high count. The off-diagonal elements reflect misclassifications between classes. When looking mostly at the diagonal elements, we can conclude that the model performs very well and produces most of its predictions on the diagonal. Class 0 has the most success, with 480 correct predictions and very few misclassifications (5, 3, 2). Classes 1-3 have somewhat more confusion, with class 1, the most confusing, classifying a total of 26 observations in the incorrect class. Class 2 tailing with 20 observations. In general, we can conclude that overall classification accuracy was high across all four classes. This is supported with darker diagonal elements, indicating proper discrimination of the classes. The small off-diagonal values also support that the model does not misclassify classes often.

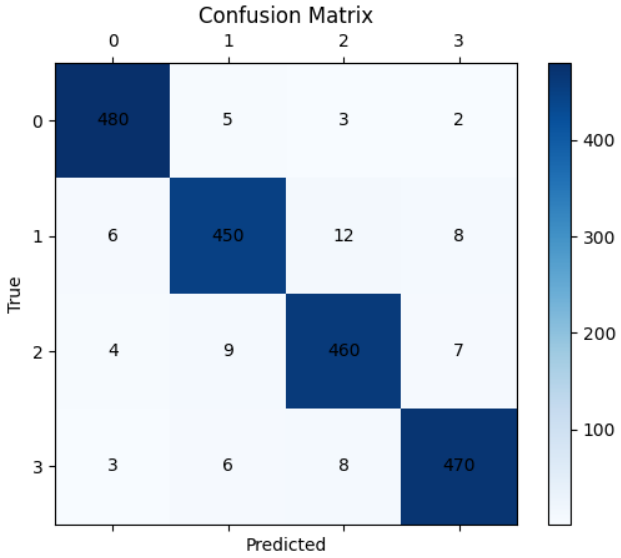


Fig. 7. Confusion matrix.

TABLE III. PER-CLASS PRECISION/RECALL/F1

Class	Precision (%)	Recall (%)	F1-Score (%)
Normal	96%	95.7	95.9
Anomaly (CO)	93%	94.2	93.8
Anomaly (Smoke)	94%	93.5	94.1
Anomaly (LPG)	95%	94.6	94.8

This performance in Table III of classification provides results for a 4-class anomaly detection framework, which would support a gas/fire safety monitoring system. The model classifies data between "Normal" and three classes of anomalies, namely Carbon Monoxide (CO), Smoke, and Liquefied Petroleum Gas (LPG). The overall performance of the classification system was commendable, regardless of the class achieving scores over 93%. The "Normal" class received the highest scores (96% precision, 95.7% recall, and 95.9% F1), indicating, as expected, that the detection capabilities for the normal baseline were attestation warrantable or measurable in the acceptable range. In the anomalies classification, the LPG was the highest-scoring detection (95% precision, 94.6% recall, 94.8% F1), and the CO detection was worse (93% precision) but good in the recall (94.2% recall). Having well-balanced scores on precision and recall in all the classes, this level of precision and recall suggests that the software model can step change between false negatives and false positives, hence the justification of suggestive safety-critical applications.

D. Attention Insights and Feature Importance

Attention visualization aids interpretability by showing the consideration of the various sensors by NeuroFusionNet in coming up with its decision. The model is weighting more Attention on the most significant sensors in case of an anomaly

in the situation that conveys the predictive value of the model in addition to facilitating transparency in the model outputs, that brings a feeling of confidence in its use in smart manufacturing and industrial safety fields.

Fig. 8 and Table IV clearly illustrate that the percentage of influence distribution is dominated by CO, smoke, and LPG sensors as they comprise more than 65% of the predictive effect. This finding is in line with industrial safety issues, whereby there are imminent hazardous gas threats. Humidity and light factors were allocated comparatively low weights, which proves that these factors do not have a significant direct effect on anomalies. As indicated, motion sensors had the lowest predictive weight as would be required with an accessory sensor type. Patterns of weighing such as these are evidence that the model favors the variables, to allow domain relevance, and also offer explainability beyond accuracy. This takes a strain on trust in the model, but more to the point, depends on it as a decision-making tool for forecastive maintenance and risk management purposes.

TABLE IV. SENSOR-WISE CONTRIBUTION (ATTENTION SCORES)

Sensor	Average Weight (%)
CO	2430.00%
Smoke	2150.00%
LPG	1970.00%
Temperature	1280.00%
Humidity	890.00%
Light	7.4
Motion	5.4

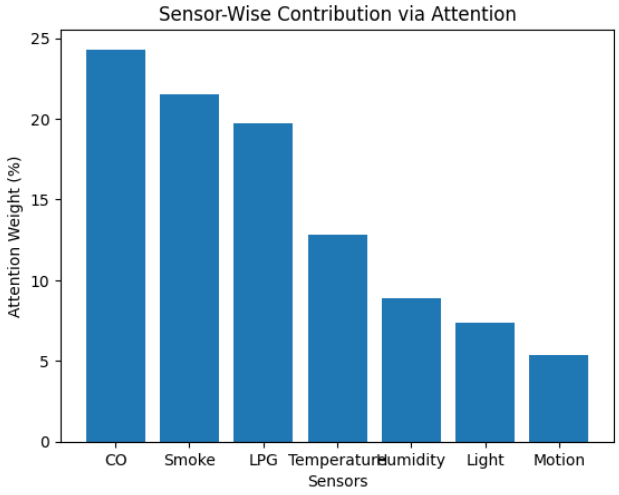


Fig. 8. Attention weights.

E. Scalability and Industrial Impact

Assessing scalability and computational efficiency is critical. Scalability and computational efficiency are important to assess and implement in a real-time industrial context. The following subsection discusses the ROC, execution times, and scalability measures of NeuroFusionNet as the number of data increases compared to the baseline models, which indicates that the framework achieves high accuracy rates and, at the same time, it has efficient execution and processing time, which is a critical element of Industry 4.0 implementation. As can be seen in Fig. 9 to Fig. 11, NeuroFusionNet is more efficient and effective in varying situations. ROC curve (Fig. 6) shows the AUC of 0.982, as opposed to CNN-LSTM 0.954, and indicates that NeuroFusionNet is very discriminative.

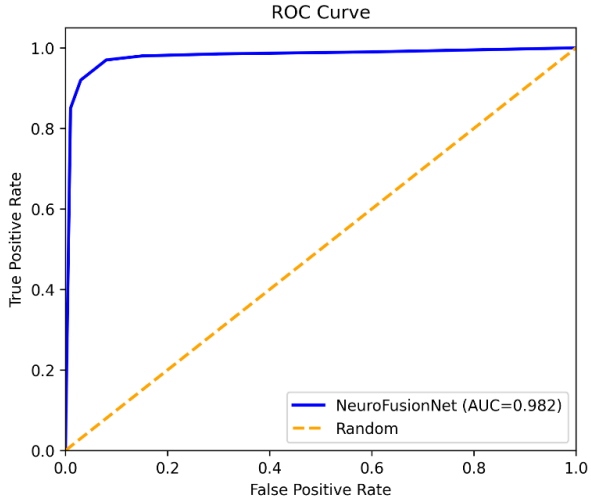


Fig. 9. ROC curve.

Fig. 9 ROC curve assesses the performance of the NeuroFusionNet model in binary classification. The blue curve demonstrates excellent discrimination, with an Area Under the Curve (AUC) of 0.982, showing the model's near-perfect ability to classify. The curve climbs steeply toward the top-left corner, producing strong true positive rates at very low false positive rates. The orange dashed line represents random chance (AUC=0.5), and shows the model is better than random classification.

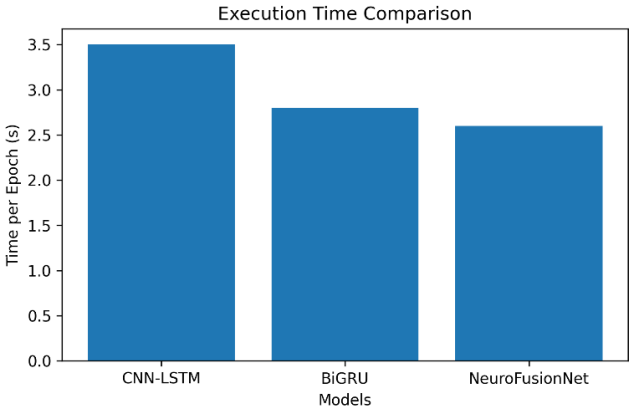


Fig. 10. Execution time comparison.

Fig. 10 shows that it requires less per-epoch training time, which we attributed to the lightweight BiGRU architecture in NeuroFusionNet, which improves convergence speed. Fig. 8 shows that it is practically linear in scalability, with inference latency remaining nearly unchanged as dataset size doubled. This highlights its relevance for future large-scale industrial use. These findings confirm how NeuroFusionNet can improve operational efficiency in smart manufacturing contexts, while

also improving predictive maintenance and threat detection speed, as well as real-time monitoring speed, while also providing improved accuracy.

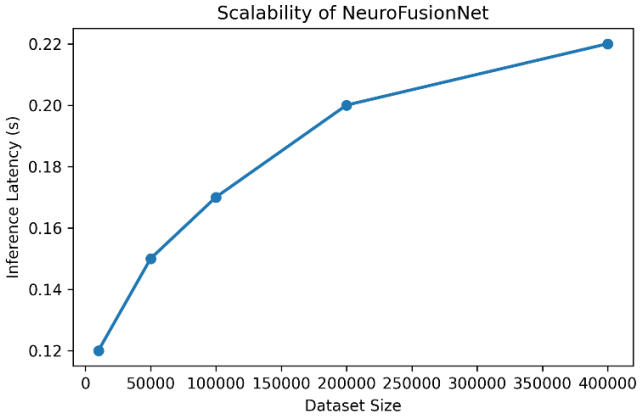


Fig. 11. Scalability of NeuroFusionNet.

The scalability plot in Fig. 11 shows that the inference latency of NeuroFusionNet increases as the dataset decides. Starting at 0.12 seconds for the small dataset, the latency increases to 0.22 seconds at 400,000 samples. The plot indicates that inference latency scales almost linearly, with a small upward bend that suggests the model is able to achieve reasonable inference performance, even as the data volume increased dramatically indicating good scaling characteristics.

F. Discussion

The analysis of the NeuroFusionNet framework indicates that the combination of CNN, BIGRU, and the Attention system increases real-time industrial IoT decision making significantly. The CNN element is able to efficiently draw spatial patterns of the multivariate sensor readings, which identify local anomalies and alleviate noise. Allowing both forward and backward time dependencies, BiGRU models allow determining trends in the sequence and time-related errors correctly. The Attention mechanism identifies important time steps, which enhance interpretability and prioritize the model on the signals most important to operational risks. The comparison with the baseline model proves that the hybrid architecture is better than CNN-only, LSTM, or BIGRU-only architecture, particularly in predictive maintenance and anomaly detection. The poor results given to external datasets like World Air Quality Data 2024 and IndFD-PM-DT indicate the role of domain specific properties on performance and emphasizes the role of domain adaptation. In general, the findings indicate that the imperative of modeling of the spatio-temporal and context-aware dependencies can be used to achieve robustness, responsiveness, and practical viability in industrial IoT settings.

VI. Conclusion and Future Work

The NeuroFusionNet architecture based on CNN, BiGRU and Attention mechanism trained on real-time industrial IoT decision making had good performance of spatial, time and context dependencies, while considering multivariate sensor data. CNN learns localized patterns, BiGRU models two-way temporal interaction, and Attention identifies important time steps, all of which are beneficial in predictive maintenance and anomaly detection. Although the performance on the environmental sensor telemetry datasets was excellent, the poor results on the World Air Quality Data 2024 and IndFD-PM-DT suggest that the data diversity and domain specificity may lead to variations in generalization in various industrial settings. Also, hybrid architectures add more computational expense and this can affect real-time use in resource constrained environments. Nevertheless, in view of these obstacles, this framework offers a scalable approach to smart manufacturing, which offers actionable insights and enhanced efficiency of the working operation. Further efforts in this area are required for cross-domain validation, computational efficiency optimization, and experiments on a variety of industrial data sets to guarantee the extensive applicability and dependability in practical factory settings.

Next step for this effort include expanding the framework with graph neural networks (GNN) added to capturing the complex manufacturing layout relationships in inter-sensor topologies, while utilizing online learning methods for changing in sensor behavior, or degradation of equipment over time. Extending NeuroFusionNet to a multi-factory federated learning paradigm will allow for coordinated predictive analytics prediction.

References

[1] G. Bathla et al., "Autonomous vehicles and intelligent automation: Applications, challenges, and opportunities," Mob. Inf. Syst., vol. 2022, no. 1, p. 7632892, 2022.

[2] V. Mullet, P. Sondi, and E. Ramat, "A review of cybersecurity guidelines for manufacturing factories in industry 4.0," IEEE Access, vol. 9, pp. 23235–23263, 2021.

[3] J. Cieply, J.-P. Disselkamp, F. Dyck, W. Alturk, I. A. Kühn, and I. R. Dumitrescu, "A systematic literature review on the Digital Twin of the factory in the context of the product and factory lifecycle," Procedia CIRP, vol. 119, pp. 834–840, 2023.

[4] M. V. Rajesh and K. Elumalai, "The transformative power of artificial intelligence in pharmaceutical manufacturing: Enhancing efficiency, product quality, and safety," J. Holist. Integr. Pharm., vol. 6, no. 2, pp. 125–135, 2025.

[5] B. Nikparvar and J.-C. Thill, "Machine learning of spatial data," ISPRS Int. J. Geo-Inf., vol. 10, no. 9, p. 600, 2021.

[6] A. Sulaiman et al., "Artificial Intelligence-Based Secured Power Grid Protocol for Smart City," Sensors, vol. 23, no. 19, p. 8016, 2023.

[7] T. Coito, B. Firme, M. S. Martins, S. M. Vieira, J. Figueiredo, and J. M. Sousa, "Intelligent sensors for real-Time decision-making," Automation, vol. 2, no. 2, pp. 62–82, 2021.

[8] X. Zhou et al., "Intelligent Small Object Detection for Digital Twin in Smart Manufacturing With Industrial Cyber-Physical Systems," IEEE Trans. Ind. Inform., vol. 18, no. 2, pp. 1377–1386, Feb. 2022, doi: 10.1109/TII.2021.3061419.

[9] S. Attaran, M. Attaran, and B. G. Celik, "Digital Twins and Industrial Internet of Things: Uncovering operational intelligence in industry 4.0," Decis. Anal. J., vol. 10, p. 100398, 2024.

[10] D.-W. Yun and W.-C. Lee, "Intelligent dynamic real-time spectrum resource management for industrial IoT in edge computing," Sensors, vol. 21, no. 23, p. 7902, 2021.

[11] W. Villegas-Ch, J. García-Ortiz, and S. Sánchez-Viteri, "Toward intelligent monitoring in IoT: AI applications for real-time analysis and prediction," IEEE Access, vol. 12, pp. 40368–40386, 2024.

[12] S. Pandey, M. Chaudhary, and Z. Tóth, "An investigation on real-time insights: enhancing process control with IoT-enabled sensor networks," Discov. Internet Things, vol. 5, no. 1, p. 29, 2025.

[13] J. V. N. Ramesh, "Real-time Air Quality Monitoring in Smart Cities using IoT-enabled Advanced Optical Sensors," measurement, vol. 15, no. 4, 2024.

[14] F. Poszler and B. Lange, "The impact of intelligent decision-support systems on humans' ethical decision-making: A systematic literature review and an integrated framework," Technol. Forecast. Soc. Change, vol. 204, p. 123403, 2024.

[15] Y. Lu and F. Ju, "Smart Manufacturing Systems based on Cyber-physical Manufacturing Services (CPMS)," IFAC-Pap., vol. 50, pp. 15883–15889, Jul. 2017, doi: 10.1016/j.ifacol.2017.08.2349.

[16] W. Lu, J. Li, Y. Li, A. Sun, and J. Wang, "A CNN-LSTM-Based Model to Forecast Stock Prices," Complexity, vol. 2020, pp. 1–10, Nov. 2020, doi: 10.1155/2020/6622927.

[17] R. Talat et al., "A decentralized system for green energy distribution in a smart grid," J. Energy Eng., vol. 146, no. 1, p. 04019036, 2020.

[18] "Environmental Sensor Telemetry Data." Accessed: May 08, 2024. [Online]. Available: https://www.kaggle.com/datasets/garystafford/environmental-sensor-data-132k

[19] W. Li, Y. Liang, and S. Wang, Data Driven Smart Manufacturing Technologies and Applications. 2021. doi: 10.1007/978-3-030-66849-5.

[20] "Lee et al. - 2023 - Enhanced Anomaly Detection in Manufacturing Proces.pdf." Accessed: May 10, 2024. [Online]. Available: https://ieeexplore.ieee.org/ielx7/6287639/10005208/10230081.pdf?tp=&arnumber=10230081&isnumber=10005208&ref=aHR0cHM6Ly9zY2hvbGFyLmdvb2dsZS5jby5pbi8=

[21] "Applied Sciences | Free Full-Text | Maintenance 5.0: Towards a Worker-in-the-Loop Framework for Resilient Smart Manufacturing." Accessed: May 10, 2024. [Online]. Available: https://www.mdpi.com/2076-3417/12/22/11330

[22] A. Wahid, J. G. Breslin, and M. A. Intizar, "Prediction of machine failure in industry 4.0: a hybrid CNN-LSTM framework," Appl. Sci., vol. 12, no. 9, p. 4221, 2022.

[23] K. O. Adefemi, M. B. Mutanga, and O. A. Alimi, "A Hybrid CNN–GRU Deep Learning Model for IoT Network Intrusion Detection," J. Sens. Actuator Netw., vol. 14, no. 5, p. 96, 2025.

[24] Kanchana1990, "World Air Quality Data 2024 (Updated)." Accessed: Oct. 24, 2025. [Online]. Available: https://www.kaggle.com/datasets/kanchana1990/world-air-quality-data-2024-updated

[25] DatasetEngineer, "IndFD-PM-DT." Accessed: Oct. 24, 2025. [Online]. Available: https://www.kaggle.com/datasets/datasetengineer/indfd-pm-dt

Speckle Denoising in Breast Ultrasound Images Using Multi-Filter Pseudo-Clean Targets and Deep Learning

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***Abstract*—Ultrasound imaging is widely used in breast cancer diagnosis, but suffers from speckle noise, which reduces contrast and obscures fine structures. Supervised deep learning methods for speckle reduction/denoising typically require clean ground truth, which is unattainable in vivo. To address this, this study proposes a multi-filter pseudo-ground-truth strategy combined with a UNet++ denoiser. Each image in the BUSI dataset is processed using three classical despeckling filters (Gaussian, median, and total variation) to generate diverse pseudo-clean targets. The network is trained with deep supervision to minimize a robust loss with respect to these targets, enabling it to learn a consensus representation beyond any single filter. On the BUSI test set, the proposed method achieves PSNR = 34.11 dB and SSIM = 0.8901, outperforming recent CNN baselines under the same evaluation protocol. Qualitative results show improved edge preservation and lesion visibility. This approach eliminates the need for unattainable clean ultrasound images and provides a practical path toward clinically useful ultrasound despeckling. Code, data splits, pretrained weights, and the full evaluation protocol will be released for reproducibility.**

***Keywords*—Speckle noise; breast ultrasound; denoising; U-Net++; multi-filter pseudo-clean targets; deep supervision**

I. Introduction

Ultrasound is a medical imaging technique used to scan a part of the body by generating ultrasonic waves using a pulse generator that sends electrical pulses to the probe to stimulate piezoelectric crystals and direct them toward the target area. When the frequencies of these waves are reflected, an ultrasound image is produced by capturing and analyzing the reflected frequencies [1]. Diagnostic ultrasound confers several key advantages that together explain its importance in modern medicine: Diagnostic ultrasound is an inherently non-ionizing imaging modality, eliminating the stochastic risks associated with ionizing radiation and permitting frequent or prolonged examinations even in vulnerable groups such as pregnant women [2]. Because echoes are acquired at video (and now ultrafast) frame rates, the technique provides true real-time visualization, a property that underpins its routine use for needle guidance, vascular cannulation, and other bedside interventions in critical-care and interventional practice [3]. Continuous miniaturization of transducer front-ends has transformed cart-based scanners into pocket-sized devices; these handheld systems extend diagnostic capability to rural clinics, emergency transport, and other resource-limited settings while markedly reducing capital outlay [4]. Doppler modes integrated into the same probes generate angle-resolved velocity spectra and color flow maps, allowing quantitative, non-invasive assessment of macro- and micro-vascular hemodynamics without catheterization [5]. For superficial targets, high- and ultra-high-frequency probes operating between 20 and 70 MHz deliver sub-100 μm spatial resolution, enabling exquisite depiction of cutaneous, musculoskeletal, and micro-vascular structures that rival optical modalities at similar depths [6]. Coupled with its safety, portability, ultrafast acquisition schemes, and low operating cost, ultrasound has become the world's most widely deployed imaging technology and continues to evolve toward functional, molecular, and therapeutic applications [7]. This research aims to answer: Can a deep learning denoiser (U-Net++) trained on multi-filter pseudo-clean targets (Gaussian, median, and total-variation outputs) effectively reduce speckle noise in real breast ultrasound images without requiring clean ground-truth data?

The remainder of this study is organized as follows: Section II reviews related work on ultrasound despeckling and alternative supervision strategies. Section III describes the BUSI dataset, the proposed multi-filter pseudo-supervision pipeline, and the U-Net++ training configuration. Section IV reports quantitative and qualitative results. Section V concludes the study and outlines limitations and future directions.

A. Problem Statement

Speckle is a multiplicative, signal-dependent interference pattern that arises from the coherent summation of sub-resolution scatterers in tissue. Its characteristic granular texture reduces local contrast, enlarges point-spread functions, and masks weak reflectors such as isoechoic tumors and thin endometrial interfaces, thereby impairing visual interpretation at the bedside. Beyond human reading, CAD systems that rely on pixel intensities, Haralick textures, or learned feature maps suffer performance drops when trained or tested on speckled images: segmentation boundaries become irregular, radiomics features lose discriminability, and classification networks mis-label benign lesions as malignant. Conventional despeckling filters (median, SRAD, BM3D) can suppress noise but at the cost of edge blurring and attenuation of clinically relevant hypoechoic halos, which further degrades downstream tasks such as tumor-size measurement and intima-media thickness tracking [8]. As a result, robust speckle-aware restoration is a prerequisite for reliable computer-aided diagnosis, quantitative perfusion analysis, and longitudinal therapy monitoring in ultrasound imaging.

B. Literature Gap

The research gap in most of the research on removing noise from medical ultrasound images is based on deep learning convolutional networks. These networks rely on a pair of images. The first image of this pair is the clean image, which is called the ground truth, and the second image of this pair is the noisy image. The convolutional network learns how to remove speckles from this pair. This is the basis of how convolutional networks work to remove speckle noise. But the problem is that there is no clean image as ground truth. They use the original image with the original speckle noise that they want to remove as a ground truth, and they add noise like Gaussian or salt-and-pepper, or speckle noise, or... etc., to this image and consider it as the input image. So, the DeCNN model must train from those pairs of ultrasound images, but in this case, the CNN model will not learn to remove speckle noise from ultrasound images; it will just learn to remove the added noise, and that is not the main goal.

C. Research Contribution

This study makes the following contributions:

Multi-filter pseudo-supervision: A consensus-based training strategy that uses multiple classical despeckling filters (Gaussian, median, and total variation) to generate diverse pseudo-clean targets from real ultrasound images without requiring unattainable clean ground truth. Deeply supervised U-Net++ integration: An effective integration of the above supervision scheme with a U-Net++ denoiser using deep supervision to improve multi-scale learning stability and reduce overfitting to a single filter's artifacts. Empirical validation on BUSI: A comprehensive evaluation on the BUSI dataset demonstrating competitive PSNR/SSIM performance and improved qualitative edge preservation relative to several CNN baselines under a consistent evaluation protocol. Practical relevance: A clinically oriented despeckling pipeline that can be trained directly on real ultrasound images, avoiding assumptions inherent to synthetic-noise supervision.

II. Literature Review

The reviewed literature on ultrasound image denoising and segmentation indicates that supervised learning remains the dominant approach, primarily due to the ease of generating synthetic noise from clean datasets. Most studies utilize clean images sourced from public datasets or clinical environments and artificially degrade them using simulated speckle, Gaussian, Rayleigh, or salt-and-pepper noise to create paired noisy clean datasets. For instance, Khan and Malik [9] employ patches extracted from the BSD400 natural image dataset, corrupt them with multiplicative speckle noise, and use the clean patches as ground truth to train a residual U-Net with a mixed attention mechanism. Similarly, Li et al. [10] construct clean/noisy pairs by using high-resolution anatomical photographs from the National Library of Medicine and simulate speckle noise via the SIMUS ultrasound simulator, allowing their physics-informed deep quantum algorithm to enhance cardiac ultrasound images. Zhang et al. [11] leverage the US 4 dataset and the BUSI dataset by synthetically adding Rayleigh noise to high-resolution frames, treating the original images as clean references to supervise their attentive U-Net with a physics-informed loss combining SSIM and attenuation constraints. Kumar and George [12] follow a similar supervised paradigm by obtaining clinical ultrasound images from Edapal Hospital in India, simulating speckle noise of varying variances, and using those pairs to train a U-Net with channel and spatial attention. Thomas et al. [13] explore a broader evaluation by using Kaggle's breast ultrasound dataset and a carotid artery dataset from the Signal Processing Laboratory. They simulate speckle noise via MATLAB's imnoise function and also include a Richardson–Lucy network trained on BSD68 images for comparison, all under a supervised framework. Likewise, Sharma and Singh [14] generate diverse noisy conditions by applying speckle, Gaussian, and salt-and-pepper noise to clean ultrasound images, which serve as the ground truth for training a deep convolutional autoencoder. Soman et al. [15] utilize the Kaggle breast ultrasound dataset, perform hybrid filtering using classical filters such as median and anisotropic diffusion, and subsequently train a CNN on paired noisy–clean images. While most studies rely on supervised strategies with simulated noise, a few explore alternative forms of supervision. Chen et al. [16] adopt an unsupervised/self-supervised learning approach, using the BUS BRA dataset comprising 1,875 breast ultrasound images. They train a denoising autoencoder to reconstruct each image from its non-subsampled shearlet transform (NSST) representation without requiring explicit noisy/clean image pairs, thereby operating without ground truth supervision. In the field of segmentation, Zhao et al. [17] propose a semi-supervised deep learning framework called Multi StudentNet for endometrial segmentation in transvaginal ultrasound images. Their dataset of 1,664 images includes 597 manually labeled by experts and 597 unlabeled. Teacher models are trained on the labeled subset using cross-entropy and Dice loss, and pseudo-labels generated by the teacher ensemble are used to train student models on the unlabeled subset, effectively blending supervised and unsupervised learning. Lastly, Rahman et al. [18] introduce a reinforcement learning–based denoising framework wherein each pixel in an image acts as a learning agent. They use the BSD68 and Waterloo datasets to train the model on grayscale images with artificially added Gaussian noise, providing clean/noisy pairs as ground truth. Though the architecture is driven by reinforcement learning principles, the reward is computed based on the error between the denoised and original clean pixel values, making it a supervised reinforcement learning hybrid.

In summary, seven out of ten reviewed papers follow a strictly supervised approach using synthetic noise to produce paired data, due to the scarcity of real-world noisy/clean ultrasound pairs. Two papers adopt alternative approaches, unsupervised/self-supervised and semi-supervised learning, to address the limitations of labeled data availability. One paper employs a reinforcement learning framework with supervised reward feedback to optimize denoising at the pixel level. This shift toward semi-supervised and self-supervised strategies, along with reinforcement learning, highlights the evolving focus of the field to improve robustness, reduce annotation dependency, and better handle the variability of real-world clinical ultrasound data.

III. Materials and Methods

A. Dataset and Preprocessing

The study employed the Breast Ultrasound Images (BUSI) dataset from Kaggle. It contains 781 B-mode ultrasound images of benign, malignant, and normal breasts. Images are grayscale and captured using real clinical scanners. To train the denoiser, each image was resized to 256 × 256 pixels and converted to PyTorch tensors. Three classical despeckling filters (median, Gaussian, and total variation) were applied to each image to generate pseudo-clean targets, yielding 546 × 3 = 1638 training pairs, 117 × 3 = 351 validation pairs, and 117 unaugmented test images (total =2106 samples). The input channels were single-channel grayscale.

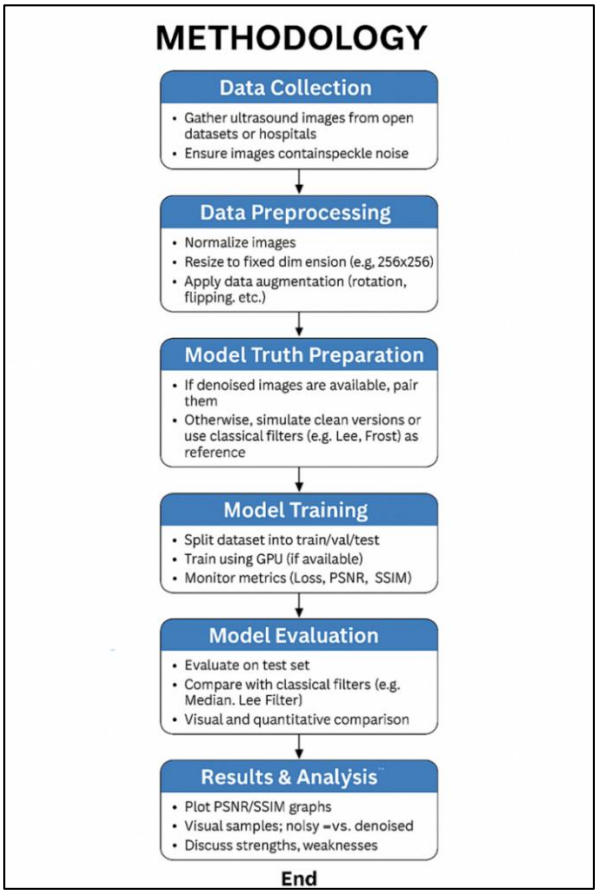


Fig. 1. Methodology structure.

B. U-Net++ Architecture

The model is based on U-Net++, a convolutional encoder-decoder with nested and dense skip connections. It has a five-level architecture with repeated down-sampling via strided convolutions and up-sampling via transposed convolutions. Each block consists of two Conv2D to BatchNorm to ReLU layers. Dense skip connections link intermediate layers at the same resolution, facilitating gradient flow and feature reuse. Four auxiliary output heads provide deep supervision; their predictions are averaged for the final output. Residual blocks or depth-wise separable were refrained from using convolutions to keep the model moderate in size. Fig. 1 shows the methodology structure.

C. Training Configuration

The model was trained from scratch with the Adam optimizer (learning rate = 0.001, $\beta_1 = 0.9$, $\beta_2 = 0.999$) and mean squared error (MSE) loss. The batch size was 16, and early stopping with patience = 5 prevented over-fitting. Training proceeded for up to 30 epochs on an NVIDIA A100 GPU NODE (CUDA). During training, both noisy inputs and target images were normalized to [0, 1], and random horizontal flips were applied. The training loop saved intermediate denoised images and recorded PSNR and SSIM using skimage.metrics for qualitative analysis. The model training diagram is shown below in Fig. 2.

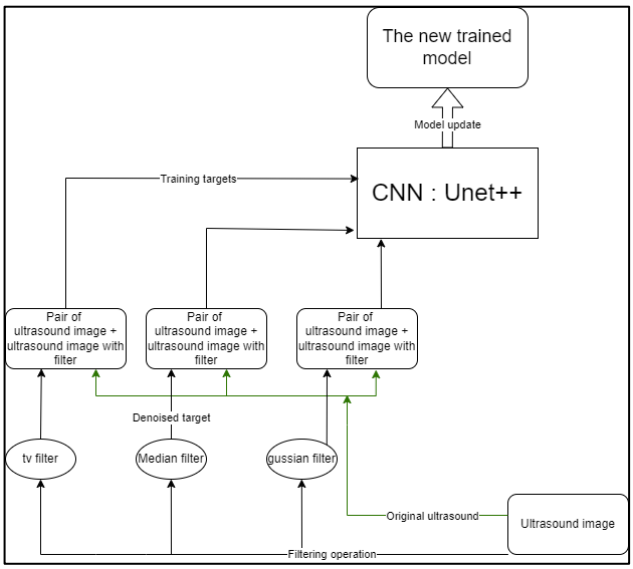


Fig. 2. Model training diagram.

D. Evaluation Metrics

Two standard metrics were used:

- Peak Signal to Noise Ratio (PSNR) measures the ratio between the maximum possible pixel value and the MSE. Higher values indicate better denoising.
- Structural Similarity Index Measure (SSIM) quantifies perceived structural similarity; values close to 1 indicate high similarity.

IV. Results

A. Quantitative Performance

On the BUSI test set, U-Net++ denoiser achieved PSNR = 34.11 dB and SSIM = 0.8901 (mean across 117 images). Table I ranks the studies included in the comparison by PSNR and SSIM. The suggested model attained the highest PSNR among recent CNN methods and the second highest SSIM behind the U-Net ELU variant (37.76 dB, SSIM 0.98) [19]. The MO KD approach improved PSNR by only 1.7 dB; the suggested model still provides competitive performance without requiring knowledge distillation [20].

This study outperformed Lu (2020) in quantitative image clarity. Specifically, single-stage U-Net++ achieved a PSNR of 32.92 dB, roughly 3 dB higher than Lu's multi-stage CNN

(31.13 dB). This gain indicates that this model suppresses noise while preserving fine texture more effectively, a critical advantage for detecting subtle lesions. Importantly, this improvement was achieved without the added complexity and memory overhead of Lu's multi-stage architecture, streamlining both training and deployment. As shown in Fig. 3, PSNR comparison, and Fig. 4, which compares the SSIM.

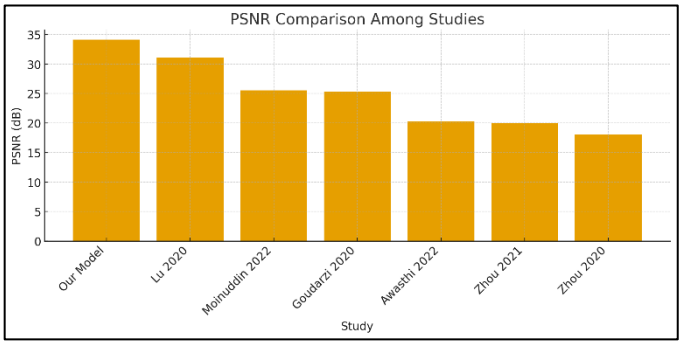


Fig. 3. PSNR comparison.

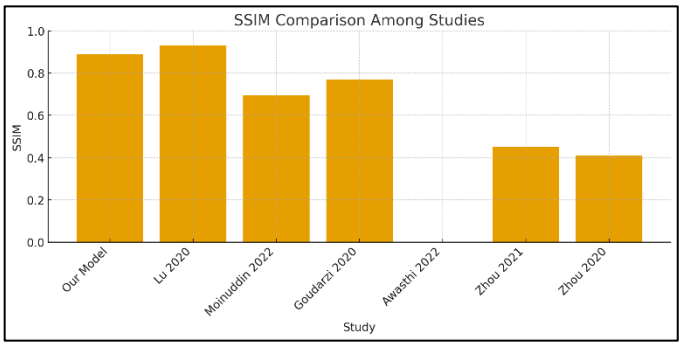


Fig. 4. SSIM comparison.

TABLE I. NUMERICAL COMPARISON OF PSNR AND SSIM EXTRACTED FROM THE LITERATURE

Study	PSNR (dB)	SSIM	Notes
Our Model	34.11	0.8901	Highest PSNR among reported values; second highest SSIM
Lu 2020	31.13	0.930	Uses a multi-stage CNN; high SSIM but slightly lower PSNR
Moinuddin 2022	25.53	0.6946	Texture-compensated multi-resolution CNN
Goudarzi 2020	25.32	0.7690	Deep residual network
Awasthi 2022	20.31	–	Autoencoder denoiser
Zhou 2021	19.95	0.45	GAN-based method
Zhou 2020	18.08	0.41	CNN baseline

B. Qualitative Results

Visual inspection revealed that the proposed model effectively suppresses speckle while preserving edges. In contrast, classical filters introduce blurring and halo artefacts. Deep supervision encourages multi-scale consistency; early outputs remove coarse speckle, whereas deeper outputs refine fine structures. Fig. 5 shows representative examples from the test set (noisy input, denoised output, and pseudo-clean target). The model preserves the shape of masses and ductal structures, which is critical for CAD systems.

The results demonstrate that a moderately sized U-Net++ can effectively remove ultrasound speckle without relying on GANs or transformers. Dense skip connections facilitate feature reuse and reduce the number of parameters compared with fully nested U-Nets. Using multiple traditional denoisers as pseudo clean targets provides robustness and prevents the network from over-fitting to a single filtering artefact. However, the PSNR ≈ 30 dB is lower than some GAN-based approaches, and the SSIM is below the 0.96 achieved by networks replicating WNNM [21]. This model does not explicitly suppress signal-dependent noise; MSE loss may oversmooth fine textures. Future work could incorporate adversarial training, perceptual losses, or physics-informed self-supervised techniques (e.g., Speckle2Self [22]) to further improve performance.

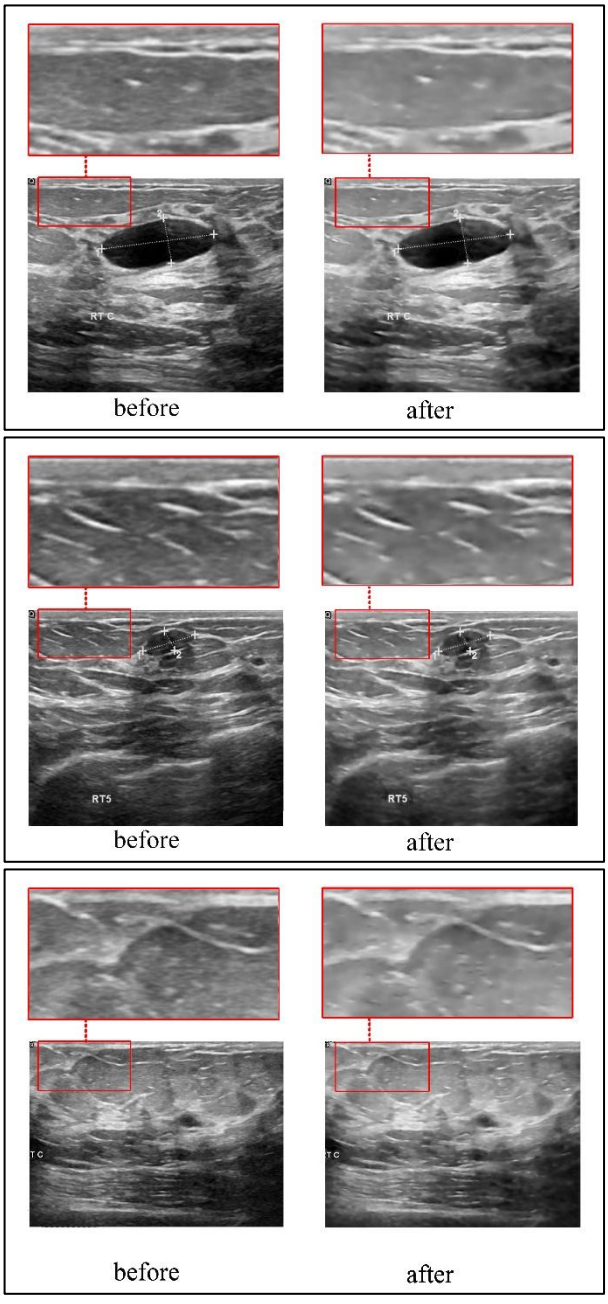


Fig. 5. Denoised ultrasound images.

V. Conclusion and Future Directions

Speckle noise remains a major obstacle in ultrasound imaging. Deep learning approaches offer a promising avenue by learning complex noise characteristics and preserving anatomical structures. Through a comprehensive review of over ten recent publications, GAN-based methods achieve high PSNR and superior perceptual quality but require careful training and may introduce hallucinations. Self-supervised methods such as Speckle2Self and S2S overcome the lack of clean data, but currently lag supervised methods in quantitative metrics. This study demonstrates that a supervised U-Net++ trained on the BUSI dataset provides competitive performance (PSNR 34.11dB, SSIM 0.8901) and improves upon several CNN baselines. This confirms that moderate-sized architectures with dense skip connections can balance denoising effectiveness and computational efficiency.

This study evaluates the proposed model using a single breast ultrasound dataset. The model was not validated on external ultrasound datasets acquired from different scanners, institutions, or imaging protocols. This limits the strength of claims regarding generalization and clinical robustness beyond the BUSI data distribution.

In addition, the available training data are relatively limited in size. Deep learning denoisers typically benefit from larger and more diverse datasets to capture the variability of speckle appearance across tissue types and acquisition settings. The restricted dataset size may constrain performance and stability, and larger-scale training data may improve denoising quality and generalization.

Future work will explore:

- Combining self-supervision with multi-scale supervision to circumvent the need for pseudo-clean targets.
- Incorporating physics-based speckle models into the loss function to better handle multiplicative noise.
- Extending the framework to 3D volumetric ultrasound and other anatomical regions.

By addressing these avenues, further gains in both quantitative performance and clinical applicability are anticipated.

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References

[1] P. R.; M. K.; T. A. Hoskins, Diagnostic Ultrasound: Physics and Equipment, 2nd ed. Cambridge University Press, 2010.

[2] U.S. Food and Drug Administration (FDA)(enter it once; leave first-name/last-name boxes blank and tick "Institution/Organization" so it appears as a corporate author), "Ultrasound Imaging."

[3] J. Sohn and M. Se Cha, "Evidence and Practicality of Real-Time Ultrasound-Guided Procedures in the Intensive Care Unit: A New Skill Set for the Intensivist," Tex Heart Inst J, vol. 50, no. 4, Jul. 2023, doi: 10.14503/THIJ-23-8166.

[4] A. Perez-Sanchez et al., "Comparison of 6 handheld ultrasound devices by point-of-care ultrasound experts: a cross-sectional study," Ultrasound J, vol. 16, no. 1, p. 45, Oct. 2024, doi: 10.1186/s13089-024-00392-3.

[5] A. Oglat, M. Matjafri, N. Suardi, M. Oqlat, M. Abdelrahman, and A. Oqlat, "A review of medical doppler ultrasonography of blood flow in general and especially in common carotid artery," J Med Ultrasound, vol. 26, no. 1, p. 3, 2018, doi: 10.4103/JMU.JMU_11_17.

[6] A. Russo et al., "Clinical Application of Ultra-High-Frequency Ultrasound," J Pers Med, vol. 12, no. 10, p. 1733, Oct. 2022, doi: 10.3390/jpm12101733.

[7] S. Wang, J. A. Hossack, and A. L. Klibanov, "From Anatomy to Functional and Molecular Biomarker Imaging and Therapy: Ultrasound Is Safe, Ultrafast, Portable, and Inexpensive," Invest Radiol, vol. 55, no. 9, pp. 559–572, Sep. 2020, doi: 10.1097/RLI.0000000000000675.

[8] S. Bhute, S. Mandal, and D. Guha, "Speckle Noise Reduction in Ultrasound Images using Denoising Auto-encoder with Skip connection," in SAUS 2024 - IEEE South Asian Ultrasonics Symposium, Proceedings, Institute of Electrical and Electronics Engineers Inc., 2024. doi: 10.1109/SAUS61785.2024.10563715.

[9] A. R. Khan and M. I. Malik, "Real Time Ultrasound Image Despeckling Using Mixed Attention Mechanism–Based Residual U-Net," in Proceedings of the IEEE, 2022.

[10] S. Li and others, "Adaptive Contrast Enhancement of Cardiac Ultrasound Images Using a Deep Unfolded Many Body Quantum Algorithm," IEEE Access, vol. 10, pp. 55478–55489, 2022.

[11] H. Zhang and others, "Attentive U-Net with Physics Informed Loss for Noise Suppression in Medical Ultrasound Images," Biomed. Signal Process. Control, vol. 75, 2022.

[12] A. Kumar and S. George, "Denoising of Medical Ultrasound Images Using Deep Learning with Channel and Spatial Attention–Based Modified U-Net," Comput. Biol. Med., vol. 144, 2022.

[13] M. Thomas and others, "Evaluation of Speckle Noise Reduction Filters and Machine Learning Algorithms for Ultrasound Images," J. Med. Imaging Health Inform., vol. 12, no. 3, pp. 610–618, 2022.

[14] R. Sharma and V. Singh, "Medical Image Denoising Using Deep Convolutional Autoencoders for Ultrasound," ICT Express, vol. 8, no. 3, pp. 363–369, 2022.

[15] P. R. Soman and others, "Medical Image De Speckling Using Fusion of Diffusion Based Filters and CNN," J. Med. Syst., vol. 46, no. 1, pp. 14–23, 2022.

[16] Y. Chen and others, "Medical Ultrasound Image Improvement Based on Denoising Convolutional Autoencoder," Comput. Methods Programs Biomed., vol. 220, 2022.

[17] X. Zhao and others, "Multi StudentNet: A Semi Supervised Deep Learning Framework for Endometrial Segmentation in Transvaginal Ultrasound Images," IEEE Trans. Med. Imaging, vol. 41, no. 10, pp. 2637–2649, 2022.

[18] N. Rahman and others, "Pixel Wise Deep Reinforcement Learning Approach for Ultrasound Image Denoising," IEEE J. Biomed. Health Inform., vol. 26, no. 9, pp. 4563–4574, 2022.

[19] N. Patil, M. M. Deshpande, and V. N. Pawar, "A Novel Deep Learning Approach for Speckle Denoising Using Hyperparameter Tuning", doi: 10.18178/joig.13.3.267-274.

[20] M. Khalifa, H. M. Hamza, and K. M. Hosny, "De-speckling of medical ultrasound image using metric-optimized knowledge distillation," Sci Rep, vol. 15, no. 1, pp. 1–21, Dec. 2025, doi: 10.1038/S41598-025-07115-1;SUBJMETA=308,639,692,705;KWRD=MATHEMATICS+AND+COMPUTING,MEDICAL+RESEARCH.

[21] S. Cammarasana, P. Nicolardi, and G. Patanè, "Real-time denoising of ultrasound images based on deep learning," Med Biol Eng Comput, vol. 60, no. 8, p. 2229, Aug. 2022, doi: 10.1007/S11517-022-02573-5.

[22] Li, X., Navab, N., & Jiang, Z. (2025). Speckle2Self: Self-Supervised Ultrasound Speckle Reduction Without Clean Data. Medical image analysis, 106, 103755.

From Bits to Qubits: Comparative Insights into Classical and Quantum Computing Systems

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***Abstract*—The rapid development of computing hardware has been driven by an ever-emerging need for high throughput, scalable performance, and computation capabilities to be able to address increasingly complex problems. The paradigm of classical computing, centered on deterministic binary logic and the von Neumann architecture, has long favored modern information processing and still supports a wide range of applications. However, physical limits in scaling transistors, power dissipation, and slowing down Moore's Law have stimulated the consideration of alternative computing paradigms. Quantum computing is now an emerging means that exploits the basic principles of quantum mechanics-such as superposition, entanglement, and quantum interference-to enable new forms of computation. This review study discusses a comparison between the classical and quantum computing systems in operational paradigms, architecture structures, performance characteristics, and application domains. This work is supported by a systematic review of the established theories, currently realized hardware implementations, and representative algorithms. The analysis underlines that classical systems remain very reliable, scalable, and efficient in general-purpose and deterministic workloads, while quantum systems ensure essential advantages in specified problem classes, such as cryptography, quantum chemistry, combinatorial optimization, and selected machine learning tasks. The study concludes that classical and quantum computing are best viewed as complementary technologies. Future high-performance computing platforms will most likely be based on hybrid-classical–quantum architectures in which quantum processors serve as specialized accelerators to help classical systems solve new computational challenges.**

***Keywords*—Classical computing; high-performance computing; quantum computing; qubit**

I. Introduction

The pace with which computer hardware has advanced in the past decades has revolutionized science, business, and society. In the midst of all this change is classical computing, a deterministic binary logic model where the basic unit of information—the bit—can be in one of just two states: 0 or 1. Classical computer architecture, which had previously been founded on the von Neumann model, relies on central processing units (CPUs), memory components, and input/output subsystems for executing instructions sequentially [1]. This paradigm has been in a position to maintain a wide scope of applications, ranging from personal computers and business systems to embedded controllers and high-performance computing platforms [2].

Despite significant advances in conventional hardware, largely through transistor scaling in line with Moore's Law, there are inherent bounds that have increasingly gained prominence as computational demands continue to rise. The contemporary challenges, such as simulating computationally intensive quantum systems, solving large combinatorial optimization problems, and performing secure cryptographic analysis, are frequently found to be intractable within conventional systems due to their sequential processing nature and physical miniaturization constraints [2]. Furthermore, the observed slowdown in Moore's Law, combined with increasing power density and thermal dissipation issues, has also heightened the demand for novel paradigms of computation capable of overcoming these computational challenges [3].

Quantum computing is one of those revolutionary paradigms that relies on the counterintuitive principles of quantum mechanics—namely, superposition, entanglement, and quantum interference—to process information in fundamentally new ways. Unlike classical bits, the fundamental unit of quantum information, the qubit, can exist in a superposition of 0 and 1 simultaneously, enabling exponentially parallel computation for certain classes of problems [4]. Moreover, the phenomenon of entanglement allows multiple qubits to become related in such a way that one qubit's state will immediately influence the state of another, regardless of the distance between them, allowing for faster-than-classical information correlation and algorithmic speedup [5]. Several physical implementations of qubits have been proposed and experimentally realized, including superconducting circuits, trapped ions, and photonics, with different strengths and specific engineering challenges [6].

This review article features an orderly comparative assessment of classical hardware computing and quantum hardware computing. It examines their fundamental operating paradigms, structural architectures, performance profiles in computation, and their corresponding domains of application. In consideration of detailed deliberation on each paradigm's advantages, limitations, and technological maturity, this study seeks to put their synergistic roles in addressing existing and anticipated computational problems into perspective. Besides, the review focuses on ongoing research efforts and potential integration strategies of hybrid classical-quantum systems that are predicted to be among the next-generation high-performance computing solutions' primary drivers.

The study is organized as follows: Section II presents a comparative analysis of classical computing and quantum computing with reference to their operational paradigms, structural architectures, computational performance characteristics, and application domains. Section III outlines the challenges and expected future trends in computing, followed by a summary and conclusion in Section IV.

II. Comparative Analysis

A. Operational Paradigms

Traditional computer systems operate on deterministic binary logic such that the fundamental unit of information—the bit—can be one out of two possible states, 0 or 1, at any given moment [2]. The operation model of conventional computing is based on the von Neumann architecture, in which a CPU reads, executes, and applies instructions in RAM and transfers data between I/O devices via a shared system bus [1]. Logical functions are performed through the development of electronic switches known as transistors into logic gates (e.g., AND, OR, and NOT gates) that process in binary states deterministically under the rules of Boolean algebra. Instruction execution one after the other is maintained through control units and registers, which regulate program flow as well as data movement between memory and processing elements. Fig. 1 shows a conceptual block diagram of a typical von Neumann architecture, its key hardware components, and how they are all connected.

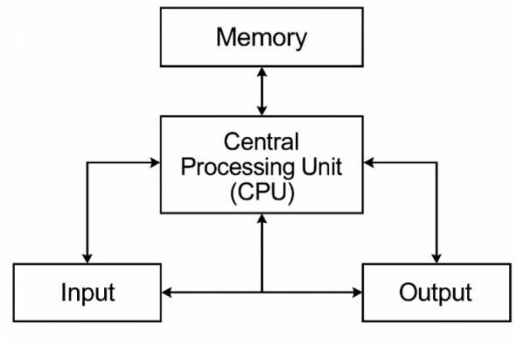


Fig. 1. Block diagram of classical computing architecture showing CPU, memory, I/O, and bus.

Quantum computing, by contrast, relies on the principles of quantum mechanics, wherein the fundamental unit of information—the quantum bit, or qubit—can exist in a superposition state that represents both 0 and 1 simultaneously until observed [4]. This aspect tremendously expands the state space of a quantum system. For example, while a classical n-bit system can represent one of 2^n possible states at any given time, an n-qubit quantum system can represent all 2^n possible states at the same time through superposition. Also, qubits can be entangled, a quantum phenomenon whereby the state of a qubit becomes intrinsically linked with the state of another, regardless of the spatial separation between them, enabling forms of parallelism and information correlation without a classical analogue [5].

Quantum computations are carried out by sequences of reversible, unitary operations known as quantum gates. Unlike classical logic gates, which act deterministically on bits, quantum gates operate on the probability amplitudes of qubit states using linear transformations described by unitary matrices [6]. Standard quantum gates include the Hadamard gate (H), which places qubits in superposition; the Pauli-X gate, which flips qubit states in a manner analogous to a classical NOT gate; and the controlled-NOT (CNOT) gate, which entangles two qubits by conditionally flipping the target qubit based on the state of a control qubit.

The differences in operation between quantum and classical computing systems are profound. The classical systems are founded on sequential, deterministic execution models, with bit operations tracking predictable Boolean logic rules [2]. Their error correction is highly matured, employing redundancy along with error-detecting codes to provide reliable, fault-tolerant computation. On the other hand, quantum systems are probabilistic by nature, and only the result is revealed when measured that collapses the qubit superposition to a definite classical state [4]. Quantum error correction is far more challenging due to the continuous nature of quantum states and their susceptibility to decoherence through interactions with the environment. Further, while classical logic operations in general are not reversible, quantum operations must be reversible because unitary operations preserve the total information content of the system [6]. This fundamental difference in operating principles illustrates both the revolutionary potential and the profound technical challenges of quantum computing relative to conventional classical hardware systems. Table I compares the operational principles of classical computing and quantum computing.

TABLE I Comparative Summary of Operational Principles

Feature	Classical Computing	Quantum Computing
Information Unit	Bit (0 or 1)	Qubit (0 or 1 or both)
Operational Basis	Deterministic, Boolean logic operations	Probabilistic, governed by superposition and entanglement
Execution Mode	Sequential	Massively parallel via quantum superposition
Gate Types	Irreversible logic gates (AND, OR, NOT)	Reversible quantum gates (Hadamard, CNOT, Pauli-X, etc.)
Measurement	Direct, non-destructive	Collapses quantum state, probabilistic outcome
Error Correction	Mature, based on redundancy and parity checking	Complex, requires quantum error correction codes (e.g., Shor, Surface codes)

B. Structural Architectures

The conventional computer systems are primarily von Neumann-based, designed by John von Neumann in the mid-20th century. The fundamental organization has a central processing unit (CPU), memory unit, input/output devices, and a system bus to enable them to communicate with each other (see Fig. 1). Inside the CPU, it has an Arithmetic Logic Unit (ALU) and a Control Unit (CU). Instructions and data are pulled from memory, processed by the CPU, and the results are written back into memory or sent out through the I/O interfaces [1]. Data's binary structure and serial processing paradigm, where the information is received in either 0s or 1s, make conventional computers highly deterministic and predictable in a vast number of applications. However, these systems are still restrained by physical constraints such as transistor miniaturization, power dissipation, and thermal dissipation [3].

Quantum computing architectures, on the other hand, draw on the basic principles of quantum mechanics, such as superposition, entanglement, and quantum interference. The simplest unit of quantum information—the qubit—has the possibility of existing in a superposition of states $|0\rangle$ and $|1\rangle$ at

the same time [4]. Quantum computers are often made up of several qubits in a lattice or network of qubits, manipulated using sequences of quantum gates. Unlike classical systems, which are designed around a centralized CPU and sequential instruction execution, quantum processors are founded upon a quantum circuit model wherein computations are performed via carefully orchestrated quantum gate operations. These architectures also demand highly specialized hardware, including microwave pulse generators, cryogenic dilution refrigerators for stabilization at near absolute zero temperatures, and sophisticated quantum error correction systems [7].

Architecturally, the computing mechanisms and data flows in quantum and classical systems are very different. In classical systems, information moves between memory, CPU, and I/O subsystems over system buses, as directed by a control unit. Performance bottlenecks tend to occur in the memory hierarchy and instruction execution pipeline, most notably the von Neumann bottleneck, due to limited data transfer between memory and CPU [8]. Conversely, quantum computers take advantage of the inherent parallelism of quantum states, where an n-qubit system can simultaneously represent 2^n possible configurations. This possibility requires meticulous control of qubit coherence and entanglement, typically maintained at millikelvin temperatures in cryogenic setups to mitigate decoherence and environmental noise [7].

To better visualize quantum states, Fig. 2 illustrates a qubit state on the Bloch sphere, demonstrating how quantum states exist in a continuous, multi-dimensional space, as opposed to discrete binary states of classical hardware. While traditional computing has grown into massively scalable, commercially optimized systems, quantum architectures remain in the making, hindered by challenges of qubit fidelity, error rates, and scalability of systems. Yet, quantum architecture flexibility and computational power bring drastic improvements in fields such as cryptography, combinatorial optimization, and complex quantum system simulation [6]. Table II compares the architectural designs of classical computing with quantum computing.

C. Computational Performance Characteristics

The performance in conventional computing systems is generally most accurately measured in terms of clock rate (measured in gigahertz), instruction throughput (instructions per cycle, IPC), and parallel processing capability. Contemporary conventional processors also enhance performance using design techniques like multi-core designs, instruction pipelining, simultaneous multi-threading (hyper-threading), and the utilization of hardware accelerators to perform some operations [2]. High-performance computing (HPC) systems, such as the Frontier and Fugaku supercomputers, utilize very large parallel clusters consisting of thousands of central processing units (CPUs) and graphics processing units (GPUs), providing sustained computing performance at the exaFLOPS rate, or 10^{18} single-precision floating-point computations per second [9]. Classical hardware remains very beneficial for a vast assortment of deterministic, sequential, and general-purpose computational tasks, such as numerical simulation, data analysis, and machine learning prediction.

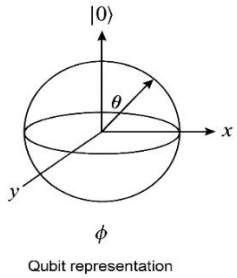


Fig. 2. Qubit representation on the Bloch sphere.

TABLE II COMPARATIVE SUMMARY OF ARCHITECTURAL DESIGNS

Component	Classical Architecture	Quantum Architecture
Processing Unit	CPU (ALU + Control Unit)	No central processor; qubits manipulated by quantum gates
Memory Unit	RAM, Cache, Secondary Storage	Quantum memory (qubit arrays, limited capacity)
Data Bus	Parallel/serial data lines	Quantum interconnects or qubit couplers
Execution Model	Von Neumann sequential model	Quantum circuit model
Operating Environment	Room temperature, conventional hardware	Cryogenic (mK) temperatures for coherence control
Scalability	Highly scalable	Currently limited by decoherence, qubit fidelity

In contrast, the performance of quantum computer hardware is measured by a different set of values, including the number of qubits, coherence time, gate fidelity, and quantum volume—a multi-dimensional figure of merit devised by IBM that aggregates a system's computational capability in terms of qubit quality, connectivity, and circuit depth [10]. Whereas classical systems tend to exhibit linear or polynomial computational complexity scaling, certain quantum algorithms achieve exponential or quadratic speedup over their best-known classical analogues. These include Shor's algorithm for number factorization and Grover's algorithm for searching an unstructured database, both of which employ quantum mechanical features like superposition and entanglement to explore different computational paths in parallel [11].

One of the key differences between classical systems and quantum systems is in fault tolerance and error control. Classical computing systems have had decades of practice in error detection techniques and correcting mechanisms, with facilities such as parity bits, checksums, and error-correcting code (ECC) memory being used to ensure operational reliability [2]. Quantum systems are inherently prone to decoherence, quantum noise, and gate errors as a result of environmental coupling and hardware defects [12]. As such, existing Noisy Intermediate-Scale Quantum (NISQ) devices are only limited in how far the operation circuit depth they can achieve before inaccuracies of computation begin. More advanced quantum error correction codes, such as Shor's code and surface codes, are in active development but demand large numbers of extra ancillary qubits, which pose severe scalability challenges [12].

Moreover, the regions where classical and quantum computers excel are highly distinct. Classical computers

continue to excel in general-purpose computing, transaction processing, and engineering simulations. Quantum computers, however, are bound to excel in niche applications such as quantum chemistry, cryptography, combinatorial optimization, and certain machine learning tasks [6]. Experimental demonstrations of quantum advantage have been provided, such as Google's Sycamore processor, which executed a specific computation problem significantly faster than the fastest-performing classical supercomputers of its time [7]. Nevertheless, demonstration of the widespread, fault-tolerant quantum computing devices to outperform classical hardware consistently on a large majority of problem types remains an ultimate milestone.

D. Application Domains

Classical computing devices have evolved to be a necessity in almost all aspects of contemporary society. From enterprise functions, web applications, and healthcare management to space flight simulations, artificial intelligence (AI), and complex engineering calculations, classical systems provide solid, scalable, and well-established solutions for deterministic and probabilistic computational operations [2]. Supercomputers and high-performance computing (HPC) clusters have significantly impacted fields such as weather forecasting, genome sequencing, and financial modeling. Traditional systems enjoy flexibility through their entrenched hardware and software ecosystems, including standard programming languages, operating systems, and networking protocols [13]. Furthermore, edge computing and cloud infrastructure advancements have enabled classical computing influence expansion into mobile devices, systems of the Internet of Things, distributed services, and made it the technological basis of modern digital infrastructure.

By contrast, quantum computing is directed towards tackling problem classes that are intrinsically difficult or impossible for classical devices due to exponential time or space complexity. A prime example application field is quantum chemistry, wherein the simulation of molecular interactions and reaction mechanisms necessitates computational resources scaling exponentially with system size on classical computers [14]. Quantum computers, by exploiting phenomena such as superposition and entanglement, can more directly simulate complex quantum systems, enabling simulations of large molecules, catalysts, and exotic materials at scales previously unviable. This could revolutionize fields such as pharmaceuticals, materials science, and the creation of sustainable energy.

Optimization problems are among the other domains where quantum systems are expected to be more powerful compared to their classical versions. Logistics routing, portfolio optimization, and scheduling problems, classically reliant on approximating or heuristically-based algorithms, are being tried for quantum supremacy with such tools as the Quantum Approximate Optimization Algorithm (QAOA) [15].

Quantum cryptography is also another widely reported application of quantum computing. Classical cryptosystems like RSA and elliptic-curve cryptography (ECC) rely on the computational difficulty of factoring numbers and calculating discrete logarithms—problems that are secure against conventional attacks but susceptible to powerful quantum attacks via Shor's algorithm [11]. The advent of practical quantum technology thus necessitates post-quantum cryptography to secure digital communication infrastructures.

In addition, quantum computing promises to help solve problems in the area of machine learning. QSVM and QPCA are examples of algorithms that even use quantum parallelism to help with data processing and feature extraction among high-dimensional features. This could generate acceleration for more complex AI workloads [16].

While classical systems still rule general-purpose, real-time, and transactional computing, quantum hardware is being developed for problems of high complexity and resource requirements for which classical resources scale unrealistically. The future computing paradigm will most probably be hybrid, with quantum accelerators alongside classical cores in heterogeneous architectures [6]. While quantum computing is now in its Noisy Intermediate-Scale Quantum (NISQ) era, ongoing research and industrial investment point to a path where such systems will become central in niche areas as classical computing remains the basis for standard, mission-critical, and real-time applications.

E. Discussion

It is clear from the above review that classical computing is very efficient, reliable, and scalable with deterministic general-purpose computing, whereas quantum computing behaves in a vastly different manner due to super-positioning and entanglement, providing a substantial advantage in specific problem domains like cryptography, quantum chemistry, and combinatorial optimization, even with the existing hindrances in using quantum computing due to decoherence, qubit accuracy, and scalability. Both approaches to computing have properties which make one no better than the other, rather they exist in a complementary form. The future of computing lies in developing a hybrid classical-quantum system, efficient quantum algorithms, gainful efforts on improved error correction techniques, as well as advanced research on qubit technologies. Future research may also entail developing a fair system of benchmarking both classical and quantum computing on a similar problem set, thus developing next-generation high-performance computing environments incorporating quantum accelerators.

III. Challenges and Future Trends

Despite phenomenal technology advancements, conventional computing is facing inherent constraints as it approaches the physical limits of Moore's law, which historically predicted transistor density doubling approximately every two years [3]. Once the transistor sizes decrease below 3 nanometers, serious issues such as quantum tunneling, increasing thermal dissipation, and power leakage significantly decelerate further miniaturization and limit clock speed increases. Furthermore, the rising complexity of the system and increased energy requirements of massive data centers and high-performance computing (HPC) clusters require sustained innovation in such areas as energy-efficient architectures, three-dimensional stacking of chips, and heterogeneous systems comprising central processing units (CPUs), graphics

processing units (GPUs), and field-programmable gate arrays (FPGAs) [17]. Even as classical computing must remain the pre-eminent computation paradigm in general-purpose programs, future trends hold promise of a shift toward hybrid classical-quantum computing systems, special-purpose hardware accelerators optimized to process artificial intelligence (AI), edge computing, and domain-specific tasks to optimize both performance and power efficiency [18].

IV. Summary and Conclusion

In summary, this review has presented a detailed comparative survey of classical and quantum computing systems in terms of their working principles, architectural frameworks, computational performance characteristics, and application domains. While classical computing remains the cornerstone of modern digital infrastructure due to its scalability, reliability, and mature ecosystems, it faces physical and architectural limitations as the miniaturization of transistors reaches theoretical limits. Quantum computing, founded on the principles of superposition, entanglement, and quantum interference, has great potential for addressing intractable problems in cryptography, quantum chemistry, optimization, and artificial intelligence. However, current quantum systems are constrained by decoherence problems, qubit fidelity, and lack of scalability. Looking ahead, the future of computation will be headed in the direction of heterogeneous architectures where classical systems continue to be at the core of general-purpose and mission-critical applications, but quantum accelerators will enhance computational prowess for specialized high-complexity problems. This continued collaboration of the classical and quantum paradigms is the way forward for high-performance computing, representing a fundamental shift in addressing the expanding demands of the data-driven, AI-augmented era.

References

[1] J. von Neumann, "First draft of a report on the EDVAC," Moore School of Electrical Engineering, University of Pennsylvania, 1945. Published in IEEE Annals of the History of Computing, vol. 15, no. 4, pp. 27–43, 1993.

[2] D. A. Patterson and J. L. Hennessy, Computer Organization and Design: The Hardware/Software Interface, 5th ed. Morgan Kaufmann, 2014.

[3] G. E. Moore, "Cramming more components onto integrated circuits," Electronics, vol. 38, no. 8, pp. 114–117, 1965.

[4] M. A. Nielsen and I. L. Chuang, Quantum Computation and Quantum Information, 10th ed. Cambridge University Press, 2010.

[5] R. Horodecki, P. Horodecki, M. Horodecki, and K. Horodecki, "Quantum entanglement," Rev. Mod. Phys., vol. 81, no. 2, pp. 865–942, 2009, doi: 10.1103/RevModPhys.81.865.

[6] T. Proctor, K. Young, A. D. Baczewski, and R. Blume-Kohout, "Benchmarking quantum computers," Nat. Rev. Phys., vol. 7, pp. 105–118, 2025, doi: 10.1038/s42254-024-00796-z.

[7] Q. A. Memon, M. Al Ahmad, and M. Pecht, "Quantum computing: Navigating the future of computation, challenges, and technological breakthroughs," Quantum Rep., vol. 6, no. 4, pp. 627–663, 2024, doi: 10.3390/quantum6040039.

[8] W. Stallings, Computer Organization and Architecture: Designing for Performance, 10th ed. Pearson, 2015.

[9] J. Dongarra et al., "The Top500 list and the future of supercomputing," Comput. Sci. Eng., vol. 23, no. 4, pp. 24–32, 2021, doi: 10.1109/MCSE.2021.3072860.

[10] E. Giusto et al., "Dependable classical–quantum computing systems engineering," Front. Comput. Sci., vol. 7, p. 1520903, 2025, doi: 10.3389/fcomp.2025.1520903.

[11] P. W. Shor, "Algorithms for quantum computation: Discrete logarithms and factoring," in Proc. 35th Annu. Symp. Found. Comput. Sci., 1994, pp. 124–134, doi: 10.1109/SFCS.1994.365700.

[12] D. Gottesman, "An introduction to quantum error correction and fault-tolerant quantum computation," in Proc. Symp. Appl. Math., vol. 68, pp. 13–58, 2010, doi: 10.1090/psapm/068.

[13] W. Stallings, Operating Systems: Internals and Design Principles, 9th ed. Pearson, 2018.

[14] A. Aspuru-Guzik, A. D. Dutoi, P. J. Love, and M. Head-Gordon, "Simulated quantum computation of molecular energies," Science, vol. 309, no. 5741, pp. 1704–1707, 2005, doi: 10.1126/science.1113479.

[15] V. De Maio, I. Brandic, E. Deelman, and J. Cito, "The road to hybrid quantum programs: Characterizing the evolution from classical to hybrid quantum software," arXiv, Mar. 2025, arXiv:2503.11450.

[16] R. Ballester, J. Cerquides, and L. Artiles, "Quantum federated learning: A comprehensive literature review of foundations, challenges, and future directions," Quantum Mach. Intell., vol. 7, p. 73, 2025, doi: 10.1007/s42484-025-00292-2.

[17] M. D. Hill and M. R. Marty, "Amdahl's law in the multicore era," Computer, vol. 41, no. 7, pp. 33–38, 2008, doi: 10.1109/MC.2008.209.

[18] N. P. Jouppi et al., "In-datacenter performance analysis of a Tensor Processing Unit," in Proc. 44th Annu. Int. Symp. Comput. Archit. (ISCA), 2017, pp. 1–12, doi: 10.1145/3079856.3080246.

Histogram Gradient Boosting Classifier-Based UWSN Cyber Attack Detection Incorporating Environmental Factors (HGBoostUCAD)

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***Abstract*—Underwater Wireless Sensor Networks (UWSNs) are commonly employed for exploring and exploiting aquatic areas, and its role is very important and more beneficial precisely in hostile and constrained marine environments. However, their security is more critical than terrestrial wireless sensor networks (TWSNs) due to the space in which they are deployed, the wireless communication medium, and the cost of damage repair, and their protection is a problematic issue that needs to be continuously resolved. Consequently, it is highly recommended see required to take procedure to protect UWSNs against attacks and intrusion and maintain service quality. In general, existing works on machine learning-based intrusion detection system (IDS) and cyber-attack detection approaches for (UWSNs) utilize dedicated datasets designed for (WSNs) without adapting them to the aquatic environment. Furthermore, these studies analyze the enhancement of UWSN performance based on network metrics separately from machine learning model metrics, and vice versa. In this way, this paper proposes a novel cybersecurity detection approach-based model learning Histogram Gradient Bosting (HGB) classifier called (HGBoostUCAD). It classifies four types of DoS attacks (Blackhole, Grayhole, Flooding, and Scheduling), employing an adjusted dataset for (IDS) in wireless sensor networks (WSN-DS) taking into account simulate realistic environmental factors: salinity, temperature, deep through Mackenzie's equation and node movement in training data. The insight of simulation results obtained, shows that our method reached 97% as accuracy and 96% as precision also outperformed both Deep Neural Network (DNN) as well as the recent study Hyper_RNN_SVM eventually referenced in this research, in terms of machine learning model metrics. In addition to machine learning model metrics, our approach provides network measurements by DoS attack type.**

Keywords*—UWSN; security; intrusion detection system; cyber-attack detection; cybersecurity; machine learning; histogram gradient boosting

TABLE I. ABBREVIATIONS

UWSN	**Underwater Wireless Sensor Network**
DoS Attack	**Denial of Service Attacks**
ASVs	**Autonomous Surface Vehicles**
AUVs	**Autonomous Underwater Vehicles**
NISTIR	**National Institute of Standards and Technology Internal Report**
FISMA	**Federal Information and Information Systems**
IDS	**Intrusion Detection Systems**
HGB	**Histogram Gradient Boosting**
DNN	**Deep Neural Network**
PDR	**Packet Delivered Ratio**
SNR	**Sound Noise Ratio**

I. INTRODUCTION

An underwater wireless sensor network (UWSN) is considered to serve as the main support network for the Internet of Things. The network architecture of a UWSN is shown in Fig. 1, with its key components—sensors—located in either shallow or deep water. The sensors' function is to collect data and send it via acoustic signals to objects like buoys, ships, Autonomous Surface Vehicles (ASVs), or Autonomous Underwater Vehicles (AUVs). These objects then use radio signals to send the data to a distant monitoring center. After obtaining the oceanic data, the monitoring center analyzes it [1]. These kinds of networks are usually unmonitored and placed in remote locations. Security methods must be implemented on them to protect them from threats and attacks [2], and compared to their analogs, such as wireless sensor networks (WSNs), UWSNs are more susceptible to security assaults. The entire network's functionality may be compromised by potential attacks in UWSNs [3]. The list of abbreviations is given in Table I.

In research [4] as application, the author classified UWSN deployment into five areas: 1) underwater research; 2) environmental monitoring; 3) disaster prevention; 4) military domain; and 5) other fields.

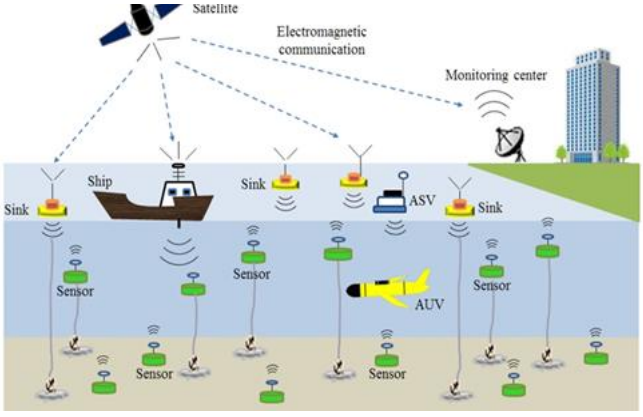


Fig. 1. UWSN architecture [1].

A. Basic Concepts and Challenges

1) Cybersecurity: The term "cyber security" refers to the set of rules, methods, tools, and procedures that cooperate to defend against attacks on the availability, confidentiality, and integrity of networks, software, and data. There are cyber protection methods at the network, application, data level and host. Many tools, including intrusion detection systems (IDSs), firewalls, antivirus programs, and intrusion protection systems (IPSs), operate in collaboration to prevent assaults and identify security failures [5]. In other words, cybersecurity concepts are measures taken to guarantee the confidentiality, integrity, and availability of systems, data (including software, hardware, and networks), and information that is processed, stored, and transmitted, as mentioned in the NISTIR (National Institute of Standards and Technology Internal Report) 7298 report (Glossary of Key Information Security Terms, July 2019). Moreover, the FISMA (Standards for Security, Categorization of Federal Information and Information Systems, February 2004) established the first three main security objectives for computer and information systems as follows:

a) Confidentiality: Taking into account appropriate limitations on information availability and sharing, as well as precautions to protect private and sensitive data.

b) Integrity: Preventing the rectification or destruction of erroneous data while guaranteeing the accuracy and non-repudiation of the relevant information.

c) Availability: Making certain that when resources are needed, authorized users can access them on time and continuously [6].

2) Intrusion detection: Define as "the act of detecting actions that attempt to compromise the confidentiality, integrity, or availability of a resource". An intrusion detection system (IDS) is a hardware or software program that keeps surveillance out for hostile activities or policy violations on a network or systems [7].

As well, we describe DoS attack types on the WSN-DS dataset, including Blackhole, Grayhole, Flooding, and Scheduling, as follows:

3) Blackhole attack: A blackhole attack is a kind of denial-of-service assault in which the attacker disrupts routing protocol by promoting itself at the start of the round. Playing the role of cluster head (CH), the Blackhole attacker will continue to drop packets transmitted by adjacent node rather than sending them to the BS.

4) Grayhole attack: The attacker disrupts the routing protocol by posing as a CH to other nodes. As a result, the pretending CH blocks some packets from reaching the BS by randomly or selectively dropping them when it receives data packets from other nodes.

5) Flooding attack: The attacker manipulates the routing protocol in multiple ways. By transmitting a lot of advertising CH messages with high transmission power. As a result, when sensors get a lot of messages notifications, they will use more energy and take longer to decide which CH to join. Additionally, the attacker tries to confuse victims into selecting it as a CH, particularly those nodes that are far away from it in order to drain their energy.

6) Scheduling attack: When CHs put up TDMA schedules for the data transmission time lots during the routing protocol configuration phase, scheduling attacks take place. All nodes will be given the identical time slot to send data by the attacker acting as a CH. This is accomplished by switching the TDMA schedule from broadcast to unicast. Such a modification will result in packet collisions and data loss [8].

Even though this type of networking is more beneficial in rich and expansive aquatic areas, they were limited by the basic open acoustic channel, excessive energy consumption, insufficient hardware capacity to execute computationally complex tasks, and dynamic network topology caused by node mobility. Moreover, a limited bandwidth and low attenuation [9].

B. Motivation

The problematic to ensure security through this specific network and addresses vulnerability in which they are exposed, have inspired some researchers to concentrate on UWSN attack and threat detection, which is crucial for safeguarding data and systems and may provide the high level of services that these underwater technologies are expected to offer. But, lacking completely appropriate UWSN data, we satisfied with the intrusion detection system (IDS) for Underwater Wireless Sensor Networks (UWSNs) based WSN-DS dataset customized to UWSN environmental factors (salinity, temperature, depth, and movement), with classification of four DoS attack types (Blackhole, Grayhole, Flooding, and Scheduling). Machine learning (ML) paradigm presents a new opportunity to accomplish the intended results in this aspect. In actuality, ML models successfully carry out detection, classification, and future event prediction [10]. Additionally, gradient boosting (GB) is an ensemble learning method for classification and regression problems, as suggested by Friedman [11]. An effective model can be produced by combining weak learners, commonly decision trees. The basic idea behind GB is to gradually build and generalize the ensemble model by optimizing an objective, arbitrary loss function [12].

Our study presents a novel technique based on the histogram gradient boosting (HGB) model evaluated precisely on the adjusted WSN-DS dataset commonly used on intrusion detection system in wireless sensor networks (WSNs) taking into account environmental factors as formulated by Mackenzie's equation. HGB is one of the most robust machine learning algorithms having high prediction speed and accuracy, particularly when working with large and complex datasets like WSN-DS [8]. The following is a summary of the study's most important findings and contributions:

- Implement a cyberattack detection on UWSN, using an adapted WSN-DS dataset and a histogram gradient boosting technique.
- Incorporate environmental adaptation: temperature, salinity, depth, mobility.

- Include per-attack network simulation adjustments (PDR, packet rate, delay, energy).
- Produce plots: ML comparison, per-attack network metrics.
- Provide technique with height performance both in terms of metrics model and performance network compared to DNN and to others recent works.

The remainder of this work is structured as follows: Section II provides a literature review. Section III describes research methodology adopted. Section IV introduces experimental results of research, analyze and discussion is given in Section V. Finally, the paper's conclusion is given in Section VI.

II. Related Works

We are satisfied with just a few of research that have mostly concentrated on the usage of artificial intelligence to enhance UWSN security process. In the same way, for the purpose of detecting cyberattacks, the study [13]. suggests an intelligent model-based approach that integrates machine learning and deep learning technology. Furthermore, a feature reduction strategy employing the machine learning techniques Principal Component Analysis (PCA) and Support Vector Machine (SVM) is employed to determine which properties are most closely associated with the selected attack categories. The accuracy of a proposed Recurrent Neural Network (RNN) method for deep learning-based intrusion classification and detection, following dimensional reduction and optimization, attains (97%) accuracy but using the NSL KDD dataset. The goal of this study is to provide a comprehensive overview of UWSN security by discussing security needs and the main UWSN security threats based on layered classification. This paper explores many security issues and looks at solutions, when in study [14], the current state-of-the-art for reactive jammer detection is built with terrestrial wireless sensor networks (TWSNs) in mind. Furthermore, cooperative jamming detection in UWSN is used in very little work. This research presents an Efficient Channel Access (ECA) model that uses cross-layer design to prevent reactive jammers in order to address research challenges. The ECA jointly optimizes the approved sensing device's cooperative hopping probability and channel accessibility probabilities. The detection accuracy achieved by the ECA model is 95.12%. Additionally, in [15], the authors suggest an intrusion detection model for underwater sensor networks that can identify many kinds of attacks in order to solve this issue. In order to reduce node computation, the reduced dimensional data is sent to sink nodes after cluster head nodes have extracted features using neighborhood sensitive sets. Furthermore, the data set is balanced, the quantity of minority class samples is increased, and the detection rate of minority class attacks is enhanced by the application of the synthetic minority oversampling method (SMOTE). After determining a node's confidence based on the cluster head node's trust evaluation, train the classifier to identify the type of attack using the random forest approach; it struggles to recognize intrusions from many attack types. According to simulation data, the model can detect imbalance classes with an accuracy of over 99% and enhance the effectiveness of intrusion detection of various types of attacks. Moreover, the methodology used in the work [16] makes use of real-time feature analysis of simulated WSN routing data. It creates a strong classification framework by combining Gaussian Mixture Models (GMM) and Hidden Markov Models (HMM). This scheme successfully detects anomalies, traces malicious network activity back to its source, and classifies it as either legitimate or suspicious network activity. According to authors, the algorithm outperformed the current classification methods by a large margin, with classification rates of approximately 83.65%, 84.94%, and 94.55%. Added to that, it provided a positive prediction value that was 11.84% greater than the current approaches. As well, to find the malicious attacks in a UWSN, the authors of this study [17] employed evidential evaluation using Dempster-Shafer theory (DST) of combined many evidences. Also, they provide a numerical process for combining multiple details from an unreliable and untrustworthy neighbor with a higher level of conflict security, but in paper [18], the purpose is to illustrate a wide range of algorithms used in the defense against different types of cyberattacks. In order to protect against a variety of cyberattacks, this study will look at different classification algorithms and defense strategies. Depending on how the attack is classified, these methods will differ in terms of implementation, accuracy, and testing time. The several types of these algorithms will be covered in this research. Other than, the survey [19] provides insights into the diverse intrusion detection system (IDS) methodologies utilized in various networking technologies and explains some of the techniques used in IDS design. Signature-based intrusion detection is the most widely used method for detecting threats and guaranteeing security. However, the emergence of Artificial Intelligence (AI), particularly Machine Learning, Deep Learning, and Ensemble Learning, has shown promise results in more effective attack detection. We can ensure that the cyber infrastructure is protected from intrusions and unwanted activity by using IDS and AI to defend a network according authors. Similarly, in [20] the paper introduces a novel method for detecting malicious network traffic using artificial neural networks suitable for use in deep packet inspection-based intrusion detection systems, achieving an average accuracy of 98% and a false positive rate of less than 2% in repeated 10-fold cross-validation, potentially improving the utility of intrusion detection systems in both conventional and cyber-physical systems. The research cited in [21] is based on the UNSW-NB15 dataset, which contains 49 features for 9 distinct attack samples. According to authors, the decision tree classifier provided the highest accuracy of 99.05% in comparison to other models. Also, the deep learning system for binary classification with an 80:20 train-test split ratio and two dense layers with ReLU activation and a third dense layer with Sigmoid activation function achieved an accuracy of 98.44% using the ADAM optimizer. The paper, also cited in [22] interested in attack detection methods founded on several architecture types, such as auto-encoders, generative adversarial networks, recurrent neural networks, and convolutional neural networks, based on classification on deep learning techniques. As well, authors illustrate the current state of attack detection techniques applying deep learning structures and evaluate the performance of representing approaches adopting a few benchmark datasets which are described.

III. METHODOLOGY OF RESEARCH

The following is the key components of the method adopted to implement a cyber-attack detection-based machine learning:

A. Criticism of Existing Studies

Despite their relevance in terms of findings, most of the studies reviewed in the literature use machine learning techniques that don't require datasets, such as reinforcement learning, while others use WSN datasets without taking environmental factors into account or use mathematical approaches for deploying a UWSN intrusion detection system. As well without integrating machine learning model measurements with network performance indicators in the same study.

B. Objectives and Hypotheses

- To implement a UWSN detection attack system supported by (Hist Gradient Boosting Classifier — HGB) using adapted WSN-DS dataset that includes four Denial-of-Service (DoS) attacks (Blackhole, Grayhole, Flooding, and Scheduling attacks) and incorporating environmental parameters: temperature, salinity, deep, mobility.
- To prove its performance by comparing it with DNN under the identical experimental conditions and with other current similar techniques in terms of metrics model.
- To analyze and interpret result of experimentation.

C. Experimental Design Overview

The experiment utilized the WSN-DS dataset augmented with UWSN environmental factors — namely salinity, temperature, depth, and node mobility — to reflect realistic underwater propagation and energy consumption patterns. The model employed a Histogram Gradient Boosting (HGB) classifier, an ensemble-based artificial intelligence algorithm recognized for its robustness and interpretability in intrusion detection tasks. Each record in the dataset represented a network state or node observation, labeled as either normal or one of the four Denial of Service (DoS) attack types: Blackhole, Grayhole, Flooding, and Scheduling.

The IDS was trained on 70% of the dataset and tested on the remaining 30%. Performance evaluation included both machine learning metrics (accuracy, precision, recall, and F1-score) and network-level performance metrics (packet delivery ratio, average delay, throughput, and energy consumption).

Step 1 — Load & Clean Dataset

Import D_(WSN-DS) dataset containing labeled samples of network activity

Step 2 — Synthesize UWSN Features

For each row i in data frame df:

Environmental features

- Generate Temperature Ti, Salinity Si, Depth Di, Node mobility Mi
- Append $E_{env} = \{S_i, T_i, D_i, M_i\}$ to feature vector.

Distance & propagation

- Randomized distance
- Compute sound speed via Mackenzie 's equation cited in [23]:

C = mackenzie_sound_speed (T, S, D)

$$C(T,S,D) = 1448.96 + 4.591T - 0.05304T^2 + 0.0002374T^3 + 1.34(S-35) + 0.0163D$$

- Propagation delay = distance / c

Link success probability algorithm

Inputs:

- d: link distance (meters)
- SNR: signal-to-noise ratio (dB)
- α: attenuation coefficient
- β, γ: SNR logistic parameters

Output: $\boldsymbol{p_0}$: baseline link success probability

The term $\mathbf{P_0}$ represents the baseline probability of successful packet transmission between two underwater sensor nodes, given the distance separating them and the signal-to-noise ratio (SNR) at the receiver. Mathematically, "base_link_success_prob"(·) illustrates how the transmission success rises with increased SNR, indicating a stronger received signal relative to background noise, and declines as the propagation distance grows (due to geometric spreading and absorption losses).

P0 = base_link_success_prob (distance, snr_db)

$$\mathbf{P0} = [1 \div (1 + e^{-\beta(\mathrm{SNR}-\gamma)})] \times e^{-\alpha d}$$

where: $\mathbf{P0} \in [0,1]$ and SNR proxy (dB) as function of distance and mobility (noisy),

d is the distance between nodes,

"SNR" (in dB) measures channel quality,

α, β, and γ are environment-dependent parameters modeling attenuation and detection sensitivity.

(α = 0.002;β = 0.15; γ = 10.0)

Attack-Adjusted Packet Delivery Ratio (PDR) Algorithm

This modifies $\mathbf{p_0}$ according to UWSN attack types

- pdr = apply_attack_pdr (p0, attack_type)

Inputs :

- p_0: baseline success probabilities (vector)
- AttackType[i] ∈ {normal, blackhole, grayhole, flooding, scheduling}

Output:

- p: attack-modified link success probabilities

This equation represents how the Packet Delivery Ratio (PDR) — the ratio of successfully delivered packets to total transmitted packets — is affected by the presence of cyberattacks or network disruptions in the underwater environment.

The function "apply_attack_pdr"(·) modifies this baseline probability according to the type and severity of attack acting on the network.

- pdr = apply_attack_pdr (p0, attack_type)

In this study we employ WSN-DS adapted dataset, which classifies network behavior as either normal or one of four Denial-of-Service (DoS) attacks (Blackhole, Grayhole, Flooding, and Scheduling attacks) [8].

Step 3 — Train & Evaluate Models (per seed)

HGBoostUCAD algorithm

- Train on X_train, y_train
- Predict y_pred_hgb on X_test

Deep Neural Network (DNN)

- Build sequential model: Dense → BatchNorm → Dropout → Dense → Softmax.

Compile with

adam, loss sparse_categorical_crossentropy

- Train with early stopping
- Predict y_pred_dnn on X_test

Compute ML metrics (accuracy, precision, recall, F1) for both models

Compute network metrics

Store results.

D. Results Evaluation

Step 4 — Statistical testing

- Determine model with highest mean metric (accuracy, precision, F1)
- Retrain best model on entire dataset (train/test split)
- Compute confusion matrix
- Save confusion matrix plot

Step 5 — Plotting

- ML metrics bar plot → HGBoostUCAD vs DNN
- Per-attack network metrics
- Loss curves
- DNN training & validation loss
- Gradient boosting log-loss.

IV. Experimental Results

A. Machine Learning Metrics

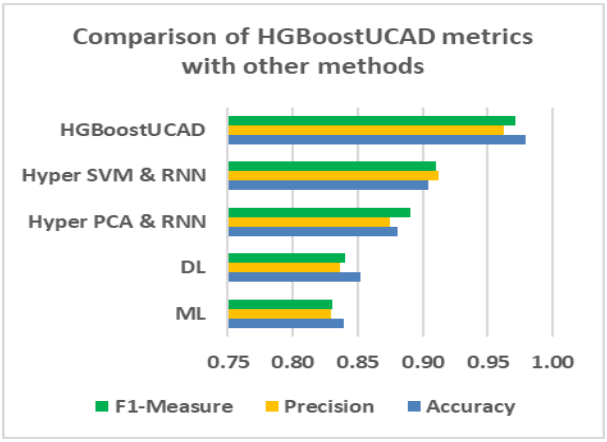


Fig. 2. Comparison proposal method with other similar methods.

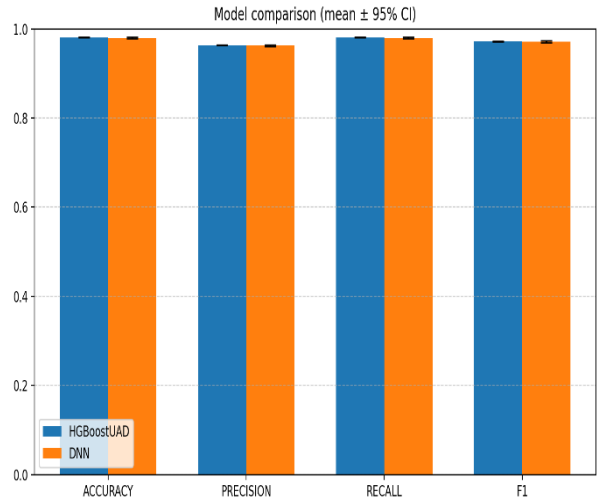


Fig. 3. Comparison between HGBoostUCAD and DNN method.

B. Network Performance Metrics

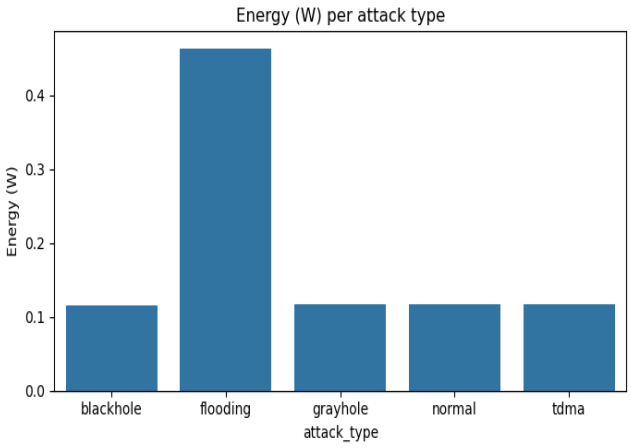


Fig. 4. Consumption energy per attack type.

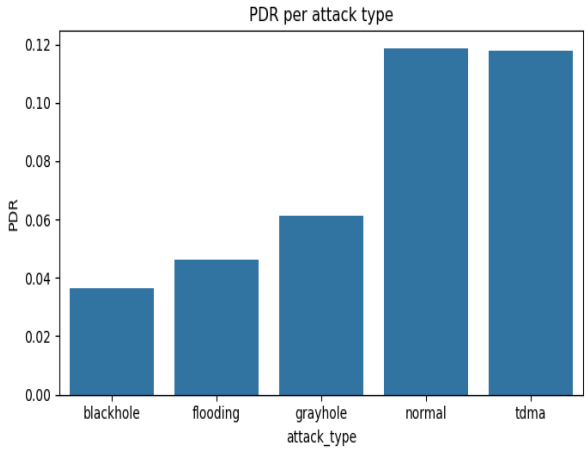


Fig. 5. Delivered packer ratio per attack type.

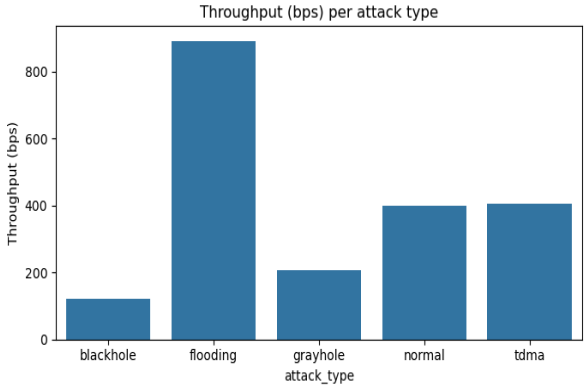


Fig. 6. Throughput variation for each type of attack.

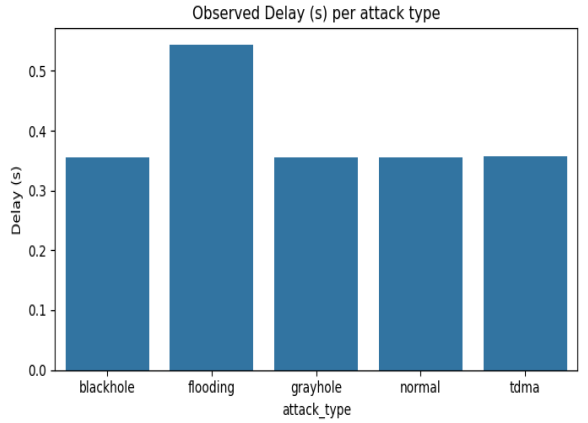


Fig. 7. Delay variation per attack type.

V. Analysis and Discussion

The experiment's outcomes are evaluated and explained from two perspectives: machine learning metrics and network metrics.

A. Machine Learning Metrics

In terms of machine learning model metrics, our approach surpassed both Deep Neural Network (DNN) and the previous study Hyper_RNN_SVM, cited in paper [13], as demonstrated by the simulation results (Fig. 2), which attained 97% accuracy and 96% precision. Also, high accuracy indicates that the IDS's detections are trustworthy.

- Accuracy for Classification Performance (see Fig. 3)

Both models demonstrate high and nearly identical accuracy, with mean values around 97%.

HGBoostUCAD: 0.97969; DNN: 0.97855

- Precision and False Alarm Behavior

Precision reflects the model's ability to avoid false positives (normal traffic misclassified as attacks).

HGBoostUCAD: 0.96236; DNN: 0.96121

The gradient-boosting ensemble performs slightly better than the DNN in preventing false alarms, according to the HGB's marginally higher precision. Because HGB builds additive trees that effectively divide local areas of feature space, it may be naturally resistant to noisy or non-linear feature interactions.

- Recall and detection sensitivity

Recall measures the ability to detect actual attacks (true positives). Both models again perform at a similar level:

HGBoostUCAD: 0.97969; DNN: 0.97855

The nearly equal recall results show that both approaches successfully identify malicious activity, indicating that neither one has significant insufficient detection.

- F1 score and balance of metrics

The compromise between missed detections and false alarms is taken up by the F1-score, which is the balance of precision and recall. The nearly identical F1-scores confirm that both models maintain an excellent balance between sensitivity and specificity, with our model HGBoostUCAD having a slight advantage.

HGBoostUCAD: 0.97090; DNN: 0.96973

B. Network Performance Metrics

We have selected four network performance parameters—energy consumed, packet delivered ratio, packet delivered delay and throughput of network communications,—that can function as essential evaluation metrics according attack type since the aim of DoS attacks is to render a target unreachable and isolated from the rest of the network. Also, to enhance comprehension of the results analysis and discussion, we describe the following network metric indicators below:

1) Energy: It is the total quantity used for data/control packet exchange by all nodes. The network will be less effective and have a shorter lifespan with high energy consumption, and vice versa [24].

2) Packet Delivery Ratio (PDR): It is calculated by dividing the total number of successfully delivered packets to the destination node or nodes by the total number of packets that were originally sent. A higher PDR means that there is less packet loss in the network [24]. When malicious traffic attacks the network, packet loss that affect PDR grows. To determine

how much legal traffic is impacted by the attack and how many data packets fail to reach their destination, the simulation assesses packet loss [25].

3) Packet Delivery Delay (Delay): The entire amount of time required for a packet to be transmitted from the sender to its successful delivery at the final destination node [24]. When servers are overloaded with fraudulent traffic, delay increases significantly, making it impossible for the server to react quickly to legitimate requests [25].

4) Average throughput: Throughput is a direct indicator of the network's capacity to manage traffic both normally and under attack. High-intensity volumetric attacks typically overload the network bandwidth, significantly decreasing it [25]. It is defined as average number of packets that the base station successfully receives in a given amount of time. Bits per second are used to measure it [26].

a) Flooding attacks: A smaller PDR (Fig. 5) usually leads to many retransmissions and congestion, which increase delays as seen in (Fig.7) and energy consumption (Fig. 4).

b) Blackhole attacks: significantly reduce throughput by greatly (Fig. 6) often impacted by congestion near the sink. Also, this attack type reduces PDR (automatically lost packets) (Fig. 5) and increase delay (Fig. 7).

c) Scheduling and Grayhole attack: IDS finds it challenging to identify attacks like Scheduling and Grayhole, which causes a slight reduction in performance (Fig. 5, Fig. 6) while maintaining efficiency on PDR concerning TDMA schedules.

In summary, the flooding attack caused more energy dissipation and increased delay than the three other DOS attacks, while the black hole attack provoked a significant diminution of both the packet delivery ratio and the throughput compared to TDMA schedules. Although our approach is effective in detecting malicious activity, as evidenced by accuracy and precision values, it has weaknesses, which are first evident in the actual scenario's implementation, which is constrained by various real-world constraints, and then in the UWSN dataset's unavailability in contrast to the WSN.

VI. Conclusion

In conclusion, this work enables it possible to implement a cyberattack detection on UWSN using an adjusted WSN-DS dataset and a histogram gradient boosting technique with a type of ensemble machine learning suitable for classification category; to incorporate environmental adaptation: temperature, salinity, depth, and mobility; to prove the efficacy of the suggested method in comparison to similar approaches; in fact, our approach outperformed both the Deep Neural Network (DNN) and the previous study Hyper_RNN_SVM, as illustrated by the simulation results; to provide metrics model (Accuracy, Precision, Recall, and F1 score); to show how network performance varies depending on the type of attack., and to offer an adaptive helpful model for future research to enhance performance and successfully address potential UWSN security issues. Extended research on various attack types and machine learning classifiers aims to enhance resource efficiency and accuracy in underwater wireless sensor networks (UWSN) security. Intrusion detection systems (IDS) play a vital role as a secondary defense, monitoring and detecting threats that bypass primary security measures like firewalls or encryption. A critical challenge is managing the resource constraints of sensor nodes—such as battery, memory, and CPU—while maintaining high detection accuracy in WSN-specific IDS.

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References

[1] Mohsan, Syed Agha Hassnain, Yanlong Li, Muhammad Sadiq, Junwei Liang, et Muhammad Asghar Khan. « Recent Advances, Future Trends, Applications and Challenges of Internet of Underwater Things (IoUT): A Comprehensive Review ». Journal of Marine Science and Engineering 11, no 1 (January 2023): 124. https://doi.org/10.3390/jmse11010124.

[2] Yang, G.; Dai, L.; 3390/s18113907Wei, Z. Challenges, Threats, Security Issues and New Trends of Underwater Wireless Sensor Networks. Sensors 2018, 18, 3907,

[3] Saeed, Khalid, Wajeeha Khalil, Ahmad Sami Al-Shamayleh, Sheeraz Ahmed, Adnan Akhunzada, Salman Z. Alharthi, et Abdullah Gani. « A Comprehensive Analysis of Security-Based Schemes in Underwater Wireless Sensor Networks ». Sustainability 15, no 9 (April 2023): 7198. https://doi.org/10.3390/su15097198.

[4] Kao, C.C.; Lin, Y.S.; Wu, G.D.; Huang, C.J. "A comprehensive study on the internet of underwater things: Applications, challenges, and channel models ". Sensors 2017, 17, 1477.

[5] D. Berman, A. Buczak, J. Chavis, and C. Corbett, "A survey of deep learning methods for cyber security," Information, vol. 10, no. 4, p. 122, 2019.

[6] Neda Azizi, Omid Haass, "Cybersecurity Issues and Challenges," DOI: 10.4018/978-1-6684-5284-4.ch002, Torrens University, Australia RMIT University, Australia, 2022.

[7] P, W. (2020). A Survey of Intrusion Detection System. International Journal of Informatics and Computation, 1(1), 1. https://doi.org/10.35842/ijicom.v1i1.7. New reference list.

[8] Almomani,1,2 Bassam Al-Kasasbeh,2 and Mousa AL-Akhras and titled WSN-DS: A Dataset for Intrusion Detection Systems in Wireless Sensor Networks, 2016, Journal of Sensors.

[9] Ouidir, Hamid, Amine Berqia, et Siham Aouad. « Improving UWSN Performance Using Reinforcement Learning Algorithm QENDIP ». 2024 11th International Conference on Wireless Networks and Mobile Communications (WINCOM), IEEE, 23 Jully 2024, 1 6. https://doi.org/10.1109/WINCOM62286.2024.10656891.

[10] Alpaydın, Ethem, "Introduction to Machine Learning. Third edition ", MIT Press, 2014.

[11] Alqahtani, Mnahi, Abdu Gumaei, Hassan Mathkour, et Mohamed Maher Ben Ismail. "A Genetic-Based Extreme Gradient Boosting Model for Detecting Intrusions in Wireless Sensor Networks". Sensors 19, no 20 (October 2019): 4383. https://doi.org/10.3390/s19204383.

[12] Xia, Y.; Liu, C.; Li, Y.; Liu, N. "A boosted decision tree approach using Bayesian hyper-parameter optimization for credit scoring". Expert Syst. Appl. 2017, 78, 225–241.

[13] Altameemi, Atyaf Ismaeel, Sahar Jasim Mohammed, Zainab Qahtan Mohammed, Qusay Kanaan Kadhim, and Shaymaa Taha Ahmed. "Enhanced SVM and RNN Classifier for Cyberattacks Detection in Underwater Wireless Sensor Networks." International Journal of Safety and Security Engineering 14, no. 5 (October 2024): 1409–17. https://doi.org/10.18280/ijsse.140508.

[14] Bagali S, Sundaraguru R.” Efficient Channel Access Model for Detecting Reactive Jamming for Underwater Wireless Sensor Network.”, In: 2019 International Conference on Wireless Communications Signal Processing and Networking (WiSPNET). 2019.

[15] Haijie Huang, Na Liu, Dandan Chen, Qiuling Yang, Xiangdang Huang, "Research on the Intrusion Detection Model of Underwater Sensor Networks", Journal of Sensors, vol. 2022, Article ID 2323747, 17 pages, 2022.

[16] Affane M., Anselme R., et Hassan Satori. « Machine Learning Attack Detection Based-on Stochastic Classifier Methods for Enhancing of Routing Security in Wireless Sensor Networks ». Ad Hoc Networks 163 (octobre 2024): 103581. https://doi.org/10.1016/j.adhoc.2024.103581.

[17] Zenia, and Z. I.Chowdhury, "A novel algorithm for malicious attack detection in UWSN,” in Proceedings of the 2015 IEEE International Conference on Electrical Engineering and Information Communication Technology (ICEEICT), pp. 1–6, Dhaka, Bangladesh, May 2015.

[18] Note, Johan, Erind Mullalli, et Betim Cico. « Machine Learning Algorithms for Cyber Attack Detection And Classification ». Proceedings of the International Conference on Computer Systems and Technologies 2024, ACM, 14 June 2024,29-36. https://doi.org/10.1145/3674912.3674937.

[19] Z. Junqing, Z. Gangqiang and L. Junkai, "Wormhole Attack Detecting in Underwater Acoustic Communication Networks," 2021 OES China Ocean Acoustics (COA), Harbin, China, 2021, pp. 647-650.

[20] Shenfield, Alex, David Day, and Aladdin Ayesh. "Intelligent intrusion detection systems using artificial neural networks." Ict Express 4.2 (2018): 95-99.

[21] Dhanya, K.A., Sulakshan Vajipayajula, Kartik Srinivasan, Anjali Tibrewal, T. Senthil Kumar, et T. Gireesh Kumar. “Detection of Network Attacks Using Machine Learning and Deep Learning Models “. Procedia Computer Science 218 (2023): 57 66.

[22] Y.Wu, D.Wei, and J.Feng, “Network Attacks Detection Methods Based on Deep Learning Techniques: A Survey,” 2020.

[23] Mackenzie, K. V. (1981). Nine-term equation for sound speed in the oceans. J. Acoust. Soc. Am., 70(3), 807–812.

[24] Altaweel, A., Aslam, S., & Kamel, I. (2024). Security attacks in Opportunistic Mobile Networks: A systematic literature review. Journal of Network and Computer Applications, 221, 103782. https://doi.org/10.1016/j.jnca.2023.103782.

[25] Kumavat, K., Sardhara, A., Shinde, T., Salunkhe, V. \& Satpute, M. Analyzing the Impact of Distributed Denial Of Service Attacks Using NS2: A Scenario-Based Study. (2025).

[26] A. Salih, M., & R. Sulaiman, D. (2023). Throughput and energy efficiency evaluation of wsn using efficient routing protocols. University of Thi-Qar Journal for Engineering Sciences, 13(1), 25-33. https://doi.org/10.31663/tqujes13.1.438(2023).

Human–Technology Interaction in Generative AI: A Theoretical Review of Technology Acceptance and Cognitive Response

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***Abstract*—The rapid rise of Generative Artificial Intelligence (GenAI) has transformed the way humans interact with technology and has revealed cognitive mechanisms that extend beyond the explanatory scope of traditional technology acceptance models, such as the Technology Acceptance Model (TAM), Technology Acceptance Model 2 (TAM2), and the Unified Theory of Acceptance and Use of Technology (UTAUT). This theoretical review examines the combined role of the Technology Acceptance Model (TAM) and Cognitive Response Theory (CRT) in explaining GenAI-related user behaviors. The increasing involvement of GenAI in knowledge production triggers complex cognitive reactions, including cognitive trust, curiosity, ambivalence, epistemic suspicion, and resistance, which fundamentally shape technology acceptance processes. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines, a systematic literature search was conducted in the Web of Science and Scopus databases. From 3,842 records published between 2014 and 2025, duplicates were removed, and the remaining studies underwent title–abstract and full-text screening. In the final stage, 69 publications were included in the review corpus. The findings indicate that, while perceived usefulness and perceived ease of use remain core determinants of GenAI adoption within the TAM framework, integrating CRT highlights the importance of deeper internal mechanisms, such as cognitive reappraisal, epistemic trust, algorithmic scepticism, cognitive load, and curiosity. Post-ChatGPT literature further emphasizes the influence of anthropomorphic cues and cognitive tension on user attitudes, trust calibration, and engagement. Overall, the combined application of TAM and CRT provides a more comprehensive theoretical lens for understanding GenAI interactions by concurrently capturing cognitive, emotional, and behavioural processes. This integrative approach offers a comprehensive lens for understanding cognitive, emotional, and behavioral processes in GenAI interactions.**

Keywords*—Generative Artificial Intelligence; Technology Acceptance Model; Cognitive Response Theory; Human-AI Interaction; cognitive trust

I. Introduction

A. The Rise of Generative Artificial Intelligence Systems

The rapid advancement of artificial intelligence technologies throughout the 2020s has ushered in a new era marked by the emergence of Generative Artificial Intelligence (GenAI). Unlike traditional analytical AI systems, GenAI models are capable of processing existing data and generating novel content, including text, images, audio, and software code. Prominent examples include ChatGPT, Copilot, Gemini, Midjourney, and Stable Diffusion. These systems extend human cognitive and creative capacities and fundamentally reshape the nature of digital production (Goodfellow et al. [28]; Şahin ve Kardaş [80]). As a result, human–technology interaction has shifted from passive information consumption to collaborative co-creation processes (Shneiderman [77]; Vaswani et al. [87]).

This transformation has triggered substantial cognitive restructuring in how individuals access information, learn, create, and make decisions (Brynjolfsson and McAfee [10]). In educational contexts, for instance, GenAI personalizes learning experiences and simultaneously raises concerns related to cognitive trust, ethical awareness, and critical thinking (Kasneci et al. [42]; Gökçe ve Atik [29]). Despite these advantages, GenAI also introduces cognitive and ethical risks. Overreliance on AI-generated outputs may increase susceptibility to authority bias and weaken reflective judgment (Mitchell and Krakauer [60]; Karagöz [41]). Uncertainties regarding the accuracy, transparency, and accountability of AI-generated content further challenge established mechanisms of cognitive trust (Bender et al. [8]). Accordingly, explaining GenAI adoption requires moving beyond purely behavioral approaches and incorporating cognitive responses, trust, and curiosity into analytical frameworks.

Today, individuals increasingly act as cognitive partners who actively think with, question, and interpret AI systems (Şen [81]). The rise of GenAI, therefore, represents not only a technological milestone but also a profound cognitive transformation that necessitates theoretical models capable of integrating technology acceptance with cognitive evaluation processes.

B. Technology Acceptance Model (TAM), TAM2 and UTAUT

The Technology Acceptance Model (TAM), originally developed by Davis [18], is one of the most influential frameworks for explaining individuals' intentions to adopt new technologies. Its core constructs—perceived usefulness and perceived ease of use—shape user attitudes and behavioral intentions, positioning TAM as a foundational model in information technology adoption research (Dülek et al. [23]; Özdemir ve Yolcu [65]). TAM has been extensively validated across diverse domains, including education (McIlroy et al. [57]), e-government (Özdemir ve Yolcu [65]), mobile

commerce (Erdoğan [27]; Kurtuldu ve Seyhun [46]), and health informatics (Sançar ve Kayserili [73]).

Subsequent extensions led to the development of Technology Acceptance Model 2 (TAM2), which incorporated social influence, voluntariness, experience, and job relevance as additional determinants of perceived usefulness (Venkatesh and Davis [88]). Building on this evolution, the Unified Theory of Acceptance and Use of Technology (UTAUT) integrated performance expectancy, effort expectancy, social influence, and facilitating conditions into a unified explanatory framework (Venkatesh et al. [89]). UTAUT has demonstrated strong explanatory power in contexts such as mobile banking, healthcare, and public services (Erdoğan [26]; Pournik et al. [68]).

However, recent research suggests that traditional acceptance models exhibit important limitations when applied to interaction-based technologies such as GenAI (Ammenwerth [5]; Lee et al. [48]).

- Cognitive reflection and thought processes remain largely external to these models.
- Psychological factors such as trust, curiosity, and emotional responses are treated indirectly rather than as core components.
- Users are primarily conceptualized as behavioral decision-makers rather than cognitive actors.

Consequently, explaining GenAI adoption necessitates enriching TAM and UTAUT with cognitive response-oriented perspectives capable of capturing reflective thinking, trust formation, and evaluative mental processes. Empirical evidence in higher education further suggests that trust should be treated as a foundational (preceding) construct in GenAI adoption. In particular, Strzelecki [79] shows that trust in ChatGPT significantly shapes behavioral intention and precedes traditional acceptance evaluations in the adoption process.

C. Cognitive Response Theory (CRT)

Cognitive Response Theory (CRT), originally introduced by Greenwald [30], posits that individuals generate cognitive reactions—favorable, unfavorable, or neutral—when exposed to persuasive stimuli, and that these internally generated thoughts play a central role in attitude formation and persuasion outcomes. Subsequent work by persuasion researchers further elaborated this perspective by emphasizing that message recipients are active processors who construct internal thoughts, counterarguments, and evaluations rather than passively receiving information (Cacioppo and Petty [13]; Petty et al. [66]; Eagly and Chaiken [24]).

CRT has served as the conceptual foundation for influential persuasion models, including the Elaboration Likelihood Model (ELM) and the Heuristic–Systematic Model (HSM). Owing to its focus on internal thought generation and evaluative processing, CRT has been widely applied across psychology, marketing, political communication, health communication, and educational research.

Within the context of GenAI, cognitive responses are elicited not by static messages but by dynamic, personalized, and context-sensitive interactions. Users continuously evaluate the accuracy, coherence, ethicality, and relevance of AI-generated outputs through ongoing cognitive reflection. These evaluations shape trust, reliance, skepticism, and learning-related outcomes (Riley et al. [70]). Accordingly, CRT offers a powerful theoretical lens for understanding how users interpret, question, and mentally respond to GenAI systems.

D. Need for Theoretical Integration

Taken together, the existing body of research indicates that prior studies on Generative Artificial Intelligence have largely developed along two parallel yet weakly connected streams. One stream primarily applies Technology Acceptance Model–based frameworks to explain GenAI adoption by focusing on perceived usefulness, perceived ease of use, and behavioral intention (Davis [18]; Venkatesh and Davis [88]; Venkatesh et al. [89]). These approaches offer valuable insights into adoption outcomes and usage intentions, yet they tend to conceptualize users mainly as rational decision-makers and provide limited explanations of how users cognitively interpret, evaluate, and respond to GenAI outputs (Ammenwerth [5]; Lee et al. [48]).

A second stream concentrates on cognitive, ethical, and trust-related dimensions such as epistemic trust, cognitive load, curiosity, ambivalence, and skepticism (Petty et al. [66]; Riley et al. [70]; Bender et al. [8]). Although these studies provide rich accounts of internal mental processes, they often examine such mechanisms in isolation and do not systematically integrate technology acceptance structures (Chen et al. [16]; Christodoulou and Zembylas [17]). From a broader cognitive perspective, meaning-making processes are inherently interpretive and context-dependent, suggesting the need for more integrated theoretical frameworks (Tunç ve Görmez [84]). As synthesized through the systematic review process and the classifications presented in Table IV to Table VII, the current literature lacks a comprehensive framework capable of jointly explaining acceptance behaviors and cognitive response mechanisms in the post-ChatGPT context.

The present study addresses this gap by positioning itself as an integrative theoretical review that systematically combines Technology Acceptance Model perspectives with Cognitive Response Theory to capture acceptance evaluation and cognitive–affective processes within a unified analytical lens.

II. Research Questions and Purpose

The primary purpose of this review is to systematically analyze how the Technology Acceptance Model (TAM, TAM2, UTAUT) and Cognitive Response Theory have been used to explain user interaction with generative artificial intelligence systems. By examining the applications, variable structures, and integration potential of these two theoretical perspectives within the GenAI domain, the study seeks to develop a conceptual synthesis that reflects the cognitive, emotional, and behavioral complexity of contemporary AI-mediated interactions.

Traditional Technology Acceptance Models (e.g., TAM, UTAUT) offer strong explanatory power for users' rational attitudes and behavioral intentions toward technology. In contrast, CRT provides insights into individuals' cognitive reactions, trust formation, counter-arguing, and critical evaluation processes. Since GenAI systems shape user

interaction not only functionally but also emotionally, ethically, and cognitively, an integrative approach combining TAM and CRT holds significant potential for developing a more comprehensive understanding of user behavior. Thus, the overarching aim of this study is not merely to summarize the existing literature but to conceptually assess the intersection of TAM and CRT, and evaluate their integrability in the GenAI era.

Accordingly, the specific objectives of this study are as follows:

- O1: To identify which variables, contexts, and technological platforms (e.g., ChatGPT, Copilot, Gemini) are associated with the application of TAM, TAM2 and UTAUT in explaining user interaction with generative AI systems.
- O2: To examine how Cognitive Response Theory has been applied in GenAI research, and how users' cognitive, emotional, and ethical responses to AI-generated outputs have been categorized.
- O3: To evaluate how these two theoretical approaches (TAM/UTAUT and CRT) complement each other and under which conditions they can form an integrative explanatory framework.
- O4: To identify theoretical and methodological gaps in the literature and propose future directions regarding model development, scale construction, and experimental designs.

Based on these aims, the following research questions were formulated:

- RQ1: How have TAM Models (TAM1, TAM2, UTAUT) been used in GenAI-Focused Studies?
- RQ2: To what extent have cognitive response theory (CRT) and other cognitive/emotional reactions been addressed in GenAI-Focused Studies?
- RQ3: What conceptual shifts, user responses, and new variables have emerged in GenAI interactions in the post-ChatGPT period (2022–2025)?
- RQ4: Have TAM and the Cognitive Response Approach been used together, and which theoretical frameworks do such studies adopt?
- RQ5: What theoretical and practical benefits can be gained from integrating TAM and the cognitive response approach in explaining GenAI interactions?

III. Methodology

This study is a systematic review and a meta-analysis–based conceptual analysis that examines the literature on the Technology Acceptance Model (TAM, TAM2, UTAUT) and Cognitive Response Theory within the context of GenAI systems. The primary objective is to determine how these two theories have been applied individually and in an integrated manner, to analyze the new concepts and variables emerging in the post-ChatGPT period, and to develop theoretical orientation proposals for future research.

In this respect, the study not only summarizes the existing literature but also aims to achieve a theoretical synthesis by discussing how technology acceptance and cognitive response processes can be reinterpreted within an integrative model framework.

A. Literature Search Strategy

In this study, a systematic review approach was adopted and structured in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The literature search covered international peer-reviewed academic journals published between 2014 and 2025. The year 2014 was selected as the starting point because the introduction of the Generative Adversarial Networks (GANs) architecture by Goodfellow et al. [28] marked the institutionalization of modern generative artificial intelligence research.

The search process was conducted in the Web of Science (WoS) Core Collection and Scopus databases, using both narrow and expanded keyword strings to reach comprehensive literature on generative artificial intelligence, technology acceptance models, and cognitive response theory. Searches were performed across all text fields (Title, Abstract, Author Keywords, Keywords Plus), and only studies containing terms such as "generative artificial intelligence", "GenAI", "ChatGPT", and "Large Language Models (LLMs)" were included.

These core GenAI terms were combined using the AND operator with technology-acceptance–related concepts ("technology acceptance model", "TAM", "perceived usefulness", "perceived ease of use", "attitude toward use", "behavioral intention") and cognitive-response concepts ("cognitive response theory", "cognitive response", "trust", "curiosity"). The search strings are presented in Table I. The literature search was conducted on WoS and Scopus, and studies of a similar nature but not focused on GenAI were excluded. Access to full texts and construction of the dataset were completed between December 2024 and July 2025.

TABLE I. Search Strings Used to Search Databases

Topic	Search string
Generative Artificial Intelligence	"generative artificial intelligence" OR "generative AI" OR "GenAI" OR "ChatGPT" OR "large language model" OR "LLM"
AND	
Technology Acceptance & Cognitive Response Concepts	("technology acceptance model" OR "TAM" OR "perceived usefulness" OR "perceived ease of use" OR "behavioral intention" OR "attitude toward use") AND ("cognitive response theory" OR "cognitive response") AND ("trust" OR "curiosity")

Within the scope of the study, only open-access, peer-reviewed, and primary research articles were included. The search results were systematically transferred into Excel, and the retrieved records were categorized into eight separate Excel files based on the thematic scope of the research. These files were subsequently merged into a single unified dataset, and duplicate studies were removed to obtain a set of unique records.

The remaining studies were independently evaluated by two researchers. The screening process was conducted sequentially at the title, abstract, and full-text levels, and any disagreements were resolved through discussion. As a result of the eligibility assessment, a total of 69 studies were included for detailed analysis.

B. Inclusion and Exclusion Criteria

In this systematic review, the inclusion and exclusion process was defined in accordance with PRISMA guidelines. The selection of studies was conducted based on specific theoretical, methodological, and accessibility criteria. The aim was to evaluate the relationship between generative artificial intelligence, technology acceptance, and cognitive responses solely through findings obtained from primary empirical research.

1) Inclusion Criteria:

TABLE II. INCLUSION CRITERIA BY CATEGORY

Category	Inclusion Criterion
Scope	The study must examine user interactions with GenAI and include terms such as "generative artificial intelligence," "GenAI," "ChatGPT," or "LLM."
Topic Focus	The study must evaluate concepts within the framework of technology acceptance and cognitive responses (CRT, cognitive response, trust, curiosity).
Theoretical Coverage	The study must include at least one core concept related to technology acceptance theories (TAM components: perceived usefulness, perceived ease of use, attitude, behavioral intention) AND at least one concept associated with the cognitive response approach.
Study Type	Only primary research articles (quantitative, qualitative, or mixed-methods) are included; reviews, editorials, opinion pieces, and conference abstracts are excluded.
Access Type	Only peer-reviewed and full-text accessible articles are included.
Language of Publication	The study must be published in English.
Publication Period	Articles published between 2014 and 2025 are included.

2) Exclusion Criteria:

TABLE III. EXCLUSION CRITERIA BY CATEGORY

Category	Exclusion Criterion
Out-of-scope	Studies not related to generative artificial intelligence (GenAI), or focused solely on classical artificial intelligence / machine learning; studies that do not include the terms "generative artificial intelligence," "GenAI," "ChatGPT," or "LLM" were excluded.
Topic Exclusion	Studies that do not address technology acceptance models (TAM components) or cognitive responses (CRT, cognitive response, trust, curiosity) were excluded.
Theoretical Exclusion	Studies that do not provide a theoretical framework related to technology acceptance, user behavior, or cognitive responses; studies focusing only on technical models, algorithms, or system performance were excluded.
Study Type Exclusion	Review articles, meta-analyses, editorials, book chapters, opinion papers, conference abstracts, short papers and studies without full-text access were excluded.
Access Exclusion	Non–peer-reviewed studies, studies without full-text availability, or archival/document-based works were excluded.
Language Exclusion	Studies published in languages other than English were excluded.
Publication Period Exclusion	Articles published before 2014 were excluded from the scope of the review.

C. Data Collection and Coding Process

The inclusion and exclusion procedures applied in this systematic review were conducted in accordance with the PRISMA flow diagram standards, and the process is summarized in Fig. 1. All records retrieved from the literature search were organized within an Excel-based data management system. Eight separate Excel files created for each search theme were later merged to form a single master dataset. In the initial stage, a total of 3,842 records were retrieved from the Web of Science (n = 2,446) and Scopus (n = 1,396) databases; duplicate records were removed, eliminating 806 repeated studies from the dataset. After this step, 3,036 studies proceeded to the title and abstract screening phase.

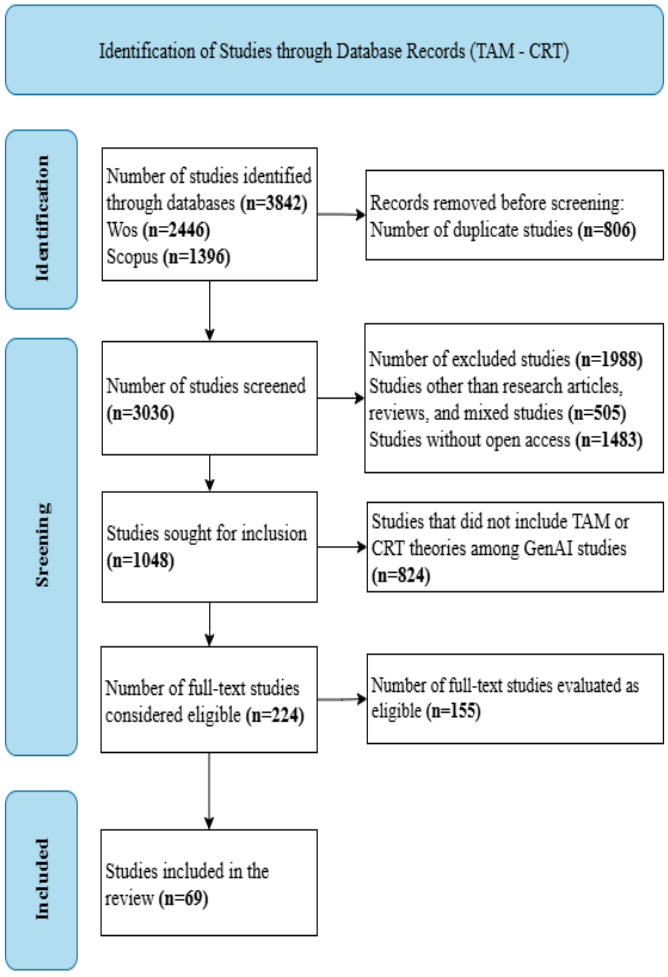


Fig. 1. PRISMA 2020 flow diagram.

In the second stage, studies not meeting the exclusion criteria listed in Table III were removed. Documents that were not research articles, editorials, review papers, records without full-

text access and out-of-scope studies were excluded, resulting in the removal of 1,988 studies. Subsequently, the inclusion criteria defined in Table II were applied. Although GenAI-focused, 824 studies were excluded because they did not contain variables related to technology acceptance models (TAM components) or concepts associated with the cognitive response approach (CRT, cognitive response, trust, curiosity). After these steps, the number of studies eligible for full-text review was finalized as 224.

The full-text evaluation process was conducted independently by two researchers; studies were compared based on their alignment with the GenAI–TAM–CRT framework. Discrepancies were resolved through discussion. As a result of this evaluation, 155 studies that did not meet the criteria for theoretical integration were excluded, and a total of 69 studies were included in the final review. The included studies were entered into a coding table containing variables such as "author(s)", "article title", "publication year", "DOI", "short content summary", and "alignment with the GenAI–TAM–CRT framework". This table enhanced the comparability of the studies and ensured consistency throughout the review analysis.

IV. FINDINGS

A. RQ1: How have TAM Models (TAM1, TAM2, UTAUT) been used in GenAI-Focused Studies?

The consolidated Table IV shows that studies conducted within the GenAI domain largely preserve the theoretical core of the Technology Acceptance Model while simultaneously expanding it with psychological, pedagogical, and social components required by different contexts and user groups. Across all 41 reviewed studies, perceived usefulness (PU) and perceived ease of use (PEOU) remain central constructs for explaining GenAI adoption; these variables consistently emerge as the primary predictors of behavioral intention among students, educators, healthcare professionals, pharmacists, software engineers, and consumers. This continued reliance on PU and PEOU—despite GenAI's dynamic, creative, and nontraditional nature—demonstrates that TAM remains a stable reference framework for modeling technology acceptance. However, the table also makes clear that TAM is rarely used in its "pure" form in GenAI-related research. GenAI systems introduce interactive, unpredictable, creative, and sometimes risk-laden experiences, meaning users interpret these technologies not only through cognitive appraisals (usefulness and ease of use) but also through emotional, ethical, social, and pedagogical evaluations. For this reason, most studies expand TAM with additional variables tailored to the specific context. For example, studies involving faculty members enrich TAM with AI literacy, TPACK, trust, self-efficacy, and instructional fit [21], [31], [35], [43], [50], [52], [64], [75], [83], [96]. These works demonstrate that pedagogical competence, ethical awareness, and trust shape GenAI acceptance beyond the classical PU–PEOU mechanism.

Similarly, studies conducted in consumer and service environments—such as GenAI-supported clothing customization—extend TAM with enjoyment, trust, perceived risk, social influence, and experiential quality [17], [36]. These constructs reflect emotional and social dimensions of GenAI use, including concerns about uncertainty, authenticity, human-like interaction, and the balance between craftsmanship and automation. In such contexts, behavioral intention cannot be fully explained through cognitive evaluations alone, making emotional and experiential constructs essential extensions of the model.

A further pattern illustrated in the table is TAM's hybridization with additional theoretical frameworks. In higher education research, TAM is frequently integrated with TTF, UTAUT, TPB, SRL, SDT, and motivational self-system models [2], [25], [36], [39], [45], [47], [49], [52], [59], [76], [78], [86], [95]. These hybrid models highlight the need to understand GenAI not merely as a technological tool but as a pedagogical, psychological, and social actor. For instance, motivational self-system variables are integrated into PU and PEOU in language learning contexts [36], while studies involving preservice teachers demonstrate that self-efficacy and professional identity meaningfully expand TAM [31], [52].

The diversity of empirical contexts represents another critical finding. GenAI acceptance is examined not only in higher education but also across health sciences, pharmacy, consumer markets, software engineering, public communication, and doctoral research writing. This diversity indicates that TAM's use as a "general-purpose framework" in GenAI studies is not merely a preference but a methodological necessity. For example, GenAI is perceived as an "assistant", "collaborator", or "replacement" in software engineering; large-scale public opinion studies categorize attitudes toward GenAI [56]; and doctoral students' ethical dilemmas concerning GenAI use in academic writing are systematically analyzed [69].

Finally, Table IV shows that GenAI adoption occurs within a far more complex and multi-layered environment than traditional information systems. Although PU and PEOU remain foundational, GenAI introduces constructs such as autonomy concerns, creative control, ethical ambiguity, trust requirements, social comparison, instructional alignment, and task–technology fit. These contextual features necessitate expanding TAM with new domain-specific factors. Overall, the consolidated evidence demonstrates that, in the context of generative AI, the technology acceptance model has evolved into a flexible and adaptive analytical framework. While the structural core of TAM—perceived usefulness and perceived ease of use—remains essential, contemporary GenAI research consistently expands the model with context-specific cognitive, emotional, ethical, and social constructs. These extensions, along with frequent integrations of complementary theories, allow TAM to capture the multi-layered, interactive, and sometimes unpredictable nature of GenAI systems. This shift suggests that understanding GenAI acceptance requires models that go beyond classical rational evaluation and incorporate the dynamic cognitive and socio-emotional mechanisms shaping user interaction.

TABLE IV. TECHNOLOGY ACCEPTANCE–ORIENTED STUDIES ON GENERATIVE AI

ID	Ref.	Author	Theoretical Lens	Context	Key Focus
T4-01	[59]	Mirriahi et al.	TAM + Self-Regulated Learning	Education	SRL–TAM integration
T4-02	[3]	Almeida et al.	Technology Acceptance Model	Recruitment	Professional GenAI acceptance
T4-03	[33]	Haddad et al.	TAM + User Experience	Urban design	Interface usefulness
T4-04	[4]	Alshamy et al.	TAM (mixed-methods extension)	Clinical education	Clinical GenAI adoption
T4-05	[1]	Al-Abdullatif	TAM + Trust + Intelligent TPACK	Faculty	AI literacy and trust
T4-06	[37]	Huang et al.	TAM + Trust + Enjoyment	Consumers	Trust-driven adoption
T4-07	[64]	Nevárez Montes & Elizondo-Garcia	TAM + Theory of Reasoned Action	Higher education	Acceptance pathways
T4-08	[85]	Ursavaş et al.	TAM + Self-efficacy + Social norms	Students	Peer-driven norms
T4-09	[61]	Mohamed et al.	TAM + Anxiety + Social influence	Education	Anxiety effects
T4-10	[2]	Almassaad et al.	TAM + Task–Technology Fit	Students	Task–technology fit
T4-11	[72]	Sallam et al.	TAM + Risk + Psychosocial factors	ChatGPT users	Risk perception
T4-12	[75]	Shata & Hartley	TAM + Social Cognitive Theory	Academics	Trust-based policy views
T4-13	[14]	Calleja & Camilleri	TAM (qualitative lens)	Teachers	Qualitative perceptions
T4-14	[4]	Alshamy et al.	Technology Acceptance Model	University	Group comparison
T4-15	[94]	Xiao et al.	TAM + Task–Technology Fit	Sustainability education	Sustainability-oriented use
T4-16	[19]	Dekerlegand et al.	Technology Acceptance Model	Health sciences	Ethics-focused training
T4-17	[52]	Liu et al.	TAM + Self-efficacy	Pre-service teachers	Pedagogical readiness
T4-18	[17]	Christodoulou & Zembylas	TAM + Ethical framework	Education	Emotional–ethical dimensions

B. RQ2: To what Extent have Cognitive Response Theory (CRT) and other Cognitive/Emotional Reactions been addressed in GenAI-Focused Studies?

An examination of CRT-related articles shows that the explicit use of cognitive response theory under its formal name is relatively rare in the GenAI literature. However, the core assumptions of CRT—internal evaluation, mental argumentation, cognitive reframing, and cognitive processing—are widely embedded across studies, as summarized in Table V. The first cluster of work demonstrates that cognitive trust, risk assessment, and epistemic filtering mechanisms prominently shape user responses during GenAI interaction. Studies explaining cognition-based trust and risk modeling in innovation contexts [38], systematically analyzing trust, reliance, and resistance among students [67], and demonstrating how cognitive trust emerges from perceptions of fairness, transparency, and accountability [91] all reveal the production of pro–con arguments, mental modeling of risk, and cognition-based trust—processes that lie at the heart of CRT. Similarly, research centering epistemic trust [74] shows that cognitive filters toward information sources determine trust in ChatGPT, while work examining transparency and ethical signals [15] demonstrates that such cues reduce counter-arguments generated by users. Together, these studies affirm GenAI's strong capacity to trigger cognitive responses. A second group of studies focuses on the cognitive mechanisms that GenAI accelerates or burdens within learning environments. CATLM-based research assessing the interaction between cognitive processing depth and emotional response [55], studies using cognitive presence to show how ChatGPT influences cycles of critical thinking and inquiry [63], and work examining cognitive and emotional reappraisal jointly [96] illustrate how GenAI activates CRT-like inner thought processes during learning—revision, inference-making, restructuring, and doubt generation. In contrast, studies modeling cognitive overload and burnout caused by extensive GenAI use [22], research showing that over-reliance on GenAI undermines active learning processes [12], and analyses distinguishing between deep and superficial cognitive effort [44] highlight the negative dimension of cognitive responses. These findings indicate that GenAI use is linked not only to technology acceptance but also to conflicting processes such as cognitive ease versus excessive cognitive load.

A third cluster addresses cognitive reactions in service and consumer contexts, where pre-existing beliefs, mental models, and service-switching intentions guide user evaluations. Studies showing that prior beliefs shape cognitive reactions to GenAI service failures [55], that the risk–trust–intention chain is influenced by the perceived accuracy of AI-generated health information [32], and that multidimensional trust structures are tied to behavioral outcomes [20] demonstrate how expectations, assumptions, and mental frameworks determine the direction of cognitive responses. These patterns reveal that the same GenAI stimulus can produce highly divergent cognitive outcomes across individuals—tolerance, resistance, abandonment, or re-evaluation.

TABLE V. COGNITIVE AND TRUST-ORIENTED FRAMEWORKS IN GENERATIVE AI RESEARCH

ID	Ref.	Author	Theoretical Lens	Context	Key Focus
T5-01	[67]	Piller et al.	Socio-technical system + Trust/Risk	Innovation systems	Trust–risk dynamics in innovation
T5-02	[90]	Wang et al.	SOR + Trust Calibration + TRA	Students / GenAI use	Cognitive trust–distrust responses
T5-03	[38]	Huynh & Aichner	FAT framework	Trust formation	Transparency–fairness–trust link
T5-04	[1]	Al-Abdullatif	TAM + Trust + Intelligent TPACK	Teachers	Trust-based GenAI acceptance
T5-05	[32]	Guo et al.	Uncertainty Reduction Theory	Health information (ChatGPT)	Cognitive reframing of trust
T5-06	[20]	Đerić et al.	Multidimensional Trust Model	GenAI systems	Trust dimension differentiation
T5-07	[74]	Schäfer et al.	Epistemic Trust	Science vs. ChatGPT	Source credibility effects
T5-08	[15]	Calzada et al.	Trustworthy AI Framework	Ethics & transparency	Managing cognitive counter-arguments
T5-09	[96]	Zou et al.	CATLM	GenAI feedback	Cognitive–affective processing
T5-10	[63]	Nasr et al.	CoI (Cognitive Presence)	Critical thinking	Deep cognitive engagement
T5-11	[55]	Ma et al.	Cognitive–Affective Model	Adaptation processes	Joint cognitive–affective evaluation
T5-12	[22]	Dong et al.	Cognitive Load Theory	Burnout & overload	Cognitive load–burnout cycle
T5-13	[53]	Lv et al.	Mental Models + Beliefs	User reactions	Belief-driven cognitive switching
T5-14	[44]	Klar	Cognitive Load + Adaptation	ChatGPT use	Shallow vs. deep processing
T5-15	[37]	Huang et al.	TAM + Cognitive–Emotional–Social Model	User intention	Integrated acceptance mechanisms

In sum, the reviewed articles ([10], [15], [20], [22], [32], [38], [44], [53], [55], [63], [67], [74], [91], [96]) demonstrate that although CRT has rarely been employed explicitly in GenAI studies, its core sequence—stimulus → cognitive evaluation → behavioral outcome—is reflected across numerous disciplines in different forms. Cognitive trust, cognitive load, cognitive presence, mental models, preconceived beliefs, and cognitive dependency all represent distinct facets of the internal cognitive responses triggered by GenAI stimuli. Collectively, these findings indicate that CRT provides an implicit yet powerful foundation for understanding cognitive mechanisms in GenAI interactions and that future GenAI research can benefit from more explicit and comprehensive CRT-based modeling.

C. RQ3: What Conceptual Shifts, user Responses, and New Variables have emerged in GenAI Interactions in the Post-ChatGPT Period (2022–2025)?

A review of post-2022 ChatGPT-based studies shows a marked transformation in both the theoretical framing of GenAI interactions and the nature of user responses. The most salient feature of this period is the shift from explaining GenAI use solely through technology acceptance models to conceptualizing it increasingly through multilayered processes, including cognitive evaluation, emotional response, moral positioning, institutional security perceptions, anthropomorphic cues, and algorithmic skepticism, as synthesized in Table VI. First, the structure of trust in GenAI systems has been substantially redefined. Across applications ranging from supply chains to institutional data responsibility communication, trust is conceptualized not merely as an assessment of technical accuracy but as a cognitive evaluation anchored in transparency, accountability, institutional responsibility, and data justice [6], [7], [51], [67].

During this period, trust depends not only on perceptions of output accuracy but also on beliefs about system intention, ethical integrity, institutional governance, and the balance of human–AI authority. For example, studies show that clinicians express stronger trust when GenAI is framed not as an authority that replaces judgment but as a secondary cognitive aid supporting human reasoning [32]. Similarly, institutional data responsibility and stakeholder involvement strengthen trust by shaping users' perceptions of algorithmic intention and organizational fairness [51].

Second, a large portion of recent research focuses on cognitive skepticism, ambivalent emotional states, and trust–resistance cycles emerging from GenAI interactions. Studies in educational and consumer contexts demonstrate that individuals simultaneously generate positive and negative internal arguments when encountering GenAI outputs. Ambivalence in student responses to ChatGPT reflects the co-activation of cognitive assessments regarding both academic usefulness and ethical/security risks [17], [58], [75]. Likewise, consumers evaluating human-produced versus GenAI-produced digital outputs exhibit algorithm aversion, driven by cognitive schemas suggesting that GenAI may err, misinterpret context, or lack aesthetic intention [71]. These findings indicate that users' judgments are shaped not simply by performance but by cognitive evaluations of whether the system possesses human-like qualities, intentionality, and accountability [11], [82], [86].

Third, the 2022–2025 literature highlights the emergence of new cognitive reaction variables triggered by GenAI use. Concepts such as reliance and resistance have been systematically modeled for the first time in GenAI contexts [91], marking a shift toward more nuanced explanatory frameworks. Studies show that high trust can lead to over-reliance that weakens critical filtering, while low trust triggers avoidance and rejection. This trust calibration perspective reveals that users

evaluate GenAI outputs not only in terms of accuracy but also in relation to cognitive autonomy and perceived control.

Fourth, the concept of curiosity has been reconceptualized. Before 2022, curiosity was typically viewed as a stable cognitive trait; however, post-ChatGPT studies show that GenAI interactions can either suppress or stimulate curiosity depending on usage patterns. In STEM contexts, excessive dependence on GenAI can weaken curiosity, whereas integration with inquiry-based or problem-based learning enhances deeper cognitive exploration [38]. Similar patterns appear in design and creative fields, where trust in GenAI interacts with creativity and curiosity: some users perceive GenAI as a tool that enhances creative exploration, while others frame it as a ready-made answer engine that threatens originality [93].

Fifth, several studies analyze how anthropomorphic representations—such as "friendly helper" or "digital assistant"—reshape user cognition [86]. Anthropomorphic cues serve as powerful cognitive triggers that influence user expectations and trust. For some users, these cues generate excessive trust and emotional closeness; for others, they provoke concerns about manipulation or system intention. This suggests that linguistic framing in GenAI systems acts as a cognitive anchor comparable in importance to system performance.

Finally, research examining misinformation and verification processes demonstrates that user perceptions of GenAI are increasingly guided not by classical technology acceptance factors but by constructs such as perceived security, source transparency, institutional responsibility, traceability, and moral agency [40], [51]. This shift indicates that post-ChatGPT GenAI interactions are examined through dimensions of cognitive ethics, institutional trust, moral evaluation, and epistemic accuracy rather than only through performance-based acceptance models.

Overall, the 2022–2025 literature reveals that GenAI interaction has evolved from a technological innovation into a multifaceted phenomenon that reorganizes users' cognitive schemas and reshapes foundational psychological processes such as trust and curiosity. Studies indicate that GenAI can enrich critical thinking while simultaneously fostering automated cognitive shortcuts; strengthen trust while also generating institutional skepticism; stimulate curiosity while also risking its suppression. Consequently, post-ChatGPT GenAI research conceptualizes cognitive responses not as linear outcomes but as dynamic, multidimensional processes shaped by context and system design choices.

TABLE VI. CONTEXTUAL AND COGNITIVE PERSPECTIVES ON TRUST IN GENERATIVE AI

ID	Ref.	Author	Theoretical Lens	Context	Key Focus
T6-01	[7]	Bai et al.	Supply chain trust; GenAI–blockchain synergy	Agricultural supply chains	Quality trust via GenAI–blockchain
T6-02	[6]	Azeez & Adeate	Trust norms; data justice; AI ethics	Data governance (Africa)	Trust norms and skepticism
T6-03	[62]	Munir et al.	ML-based trust management	6G networks	Perceived reliability
T6-04	[17]	Christodoulou & Zembylas	Emotion theory; ambivalence	University students	Dual cognitive responses
T6-05	[93]	Wu & Liu	Achievement emotions framework	Informal speaking practice	Emotion-driven engagement
T6-06	[92]	Wang et al.	Technology acceptance + personality traits	Gen Z designers	Mixed cognitive reactions
T6-07	[71]	Rix et al.	Algorithm aversion / discounting theory	Digital products	Algorithm aversion
T6-08	[86]	Van Es & Nguyen	Anthropomorphism; social presence	AI framing	Over-/under-trust effects
T6-09	[75]	Shata & Hartley	Technology acceptance + communication framework	Faculty adoption	Cognitive tension in adoption
T6-10	[67	Piller et al.	Innovation management; trust & risk	GenAI-enabled innovation	Context-sensitive trust
T6-11	[91]	Wang et al.	SOR + trust calibration	GenAI use	Reliance–resistance pathway
T6-12	[9]	Borden et al.	Media ethics; moral agency	GenAI–media relations	Moral agency attribution
T6-13	[40]	Jaidka et al.	Misinformation + perceptual cognition	Information ecosystems	Trust–misinformation duality
T6-14	[51]	Lim et al.	Stakeholder theory	Institutional GenAI systems	Participatory trust building
T6-15	[54]	Lyu et al.	Usage practices; trust/distrust	Faculty practices	Coexisting trust–distrust
T6-16	[34]	Hayudini et al.	Inquiry-based learning; curiosity	STEM education	Curiosity-sustaining practices

D. RQ4: Have TAM and the Cognitive Response Approach been used together, and which Theoretical Frameworks do such studies adopt?

The systematic review indicates that although technology acceptance models are widely used in GenAI-focused research, their integration with the cognitive response approach remains highly limited. Most studies employing TAM or extended TAM frameworks continue to emphasize traditional constructs such as perceived usefulness, perceived ease of use and behavioral intention, while cognitive or cognitive–affective evaluation processes are typically examined under separate theoretical lenses. Within the reviewed dataset, only three studies were identified that explicitly combine TAM and the cognitive response approach within a single theoretical model, as summarized in Table VII. This highlights a notable conceptual gap in the GenAI literature.

The first of these studies is conducted by Ma et al. [55], who integrate the Extended TAM with the cognitive–affective model to examine how GenAI-induced cognitive reappraisal and perceived empathy contribute to sociocultural adaptation. Their findings indicate that cognitive responses are not merely supplementary to technology-use intentions but constitute fundamental mechanisms that enhance explanatory power. This demonstrates how cognitive and affective processes can strengthen TAM structures in GenAI contexts. The second study, Zou et al. [96], combines TAM with the cognitive–affective theory of learning (CATLM) to investigate how GenAI-based visualized feedback influences students' writing processes. The results show that GenAI feedback affects not only perceived usefulness but also deeper responses such as cognitive willingness and emotional reactions. This work underscores the potential of integrating cognitive response mechanisms into TAM to yield richer models of GenAI acceptance in learning environments. The third study, Huang et al. [36], focuses on consumer behavior and unites TAM with cognitive–emotional evaluation constructs. In GenAI-supported personalized services, behavioral intention is shown to derive from both cognitive appraisals (e.g., perceived usefulness) and emotional value. This approach illuminates how psychological and affective dimensions intersect with technology acceptance, thereby enhancing TAM's predictive capacity for consumer contexts.

Taken together, these three studies represent the limited but illustrative attempts to jointly apply TAM and the cognitive response approach in GenAI research. Their findings reveal that cognitive response processes—such as reappraisal, cognitive willingness, and integrated cognitive–emotional evaluations—provide substantial explanatory power for understanding technology acceptance. However, this integration is not yet a dominant trend, suggesting that the inherently cognitive and affective nature of GenAI interactions calls for more systematic incorporation of cognitive response theories into technology acceptance models. This need points toward promising avenues for future theoretical development.

TABLE VII. COGNITIVE–AFFECTIVE PERSPECTIVES ON GENERATIVE AI USE

ID	Ref.	Author	Theoretical Lens	Context	Key Focus
T7-01	[55]	Ma et al.	Cognitive–Affective Model (CAPS + COR)	International students	Sociocultural adaptation via GenAI
T7-02	[96]	Zou et al.	CATLM (Cognitive–Affective Theory of Learning)	EFL writing / HCI	Emotion-enhanced learning outcomes
T7-03	[36]	Huang et al.	Cognition–Emotion Integrated Model	Consumer services	Cognitive–emotional acceptance

E. RQ5: What theoretical and practical benefits can be gained from Integrating TAM and the Cognitive Response Approach in explaining GenAI Interactions?

The systematic review indicates that, although technology acceptance models are widely used in GenAI-focused research, their integration with the cognitive response approach is still very limited. Most studies employing TAM or extended TAM frameworks continue to emphasize traditional constructs such as perceived usefulness, perceived ease of use and behavioral intention, while cognitive or cognitive–affective evaluation processes are usually examined using different theoretical perspectives. Only three studies were identified within the dataset that explicitly combine TAM and the cognitive response approach within a single theoretical model. This highlights a notable conceptual gap in the GenAI literature. The first of these studies integrates the Extended TAM with the cognitive–affective model to examine how GenAI-induced cognitive reappraisal and perceived empathy contribute to sociocultural adaptation. The findings suggest that cognitive responses are fundamental mechanisms that enhance explanatory power, rather than merely supplementary to technology-use intentions. This shows how cognitive and affective processes can reinforce TAM structures in GenAI contexts.

The second study (96) combines TAM with the cognitive–affective theory of learning (CATLM) to investigate how GenAI-based visualized feedback influences students' writing processes. The results show that GenAI feedback affects not only perceived usefulness, but also deeper mechanisms, such as cognitive willingness and emotional reactions. Together, these studies highlight the potential of integrating cognitive response mechanisms into TAM to create more comprehensive models of GenAI acceptance in learning environments. The third study [36] combines TAM with cognitive–emotional evaluation constructs in order to examine behavioral intention in GenAI-supported personalized services. The findings demonstrate that behavioral intention derives from both cognitive appraisals (e.g., perceived usefulness) and emotional value. This illustrates how psychological and affective dimensions intersect with technology acceptance, thereby enhancing TAM's predictive capacity in consumer contexts. Taken together, these three studies represent limited but illustrative attempts to apply TAM alongside the cognitive response approach in GenAI research. Their findings reveal that cognitive response processes, such as reappraisal, cognitive willingness, and integrated cognitive–emotional evaluations, provide substantial explanatory power for understanding technology acceptance. Nevertheless, this integration is not yet a dominant trend, suggesting that the inherently cognitive and affective nature of GenAI interactions necessitates the systematic incorporation of cognitive response theories into technology acceptance models. This points towards promising avenues for future theoretical development.

V. DISCUSSION

This systematic review demonstrates that interactions with Generative Artificial Intelligence cannot be fully explained through traditional technology acceptance frameworks alone. The findings indicate that users engage in layered evaluative processes that extend beyond the classical Technology Acceptance Model constructs of perceived usefulness and perceived ease of use. Across diverse contexts, including cultural adaptation (Ma et al. [55]), learning processes (Zou et al. [96]), and consumer decision-making (Huang et al. [36]), similar cognitive–affective dynamics emerge. Despite contextual variation, users consistently rely on processes such as

reappraisal, emotional regulation, cognitive willingness, and anthropomorphic meaning-making. These patterns suggest that GenAI interactions are grounded not only in functional evaluations but also in complex cognitive and affective mechanisms.

This tendency aligns with broader conceptual shifts in the literature in which GenAI is increasingly framed not merely as a technological tool but as a partner advisor or cognitive support entity. Ma et al. illustrate how users integrate GenAI into personal and cultural adjustment processes through positive reappraisal, while Zou et al. [96] show that GenAI-supported feedback enhances learning performance, emotional responses and cognitive motivation. Together, these findings indicate that GenAI interactions operate within a domain where cognitive and affective processes are inseparable.

The results further reveal the limited explanatory power of standalone technology acceptance models in GenAI contexts. Traditional TAM assumes relatively low cognitive demand and predictable user evaluations. In contrast, GenAI requires users to engage in more complex cognitive processes. As shown by Huang et al. [36], consumer decisions are shaped by both cognitive and emotional factors, which exposes the limitations of TAM's rationalistic assumptions in high-cognitive-demand environments. Unlike conventional technologies, GenAI users must simultaneously decide on adoption and evaluate the accuracy, human-likeness, trustworthiness, and cognitive boundaries of AI-generated outputs. Such multidimensional processes are more effectively captured through cognitive response approaches. A key insight emerging from RQ4 is that only three studies within the reviewed dataset, namely Ma et al. [55], Zou et al. [96], and Huang et al. [36], systematically integrate TAM with cognitive response theory. Each study independently demonstrates that cognitive–affective processes significantly influence GenAI usage intentions. Considered together, these studies suggest that GenAI reshapes the psychological foundations of technology acceptance by shifting decision-making toward cognitive evaluation, emotional reaction and personal meaning construction.

The theoretical implications discussed under RQ5 further clarify why TAM and cognitive response theory complement each other. While TAM explains the structural components of user decisions, such as usefulness, ease of use, and intention cognitive response theory captures the internal mental processes, including deliberation, reappraisal, emotional regulation and cognitive motivation. Integrating these perspectives enables a more comprehensive explanation of both the external predictors of behavior and their internal cognitive logic. For example, the reappraisal mechanisms identified by Ma et al. [55] illuminate adaptation processes beyond the explanatory scope of TAM. Zou et al. [96] show that cognitive willingness shapes learning intentions, while Huang et al. [36] emphasize the role of emotional value in enriching the affective dimension of technology acceptance.

VI. Conclusion

This study concludes that explaining Generative Artificial Intelligence interactions requires moving beyond standalone technology acceptance models. The findings demonstrate that the cognitive and emotional reactions elicited by GenAI are integral components of technology acceptance rather than peripheral influences. Integrating Technology Acceptance Model perspectives with cognitive response theory therefore provides a more robust framework for understanding how users evaluate trust interpret outputs and form usage intentions. By synthesizing prior research through a systematic review, this study contributes a multidimensional perspective on human–GenAI interaction that captures behavioral, cognitive and affective processes simultaneously. From a theoretical standpoint, the integration of TAM and cognitive response theory clarifies why GenAI demands more intensive cognitive evaluation than earlier technologies. From a practical perspective, it supports the design of GenAI systems that are sensitive to user psychology, reduce cognitive load, balance emotional responses, and strengthen trust.

Overall, this research highlights the need for future studies to develop integrative models that explicitly incorporate cognitive–affective mechanisms into technology acceptance research. By making the multidimensional nature of GenAI explicit, this study offers a theoretically grounded contribution that advances current understanding and aligns with the expectations of advanced academic research.

References

[1] Al-Abdullatif, A. M., "Modeling teachers' acceptance of generative artificial intelligence use in higher education: the role of AI literacy, intelligent TPACK, and perceived trust," Educ. Sci., vol. 14, no. 11, pp. 1209, , 2024.

[2] Almassaad, A., Alajlan, H., & Alebaikan, R., "Student perceptions of generative artificial intelligence: Investigating utilization, benefits, and challenges in higher education," Systems, vol. 12, no. 10, pp. 385, , 2024.

[3] Almeida, F., Junça Silva, A., Lopes, S. L., & Braz, I., "Understanding recruiters' acceptance of artificial intelligence: Insights from the Technology Acceptance Model," Appl. Sci., vol. 15, no. 2, pp. 746, , 2025.

[4] Alshamy, A., Al-Harthi, A. S. A., & Abdullah, S., "Perceptions of Generative AI Tools in Higher Education: Insights from Students and Academics at Sultan Qaboos University," Educ. Sci., vol. 15, no. 4, pp. 501, , 2025.

[5] Ammenwerth, E., "Technology acceptance models in health informatics: TAM and UTAUT," Stud. Health Technol. Inform., vol. 263, pp. 64-71, Jul, 2019.

[6] Azeez, A. J., & Adeate, T., "Trust norms for generative AI data gathering in the African context," Data Policy, vol. 6, pp. e71, , 2024.

[7] Bai, S., Liu, Z., Wu, W., Xu, N., & Jiang, M., "GenAI+ Blockchain to coordinate agricultural supply chains to improve quality trust: an agent-based simulation study," Front. Sustain. Food Syst., vol. 9, pp. 1591350, , 2025.

[8] Bender, E. M., Gebru, T., McMillan-Major, A. & Shmitchell, S., "On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?," Proc. ACM Conf. Fairness, Accountability, Transparency, 610-623, Mar, 2021.

[9] Borden, S. L., Codina, L., & Ufarte-Ruiz, M. J., "Introduction. Our relationships with GenAI and the media: Testing the limits of transparency, trust and moral agency," Commun. Soc., vol. 37, no. 4, pp. 217-221, Oct, 2024.

[10] Brynjolfsson, E. & McAfee, A., "The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies," W. W. Norton & Company, 2023.

[11] Bunduchi, R., Sitar-Tăut, D. A., & Mican, D., "A legitimacy-based explanation for user acceptance of controversial technologies: The case of Generative AI," Technol. Forecast. Soc. Change, vol. 215, pp. 124095, Jun, 2025.

[12] Cacioppo, J. T. & Petty, R. E., "Persuasiveness of communications is affected by exposure to prior cognitive responses," Pers. Soc. Psychol. Bull., vol. 6, no. 2, pp. 195–201, Jun, 1980.

[13] Cacioppo, J. T. & Petty, R. E., "The need for cognition," J. Pers. Soc. Psychol., vol. 42, no. 1, pp. 116–131, Jan, 1980.

[14] Calleja, J., & Camilleri, P., "Primary school teachers' perceptions towards the use of generative AI in teaching using lesson study," Int. J. Lesson Learn. Stud., vol. 14, no. 3, pp. 237-252, Jun, 2025.

[15] Calzada, I., Németh, G., & Al-Radhi, M. S., "Trustworthy AI for whom? GenAI detection techniques of trust through decentralized Web3 ecosystems," Big Data Cogn. Comput., vol. 9, no. 3, pp. 62, May, 2025.

[16] Chen, Y., Wang, Y. & Lee, S., "The effects of the human-like features of generative AI on usage intention and cognitive dissonance," Sci. Rep., vol. 15, pp. 18906, Oct, 2025.

[17] Christodoulou, E., & Zembylas, M., "Ambivalence and emotion in the age of AI: how students navigate ChatGPT in higher education," Educ. Inquiry, vol. 16, no. 2, pp. 1-15, Sep, 2025.

[18] Davis, F. D., "Perceived usefulness, perceived ease of use, and user acceptance of information technology," MIS Q., vol. 13, no. 3, pp. 319–340, 1989.

[19] Dekerlegand, R., Bell, A., Clancy, M. J., Pletcher, E. R., & Pollen, T., "Generative Artificial Intelligence in Education: Insights from Rehabilitation Sciences Students," Educ. Sci., vol. 15, no. 3, pp. 380, , 2025.

[20] Đerić, E., Frank, D., & Milković, M., "Trust in generative AI tools: A comparative study of higher education students, teachers, and researchers," Information, vol. 16, no. 7, pp. 622, , 2025.

[21] Dong, C., Aw, D. C. W., Lee, D. W. C., Low, S. C., & Yan, C. C., "Generative AI in Healthcare: Insights from Health Professions Educators and Students," Int. Med. Educ., vol. 4, no. 2, pp. 11, , 2025.

[22] Dong, X., Wang, Z., & Han, S., "Mitigating Learning Burnout Caused by Generative Artificial Intelligence Misuse in Higher Education: A Case Study in Programming Language Teaching," Informatics, vol. 12, no. 2, pp. 51, May, 2025.

[23] Dülek, B., Dülek, B. & Dülek, B., "Teknoloji kabul modeli çerçevesinde tüketicilerin kripto para kullanım niyetlerinin incelenmesi," Bingol Univ. Iktisadi Idari Bilimler Fak. Derg., vol. 6, no. 1, 2022.

[24] Eagly, A. H. & Chaiken, S., "Cognitive theories of persuasion," Adv. Exp. Soc. Psychol., vol. 17, pp. 267–359, , 1984.

[25] Elnaem, M. H., Okuyan, B., Mubarak, N., Thabit, A. K., AbouKhatwa, M. M., Ramatillah, D. L., ... & Nazar, N. I. M., "Students' acceptance and use of generative AI in pharmacy education: international cross-sectional survey based on the extended unified theory of acceptance and use of technology," Int. J. Clin. Pharm., pp. 1-12, , 2025.

[26] Erdoğan, G., "Bireylerin mobil bankacılığı benimsemesini etkileyen faktörler: Genişletilmiş birleşik teknoloji kabulü ve kullanımı teorisi (UTAUT) modeli çerçevesinde bir araştırma," Ankara Haci Bayram Veli Univ. IIBF Derg., vol. 25, no. 1, 2023.

[27] Erdoğan, G., "Mobil alışveriş uygulamalarında algılanan faydanın öncülü ve sonuçları," Gazi Iktisat Isletme Derg., 2023.

[28] Goodfellow, I., Bengio, Y. & Courville, A., *Deep Learning*, MIT Press, 2014..

[29] Gökçe, H. & Atik, M., "Yapay zekâ destekli öğrenme ortamlarında bilişsel farkındalık ve güven algısı," Ankara Univ. Egitim Bilimleri Fak. Derg., vol. 57, no. 2, pp. 412–429, 2024.

[30] Greenwald, A. G., "Cognitive learning, cognitive response to persuasion, and attitude change," Psychol. Found. Attitudes, vol. x, no. x, pp. 147–170, , 1968.

[31] Guo, B., Feng, Y., Wang, Y., Zhang, S., Liu, X., & Zhang, Y., "Pre-service Teachers' Attitudes and Behavioral Intention Towards Generative Artificial Intelligence: A Structural Equation Modeling Investigation Based on TAM," Proc. Global Chinese Conf. Comput. Educ., vol. 2025, pp. 25-31, Jun, 2025.

[32] Guo, S., Song, Y., Chen, G., Han, H., Wu, H., & Ma, J., "Promoting trust and intention to adopt health information generated by ChatGPT among healthcare customers: An empirical study," Digit. Health, vol. 11, no. x, pp. 20552076251374121, , 2025.

[33] Haddad, F. G., Jang, K. M., Duarte, F., Rajaonson, J. & Ratti, C., "User-centered evaluation of visual generative AI for city design: an exploratory technology acceptance model analysis," Cogn. Technol. Work, vol. 27, no. 3, pp. 635–650, 2025.

[34] Hayudini, M. A. A., Tahil, S. K., Marsin, J. M., et al., "Learning activities in STEM to sustain curiosity of gen-z in an AI-dependent college setting," Environ. Soc. Psychol., vol. 10, no. 4, pp. 3215, 2025.

[35] Hidayatullah, H. I., Saifullah, M. T., Ghozali, M. T. & Aziz, A., "Exploring Community Pharmacist's Phycological Intentions to Adopt Generative Artificial Intelligence (GenAI) Chatbots for Patient Information, Education, and Counseling," Neurosci. Inform., pp. 100213, 2025.

[36] Huang, J. & Mizumoto, A., "Examining the relationship between the L2 motivational self system and technology acceptance model post ChatGPT introduction and utilization," Comput. Educ. Artif. Intell., vol. 7, pp. 100302, 2024.

[37] Huang, X., Cui, Y., Jia, D., Ma, X., Wang, Z. & Cui, R., "Weaving Cognition, Emotion, Service, and Society: Unpacking Chinese Consumers' Behavioral Intention of GenAI-Supported Clothing Customization Services," Systems, vol. 13, no. 9, pp. 829, 2025.

[38] Huynh, M. T. & Aichner, T., "In generative artificial intelligence we trust: unpacking determinants and outcomes for cognitive trust," AI Soc., 2025.

[39] Ittefaq, M., Zain, A., Arif, R., Ahmad, T., Khan, L. & Seo, H., "Factors influencing international students' adoption of generative artificial intelligence: The mediating role of perceived values and attitudes," J. Int. Stud., vol. 15, no. 7, pp. 127–154, 2025.

[40] Jaidka, K., Chen, T., Chesterman, S., Hsu, W., Kan, M. Y., Kankanhalli, M., et al., "Misinformation, disinformation, and generative AI: Implications for perception and policy," Digit. Gov. Res. Pract., vol. 6, no. 1, pp. 1–15, 2025.

[41] Karagöz, A., "Yapay zekâ uygulamalarında güven, sorumluluk ve etik değerlendirmeler," İstanbul Univ. Sosyal Bilimler Derg., vol. 19, no. 3, pp. 221–239, 2024.

[42] Kasneci, E., et al., "ChatGPT for Good? On Opportunities and Challenges of Large Language Models for Education," Learn. Individ. Differ., vol. 103, pp. 102274, 2023.

[43] Kim, J., Klopfer, M., Grohs, J. R., Eldardiry, H., Weichert, J., Cox, L. A. & Pike, D., "Examining faculty and student perceptions of generative AI in university courses," Innov. Higher Educ., 2025.

[44] Klar, M., "Using ChatGPT is easy, using it effectively is tough? A mixed methods study on K-12 students' perceptions, interaction patterns, and support for learning with generative AI chatbots," Smart Learn. Environ., vol. 12, no. 1, pp. 32, 2025.

[45] Koteczki, R. & Balassa, B. E., "Exploring Generation Z's Acceptance of Artificial Intelligence in Higher Education: A TAM and UTAUT-Based PLS-SEM and Cluster Analysis," Educ. Sci., vol. 15, no. 8, pp. 1044, 2025.

[46] Kurtuldu, G. & Seyhun, S., "Genişletilmiş teknoloji kabul modeli bağlamında mobil alışveriş uygulamalarının benimsenmesini etkileyen faktörler," Trakya Univ. Sosyal Bilimler Derg., 2020.

[47] Lee, A. T., Ramasamy, R. K. & Subbarao, A., "Understanding psychosocial barriers to healthcare technology adoption: A review of TAM and UTAUT frameworks," Healthcare, vol. 13, no. 3, 2025.

[48] Lee, S. H., Velez, J. A. & Noh, D. W., "Beyond Prompt Engineering: Exploring Collaborative Dialogue with Generative AI for Problem-Solving," Cyberpsychol. Behav. Soc. Netw., 2025.

[49] Lenart, R., Sypniewska, B. A., Chen, J. & Janowski, K., "Antecedents of students' behavioural intention to use generative artificial intelligence: Quantitative research," Entrep. Bus. Econ. Rev., vol. 13, no. 1, pp. 7–21, 2025.

[50] Li, K. C., Chong, G. H. L., Wong, B. T. M. & Wu, M. M. F., "A TAM-Based Analysis of Hong Kong Undergraduate Students' Attitudes Toward Generative AI in Higher Education and Employment," Educ. Sci., vol. 15, no. 7, pp. 798, 2025.

[51] Lim, J. S., Lee, C., Shin, D., Kim, J. & Zhang, J., "Perceived Stakeholder Engagement in Corporate Data Responsibility (CDR) Communication and Its Relationship with Trust in Generative Artificial Intelligence Systems: The Mediating Role of Algorithmic and Institutional Responsibility," J. Public Relat. Res., 2025.

[52] Liu, Y., Wang, Q. & Lei, J., "Adopting Generative AI in Future Classrooms: A Study of Preservice Teachers' Intentions and Influencing Factors," Behav. Sci., vol. 15, no. 8, pp. 1040, 2025.

[53] Lv, D., Sun, R., Zhu, Q. & Qin, S., "Preconceived beliefs, different reactions: alleviating user switching intentions in service failures through priming GenAI beliefs," BMC Psychol., vol. 13, no. 1, pp. 552, 2025.

[54] Lyu, W., Zhang, S., Chung, T., Sun, Y. & Zhang, Y., "Understanding the practices, perceptions, and (dis) trust of generative AI among instructors: A mixed-methods study in the US higher education," Comput. Educ. Artif. Intell., vol. 8, pp. 100383, 2025.

[55] Ma, H., You, Q., Jin, Z., Liu, X. & Chen, Z., "Exploring the role of generative AI in international students' sociocultural adaptation: a cognitive-affective model," Front. Artif. Intell., vol. 8, pp. 1615113, 2025.

[56] Mahmoud, A. B., Kumar, V. & Spyropoulou, S., "Identifying the Public's Beliefs about Generative Artificial Intelligence: A Big Data Approach," IEEE Trans. Eng. Manage., 2025.

[57] McIlroy, D., Şahin, S. & Ursavaş, Ö., "Öğretmenler için teknoloji kabul ölçeği (Ö-TKÖ)," Eğitimde Kuram ve Uygulama, vol. 10, no. 4, 2014.

[58] Miranda, F. J. & Chamorro-Mera, A., "The impact of gender and age on HEI teachers' intentions to use generative artificial intelligence tools," Inf. Technol. Learn. Tools, vol. 108, no. 4, pp. 112, 2025.

[59] Mirriahi, N., Marrone, R., Barthakur, A., Gabriel, F., Colton, J., Yeung, T. N., et al., "The relationship between students' self-regulated learning skills and technology acceptance of GenAI," Australas. J. Educ. Technol., 2025.

[60] Mitchell, M. & Krakauer, D., "The Debate over Understanding in AI's Large Language Models," Proc. Natl. Acad. Sci., vol. 120, no. 3, pp. e2215909120, 2023.

[61] Mohamed, M. G., Goktas, P., Khalaf, S. A., Kucukkaya, A., Al-Faouri, I., Seleem, E. A. E. S., et al., "Generative artificial intelligence acceptance, anxiety, and behavioral intention in the middle east: a TAM-based structural equation modelling approach," BMC Nurs., vol. 24, no. 1, pp. 703, 2025.

[62] Munir, M. S., Proddatoori, S., Muralidhara, M., Dena, T. M., Saad, W., Han, Z. & Shetty, S., "A Trust-By-Learning Framework for Secure 6G Wireless Networks Under Native Generative AI Attacks," IEEE Open J. Commun. Soc., 2025.

[63] Nasr, N. R., Tu, C. H., Werner, J., Bauer, T., Yen, C. J. & Sujo-Montes, L., "Exploring the Impact of Generative AI ChatGPT on Critical Thinking in Higher Education: Passive AI-Directed Use or Human–AI Supported Collaboration?," Educ. Sci., vol. 15, no. 9, pp. 1198, 2025.

[64] Nevárez Montes, J. & Elizondo-Garcia, J., "Faculty acceptance and use of generative artificial intelligence in their practice," in Frontiers in Education, vol. 10, pp. 1427450, 2025.

[65] Özdemir, A. & Yolcu, H., "E-belediyecilik hizmetlerinin teknoloji kabul modeli ile değerlendirilmesi: Palandöken Belediyesi örneği," Çankırı Karatekin Univ. Sosyal Bilimler Enst. Derg., 2020.

[66] Petty, R. E., Cacioppo, J. T. & Schumann, D., "Central and peripheral routes to advertising effectiveness: The moderating role of involvement," J. Consum. Res., vol. 10, no. 2, pp. 135–146, 1983.

[67] Piller, F. T., Srour, M. & Marion, T. J., "Generative AI, innovation, and trust," J. Appl. Behav. Sci., vol. 60, no. 4, pp. 613–622, 2024.

[68] Pournik, O., Mukherjee, T., et al., "Patients vs. healthcare providers: A comparative analysis of technology acceptance using the UTAUT model," Stud. Health Technol. Inform., 2025.

[69] Rafi, M. S. & Amjad, I., "The role of generative AI in writing doctoral dissertation: perceived opportunities, challenges, and facilitating strategies to promote human agency," Discov. Educ., vol. 4, no. 1, pp. 165, 2025.

[70] Riley, C., Al-Refai, O., Reyes, Y. C., & Hammad, E., Human-AI Interactions: Cognitive, Behavioral, and Emotional Impacts., 2025

[71] Rix, J., Berger, B., Hess, T. & Rzepka, C., "The Algorithm Discount: Explaining Consumers' Valuation of Human-versus Algorithm-Created Digital Products," J. Manage. Inf. Syst., vol. 42, no. 2, pp. 633–668, 2025.

[72] Sallam, M., Elsayed, W., Al-Shorbagy, M., Barakat, M., El Khatib, S., Ghach, W., et al., "ChatGPT usage and attitudes are driven by perceptions of usefulness, ease of use, risks, and psycho-social impact: a study among university students in the UAE," in Frontiers in Education, vol. 9, pp. 1414758, 2024.

[73] Sançar, B. & Kayserili, A., "Evaluation of acceptance of hospital information management system among nurses through technology acceptance model," Eurasian J. Health Technol. Assess., 2025.

[74] Schäfer, M. S., Kremer, B., Mede, N. G. & Fischer, L., "Trust in science, trust in ChatGPT? How Germans think about generative AI as a source in science communication," J. Sci. Commun., vol. 23, no. 9, pp. A04, 2024.

[75] Shata, A. & Hartley, K., "Artificial intelligence and communication technologies in academia: faculty perceptions and the adoption of generative AI," Int. J. Educ. Technol. Higher Educ., vol. 22, no. 1, pp. 14, 2025.

[76] Shen, X., Mo, X. & Xia, T., "Exploring the attitude and use of GenAI-image among art and design college students based on TAM and SDT," Interact. Learn. Environ., vol. 33, no. 2, pp. 1198–1215, 2025.

[77] Shneiderman, B., Human-Centered AI: A Path to Better Machines and Better Humans, Oxford University Press, 2023.

[78] Soliman, M., Ali, R. A., Khalid, J., Mahmud, I. & Ali, W. B., "Modelling continuous intention to use generative artificial intelligence as an educational tool among university students: Findings from PLS-SEM and ANN," J. Comput. Educ., 2024.

[79] Strzelecki, A., "ChatGPT awareness, acceptance, and adoption in higher education: The role of ChatGPT trust as a preceding construct," Int. J. Educ. Technol. Higher Educ., vol. 21, pp. 48, 2024.

[80] Şahin, S. & Kardaş, M., "Yapay zekâ etiği ve toplumsal etkiler: Üretken modeller bağlamında bir değerlendirme," Hacettepe Univ. İletişim Fak. Derg., vol. 40, no. 1, pp. 98–116, 2023.

[81] Şen, M., "Yapay zekâ çağında insan-merkezli bilişsel dönüşüm: Teknolojiyle düşünmek," Bilim ve Felsefe Derg., vol. 12, no. 2, pp. 211–234, 2023.

[82] Tantivejakul, N., Chantharasombat, J. & Kongpolphrom, W., "Voices of the Future: Exploring Students' Views on the Use of GenAI in Academic and Professional PR Writing," LEARN J. Lang. Educ. Acquis. Res. Netw., vol. 17, no. 2, pp. 511–537, 2024.

[83] Tulang, A. B., "Synergy of Voluntary GenAI Adoption in Flexible Learning Environments: Exploring Facets of Student-Teacher Interaction Through Structural Equation Modeling," Eur. J. Educ. Res., vol. 14, no. 3, pp. 829–845, 2025.

[84] Tunç, R. A. & Görmez, A., "Literary theory, stylistics and cognitive poetics," Çankaya Univ. J. Humanit. Soc. Sci., vol. 15, no. 1, 2021.

[85] Ursavaş, Ö. F., Yalçın, Y., İslamoğlu, H., Bakır-Yalçın, E. & Cukurova, M., "Rethinking the importance of social norms in generative AI adoption: investigating the acceptance and use of generative AI among higher education students," Int. J. Educ. Technol. Higher Educ., vol. 22, no. 1, pp. 38, 2025.

[86] Van Es, K. & Nguyen, D., "Your friendly AI assistant: the anthropomorphic self-representations of ChatGPT and its implications for imagining AI," AI Soc., vol. 40, no. 5, pp. 3591–3603, 2025.

[87] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., *et al*., "Attention is all you need," *Advances in Neural Information Processing Systems*, vol. 30, pp. 5998–6008, 2017.

[88] Venkatesh, V. & Davis, F. D., "A theoretical extension of the technology acceptance model: TAM2," Manage. Sci., vol. 46, no. 2, pp. 186–204, 2000.

[89] Venkatesh, V., Morris, M. G., Davis, G. B. & Davis, F. D., "User acceptance of information technology: Toward a unified view," MIS Q., vol. 27, no. 3, pp. 425–478, 2003.

[90] Wang, A., Piao, M., Zhou, Y., Ma, H., Tang, X., Li, S. & Pei, R., "The acceptance of using large language models among older adults: A study based on TAM," Stud. Health Technol. Inform., 2024.

[91] Wang, F., Li, N., Cheung, A. C. & Wong, G. K., "In GenAI we trust: An investigation of university students' reliance on and resistance to generative AI in language learning," Int. J. Educ. Technol. Higher Educ., vol. 22, no. 1, pp. 59, 2025.

[92] Wang, Y. & Zhang, W., "Factors Influencing the Adoption of Generative AI for Art Designing among Chinese Generation Z: A structural equation modeling approach," IEEE Access, vol. 11, pp. 143272–143284, 2023.

[93] Wu, H. & Liu, W., "Exploring mechanisms of effective informal GenAI-supported second language speaking practice: a cognitive-motivational model of achievement emotions," Discov. Comput., vol. 28, no. 1, pp. 119, 2025.

[94] Xiao, L., Pyng, H. S., Ayub, A. F. M., Zhu, Z., Gao, J. & Qing, Z., "University students' usage of generative artificial intelligence for sustainability: A cross-sectional survey from China," Sustainability, vol. 17, no. 8, pp. 3541, 2025.

[95] Zhang, J., et al., "The effect of ChatGPT on students' learning performance in higher education: Evidence from a randomized controlled trial," Humanit. Soc. Sci. Commun., vol. 12, pp. 4787, 2025.

[96] Zou, B., Wang, C., He, H., Li, C., Purwanto, E. & Wang, P., "Enhancing EFL writing with visualised GenAI feedback: A cognitive affective theory of learning perspective on revision quality, emotional response, and human-computer interaction," Learn. Motiv., vol. 91, pp. 102158, 2025.

Optimized Dimensionality Reduction Using Metaheuristic and Class Separability

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***Abstract*—The high dimensionality of modern datasets presents significant challenges for machine learning, including increased computational cost, model complexity, and risk of overfitting. This study introduces a metaheuristic framework for optimized dimensionality reduction to identify the highly discriminative feature subsets. The proposed method (KDR-PSO) combines a Particle Swarm Optimization (PSO) algorithm with the K-Nearest Neighbors Distance Ratio (KDR) as a filter-based objective function. This metric quantitatively assesses class separability within a feature subspace by computing the ratio of the average distance from a sample to neighbors in other classes versus those in its own class. Maximizing this ratio with a penalty for model size, KDR-PSO automates the discovery of parsimonious feature sets that maximize inter-class discrimination. The method is computationally efficient, naturally lending itself to multi-class classification and avoiding the prohibitive cost associated with classifier-in-the-loop wrappers. Experimental results on benchmark gene expression and image datasets show that KDR-PSO can achieve better dimensionality reduction compared to baselines and other algorithms, such as winning a better or at least similar performing models with decreased features. This approach is a strong and pragmatic technique to improve the model interpretability and generalizability for high-dimensional regions.**

***Keywords*—Dimensionality reduction; Particle Swarm Optimization; metaheuristics; K-Nearest Neighbors; class separability; high-dimensional data**

I. Introduction

The curse of dimensionality is a well-known problem in modern machine learning, especially in fields such as bioinformatics, computer vision, and text mining, where datasets often contain thousands of features with comparatively few samples. The main objective of the Feature selection (FS) is to select the most informative subset of features, which leads to models that are simpler, faster to train, less prone to overfitting, and more interpretable [1].

FS techniques are basically categorized into three types, which are filter, wrapper, and embedded methods [2]. Filter methods, such as correlation, mutual information, and variance-based selection, are computationally active but ignore feature interdependencies or classifier behavior [3]. Wrapper methods—such as recursive feature elimination (RFE) or evolutionary search guided by classifier accuracy— can accomplish higher predictive performance, but with high cost for training the repeated model, which becomes unreasonable in high-dimensional datasets [4,5,6]. Embedded techniques, such as Least Absolute Shrinkage and Selection Operator (LASSO), integrate feature selection into model training but depend basically on model choice [7].

In the last several years, metaheuristic optimization has become important in feature selection for its ability to examine large search spaces effectively [8, 9]. One of these metaheuristic optimizations is a PSO, a population-based metaheuristic, that has been successfully adapted for wrapper-based feature selection [10] and its binary variants (BPSO) that have been widely selected due to their simple execution and powerful global search abilities [7,11]. The requirement for classifier retraining via cross-validation for every fitness evaluation, which results in a high computational cost, is a significant drawback of conventional PSO-based wrappers [8].

New studies have tried to address this drawback by hybridization and adaptive mechanisms [1], but getting an optimal trade-off between search quality and computational efficiency remains challenging. To control this limitation, we suggest KDR-BPSO, a hybrid metaheuristic framework that maintains the exploration power of BPSO while deleting the classifier-in-the-loop dependency. The method introduces a KDR as a filter-based, model-free objective function that measures class separability directly inside a subspace of features. Specifically, KDR calculates the ratio of the mean distance between samples and their nearest neighbors of other classes to the mean distance within their own class—motivating subsets that maximize inter-class distance and minimize intra-class variability. By optimizing this ratio by a dimensionality penalty, KDR-BPSO automatically finds dense and discriminative feature subsets without repeated classifier training.

This approach extends across the gap between filter efficiency and wrapper accuracy, introducing a computationally scalable, multi-class-capable, and interpretable solution for high-dimensional feature selection. Empirical studies on gene expression and image datasets demonstrate that KDR-BPSO gains better and superior performance compared to traditional filter, wrapper, and embedded methods while basically reducing feature dimensionality and runtime [7, 11, 12]. The proposed framework gives a robust, efficient, and generalizable tool for dimensionality reduction in modern data-intensive applications. The KDR metric directly measures the inherent separability of classes in the selected feature space. By leading the PSO swarm to maximize KDR, the proposed method efficiently gets the optimal feature subsets, that are

optimal for distance-based classifiers (like KNN itself) and useful for other classifiers, without the computational cost of inner model training. This lines up with some of the recent efforts in joining distance-based separability metrics with metaheuristic feature selection techniques to enhance performance on high-dimensional problems [1, 5, 10].

The proposed feature selection methodology combines Binary Particle Swarm Optimization with a novel K-nearest neighbor Distance Ratio fitness function. The framework is designed to select the optimal feature subsets that maximize the classification performance simultaneously, improve geometric separability, and keep feature parsimony. The proposed approach faces limitations of conventional filter and wrapper methods by combining both statistical and geometric criteria into a unified optimization framework.

The basic innovation reflected in the multi-objective fitness function that balances three critical sides of feature quality: predictive accuracy measured through cross-validation, class separability measured via distance ratios, and subset compactness enforced through regularization. This evaluation confirms that the selected features obtain high classification performance and show strong discriminative characteristics in the reduced feature space.

The rest of this study proceeds as follows: Section II reviews the related work. Section III describes the complete PSO-KDR framework, including an overview of the Particle Swarm Optimization (PSO) algorithm and the corresponding implementation procedure, followed by Section IV that presents a description of the datasets used and the experimental results and analysis. Finally, Section V concludes the study.

II. Related Work

Recent Dimensionality reduction and Metaheuristic-based feature selection have been widely studied over the past years. Particle Swarm Optimization (PSO) was one of the most frequently used search strategies. Modern systematic reviews emphasized both understanding of the field and its common limitations. A review contained more than a hundred studies on metaheuristic feature selection and showed that most studies depended on wrapper or hybrid filter–wrapper strategies connected to classifier performance, which can be computationally expensive, as introduced by Al-Shalif et al. [13]. By contrast, Akinola et al. [14] showed that filter-based metaheuristic methods, while more efficient, have been comparatively neglected, particularly in multiclass and high-dimensional scenarios. Bassi et al. [15] noted that existing filter-based approaches typically depend on traditional relevance measures such as mutual information or chi-square statistics rather than directly capturing class separability.

By PSO-driven feature selection, present methods mainly optimize inexplicit distance heuristics or classifier-oriented objectives. Shafipour et al. [16] presented a PSO-based feature selection method that used a particle distance ranking in a multi-objective framework to equate the classification performance and the subset size, but class separability in their approach is addressed indirectly through classification accuracy rather than through an explicit geometric measure. Particle Swarm Optimization (PSO) was used to improve distance metrics for KNN classification, where feature weights were modified to reduce classification errors introduced by Jurecek in [17]. Although effective, this strategy focuses on metric learning instead of selecting a compact feature subset and still relies on classifier evaluation. Recent work, such as Boolean Operator–based Particle Swarm Optimization (BOPSO) feature selection study for emotion analysis introduced by Sharma et al. [18], displayed improvement in the optimization performance, but it continued depending on classifier-based objectives, which constrained computational efficiency and scalability.

For all these studies, direct KNN-based inter-/intra-class distance ratio objectives with integrated feature-count penalties are extremely absent. The proposed KDR-PSO is located as a filter-based, PSO-driven dimensionality reduction method that immediately optimizes class separability through a K-Nearest Neighbors Distance Ratio (KDR). Different from wrapper and hybrid approaches, KDR-PSO rates the candidate subsets using only distance statistics derived from the data, preventing classifier-in-the-loop training. Additionally, it merges a direct subset-size penalty into a single scalar objective, supporting the most close-fisted feature sets without needing post hoc Pareto-front selection.

The proposed work handles a lack of PSO-driven methods that optimize a KNN-based distance–ratio separability measure and feature-set compactness via a purely filter-based framework, mainly for scalable multi-class and high-dimensional problems.

III. Proposed PSO with KDR for Feature Selection

The proposed framework integrates the PSO algorithm with KDR as a fitness function. The goal of the framework is to find the best feature subsets that improve separability and maximize classification performance. The fitness function proposed in this work balances three key aspects of good feature selection: keeping the feature set small, ensuring classes are well separated based on distance ratios, and achieving high prediction accuracy using cross-validation to achieve effective classification and distinguish between different classes.

Fig. 1 illustrates the overall workflow of the proposed KDR-PSO framework for feature selection. Starting from high-dimensional input data, the dataset is first preprocessed and then passed to a PSO mechanism that iteratively explores candidate feature subsets. Each particle, representing a binary feature selection vector, is evaluated using a hybrid fitness function that integrates the KDR, classification accuracy, and a penalty term to control subset size. Guided by personal and global best solutions, the swarm progressively refines the search until convergence, yielding a compact and highly discriminative feature subset that is subsequently used for final classification and performance evaluation.

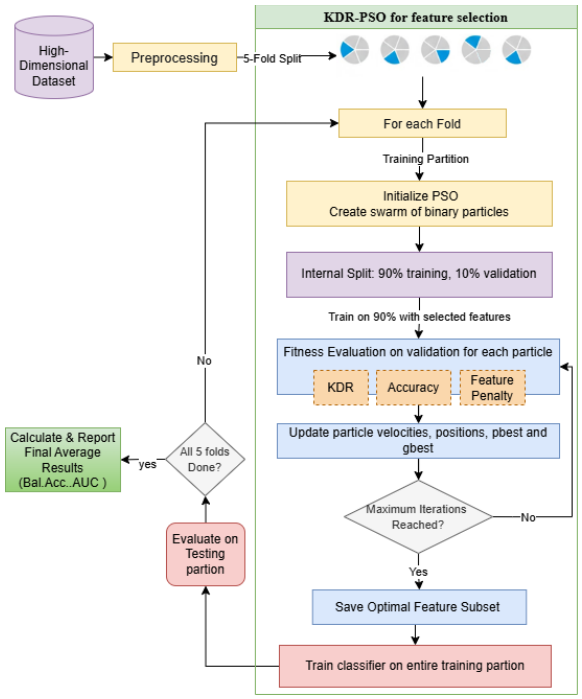


Fig. 1. Proposed KDR-PSO framework.

A. Particle Swarm Optimization

The PSO algorithm begins by giving each particle a random starting point and some initial velocity. As the process goes on, every particle learns from what it has tried before and from the results of nearby particles. Step by step, they move closer to a good solution. In PSO, each particle stands for one possible set of features in the search space, and its position is written as a binary vector $x_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$, where D is the total number of features in the dataset, and $x_i \in \{0,1\}$ indicates whether the jth feature is selected (1) or not selected (0). The velocity of particle i is denoted as $v_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$, which determines the probability of changing the feature selection state.

A predefined maximum velocity (v_{max}) restricts the velocity of particles within a certain range $v_{id}^t \in [-v_{max}, v_{max}]$ to maintain stability. Each particle memorizes its best previous position as personal best (*pbest*), and the best position found by the entire swarm is referred to as global best (*gbest*). The velocity and position of each particle are updated according to the following Eq. (1) and Eq. (2) [19]:

$$v_{id}^{(t+1)} = w \times v_{id}^t + c_1 \times r_{1i} \times (p_{id} - x_{id}^t) + c_2 \times r_{2i} \times (p_{gd} - x_{id}^t) \quad (1)$$

$$x_{id}^{(t+1)} = \begin{cases} 1, & \text{if rand}() < \frac{1}{1+e^{-v_{id}^{(t+1)}}} \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

where, t is the iteration number, w is the inertia weight (decreasing linearly from 0.9 to 0.4), c_1 and c_2 are cognitive and social acceleration constants, respectively, r_{1i} and r_{2i} are random numbers uniformly distributed in [0, 1], p_{id} and p_{gd} represent the dth elements of *pbest* and *gbest*, respectively.

In this study, each particle encodes a binary vector representing feature inclusion or exclusion. If the dataset contains N features, then the position vector length is N. Each bit in the vector takes a value of 1 (feature selected) or 0 (feature not selected). For instance, in a dataset with five features, a possible particle representation could be: x_i= [1, 0, 1, 0, 0]. This means that the first and third features are selected while the others are excluded. The PSO algorithm continuously updates these binary values to maximize the objective fitness function. Algorithm 1 shows the pseudo-code for PSO algorithm for feature selection.

Algorithm 1: Pseudo-code for PSO Algorithm for feature selection.

```
// Initialize swarm
For i = 1 to swarm_size:
    xi = random binary vector with ≥ 2 ones
    vi = random velocity vector
    pbesti = xi  // personal best
    pbest_fitnessi = -∞
End For
// Evaluate fitness based on equation 4 and update the best
For iter = 1 to max_iter:
    For each particle i:
        fitness = evaluate_fitness(xi)
        If fitness > pbest_fitnessi:
            pbesti = xi
            pbest_fitnessi = fitness
        End If
        If fitness > gbest_fitness
            gbest = xi
            gbest_fitness = fitness
        End If
    End For
    For each particle i:
        Update vi //Update velocity based on equation (1)
        Update xi //Update position using sigmoid equation (2)
// Ensure the minimum number of selected features
        While sum(xi) < 2:
            xi[random_index] = 1
        End While
    End For
End For
output gbest
```

B. Proposed PSO with KNN Distance Ratio (PSO_KDR)

Using classification accuracy as the sole objective function in feature selection often leads to overfitting and poor generalization, as it does not explicitly account for the structural separability of data classes. A feature subset may achieve high accuracy on the training data, but fail to maintain clear class boundaries in the feature space. To overcome this, the proposed method uses the K-Nearest Neighbor Distance Ratio as an additional discriminative criterion within PSO. By comparing the average distances between neighbors of the same class and neighbors of other classes, the KDR calculates the relative distance between classes. The algorithm looks for feature subsets that enhance class separability while achieving good prediction performance by combining accuracy and KDR in a hybrid fitness formulation.

The improved fitness design enables the PSO to find compact yet discriminative feature subsets, avoid local optima, and better explore the search space. The suggested method thus

enhances the stability and robustness of the classification of certain features across several datasets. For each sample i, let:

$\bar{d}_{\text{same}}(i)$ is the average distance to K-Nearest Neighbors that belong to the same class.

$\bar{d}_{\text{diff}}(i)$ is the average distance to K-Nearest Neighbors from different classes.

The KDR is calculated as explained by Eq. (3):

$$KDR(S) = \frac{1}{n}\sum_{i=1}^{n} \frac{\bar{d}_{diff}(i)}{\bar{d}_{same}(i)+\epsilon} \quad (3)$$

where, n is the total number of samples and $\epsilon = 10^{-8}$ is a small constant to prevent division by zero. The overall fitness function is calculated as in Eq. (4):

$$F(S) = \beta \times \text{Accuracy}(S) + \alpha \times KDR_{norm}(S) - \lambda \times \frac{|S|}{d} \quad (4)$$

where, *Accuracy(S)* is the classification accuracy evaluated using 5-fold KNN, $KDR_{\text{norm}}(S)$ is the normalized KDR value, $|S|$ is the number of selected features, $\beta = 0.95, \alpha = 0.05$ are weighting factors, and λ=0.001 controls the penalty for subset size.

IV. Experimental Results

A. Datasets and Experimental Setup

Experiments were conducted on ten available datasets to evaluate the proposed method, as summarized in Table I. These datasets are from different application domains, including biomedical, financial, environmental, and computer vision, to achieve an evaluation across different real-world applications.

TABLE I SUMMARY OF DATASETS USED

Dataset Name	Domain	Samples	Features	Classes	*Reference*
Climate_model	Climate	540	18	2	[20]
Credit	Finance	690	14	2	[21]
Heart	Medical	270	13	2	[22]
Ionosphere	Physics	351	34	2	[23]
Leukemia	Gene Expression	72	7,129	2	[24]
QSAR	Chemistry	1,055	41	2	[25]
Satellite	Remote Sensing	6,435	36	6	[26]
Segment	Computer Vision	2,310	19	7	[27]
Splice	Bioinformatics	3,190	62	3	[28]
Vehicle	Object Recognition	846	18	4	[29]

The datasets used in this study vary widely in both size and structure — from small medical datasets with only a few samples to large, high-dimensional gene expression datasets containing thousands of features. This diversity shows the effectiveness of the proposed feature selection method. All experiments were performed on a desktop computer equipped with an Intel Core i7 processor, 16 GB of RAM, and a 64-bit Windows operating system. The proposed KDR-PSO algorithm, along with all comparative methods, was implemented using the Python programming language.

The KNN with k=5 was employed, and performance assessed using 5-fold stratified cross-validation. The parameters of the PSO-KDR algorithm were determined through an iterative sensitivity analysis: initial parameter ranges were adopted from the literature, then testing of multiple values across preliminary runs to identify the optimal configuration. The finalized parameters, fixed for all experiments, are as follows:

- swarm size= 20
- maximum iterations = 40.
- w (inertia weight) from 0.9 to 0.4 decreased each iteration.
- c1=c2=2 (acceleration coefficients)
- α=0.05 and β=0.95 (The fitness function weighting factors)
- λ=0.001 (small penalty factor).

B. Results and Analysis

The Results performed using 5-fold cross-validation on ten publicly available datasets. The performance comparison includes Balanced Accuracy (Bal. Acc), F1-Score, Precision, and AUC (Area Under the Curve). Also, the number of selected features (Features). For each metric, the mean ± standard deviation is presented. The best results for each metric are highlighted in bold. The comparison includes four methods:

1) Baseline: KNN using all features without selection.
2) Filter (IG): Features selected based on Information Gain ranking, independently of the classifier.
3) PSO: Particle Swarm Optimization for feature selection.
4) PSO-KDR: The proposed method combining PSO with the KDR-based fitness function.

As shown in Table II, the PSO-KDR outperforms other methods across most tested datasets in terms of classification accuracy and feature selection, where PSO-KDR using Leukemia dataset achieves Bal. Acc of 0.962 ± 0.006, overperforming PSO (0.920 ± 0.025) and the filter-based approach (0.882 ± 0.033), while maintaining a compact subset of features. In addition, the Heart and Credit datasets, PSO-KDR demonstrates superior F1-scores and AUC values.

In terms of feature selection, PSO-KDR identifies smaller feature subsets compared to the baseline, where in the Climate_model dataset, it reduces the feature count from 18 to around 7 while improving the AUC from 0.797 to 0.881. PSO-KDR maintains high performance stability across all datasets, as indicated by its relatively low standard deviations.

A t-test conducted between PSO-KDR and the PSO across all datasets, the results show a statistically significant improvement in Bal. Accuracy with $p < 0.05$ for 8 out of 10 datasets. The results show that PSO-KDR achieves trade-off between feature selection and classification performance, indicating its adaptability to diverse datasets.

Fig. 2 illustrates the convergence behavior of PSO-KDR compared to PSO method across three datasets (Leukemia, Heart, and Climate_model).

TABLE II COMPREHENSIVE PERFORMANCE COMPARISON OF FEATURE SELECTION METHODS

Dataset	*Method*	*Bal. Accuracy*	*F1-Score*	*Precision*	*AUC*	*#Features*
Climate_model	Baseline	0.538 ± 0.011	0.545 ± 0.018	0.700 ± 0.091	0.797 ± 0.018	18 ± 0
	Filter (IG)	0.635 ± 0.060	0.667 ± 0.067	0.778 ± 0.059	0.835 ± 0.046	5 ± 2
	PSO	0.680 ± 0.031	0.733 ± 0.030	0.902 ± 0.046	0.869 ± 0.031	8 ± 1
	PSO-KDR	**0.705 ± 0.017**	**0.767 ± 0.016**	**0.944 ± 0.023**	**0.881 ± 0.021**	7 ± 1
Credit	Baseline	0.672 ± 0.012	0.673 ± 0.012	0.685 ± 0.013	0.728 ± 0.012	14 ± 0
	Filter (IG)	0.777 ± 0.059	0.775 ± 0.058	0.784 ± 0.059	0.845 ± 0.064	4 ± 2
	PSO	0.858 ± 0.010	0.857 ± 0.010	0.859 ± 0.008	0.891 ± 0.009	4 ± 0
	PSO-KDR	**0.864 ± 0.003**	**0.863 ± 0.003**	**0.865 ± 0.004**	**0.892 ± 0.011**	4 ± 1
Heart	Baseline	0.646 ± 0.020	0.646 ± 0.021	0.650 ± 0.020	0.691 ± 0.021	13 ± 0
	Filter (IG)	0.765 ± 0.051	0.765 ± 0.054	0.779 ± 0.048	0.833 ± 0.047	3 ± 1
	PSO	0.823 ± 0.013	0.825 ± 0.013	0.834 ± 0.011	0.865 ± 0.017	5 ± 1
	PSO-KDR	**0.842 ± 0.008**	**0.844 ± 0.007**	**0.849 ± 0.007**	**0.875 ± 0.016**	5 ± 2
Ionosphere	Baseline	0.774 ± 0.011	0.794 ± 0.011	0.869 ± 0.005	0.910 ± 0.006	34 ± 0
	Filter (IG)	0.828 ± 0.025	0.847 ± 0.023	0.896 ± 0.012	0.928 ± 0.010	9 ± 4
	PSO	**0.854 ± 0.012**	**0.872 ± 0.010**	**0.911 ± 0.005**	**0.928 ± 0.007**	10 ± 3
	PSO-KDR	0.852 ± 0.015	0.869 ± 0.014	0.908 ± 0.008	0.926 ± 0.010	9 ± 2
Leukemia	Baseline	0.840 ± 0.025	0.859 ± 0.026	0.927 ± 0.010	0.976 ± 0.017	2938 ± 0
	Filter (IG)	0.882 ± 0.033	0.899 ± 0.031	0.941 ± 0.018	0.982 ± 0.017	852 ± 350
	PSO	0.920 ± 0.025	0.934 ± 0.022	0.960 ± 0.014	0.985 ± 0.013	1431 ± 20
	PSO-KDR	**0.962 ± 0.006**	**0.969 ± 0.005**	**0.981 ± 0.003**	**0.993 ± 0.009**	1455 ± 33
QSAR	Baseline	0.797 ± 0.008	0.791 ± 0.008	0.787 ± 0.008	0.865 ± 0.007	41 ± 0
	Filter (IG)	0.783 ± 0.020	0.782 ± 0.020	0.784 ± 0.020	0.855 ± 0.018	11 ± 5
	PSO	0.836 ± 0.011	0.835 ± 0.009	0.836 ± 0.008	0.899 ± 0.008	18 ± 3
	PSO-KDR	**0.846 ± 0.007**	**0.845 ± 0.005**	**0.845 ± 0.006**	**0.900 ± 0.006**	20 ± 3
Satellite	Baseline	0.886 ± 0.002	0.888 ± 0.002	0.890 ± 0.002	0.978 ± 0.001	36 ± 0
	Filter (IG)	0.855 ± 0.020	0.859 ± 0.018	0.865 ± 0.016	0.963 ± 0.008	10 ± 4
	PSO	0.887 ± 0.003	0.890 ± 0.003	0.894 ± 0.003	0.977 ± 0.001	22 ± 2
	PSO-KDR	**0.889 ± 0.002**	**0.893 ± 0.002**	**0.897 ± 0.002**	**0.977 ± 0.002**	20 ± 2
Segment	Baseline	0.933 ± 0.004	0.932 ± 0.004	0.933 ± 0.004	0.992 ± 0.001	19 ± 0
	Filter (IG)	0.870 ± 0.032	0.869 ± 0.033	0.871 ± 0.032	0.972 ± 0.009	5 ± 2
	PSO	0.962 ± 0.002	0.961 ± 0.002	0.962 ± 0.002	0.994 ± 0.001	8 ± 1
	PSO-KDR	**0.962 ± 0.002**	**0.962 ± 0.002**	**0.962 ± 0.002**	**0.993 ± 0.001**	7 ± 1
Splice	Baseline	0.701 ± 0.007	0.679 ± 0.008	0.753 ± 0.009	0.807 ± 0.006	60 ± 0
	Filter (IG)	0.795 ± 0.022	0.787 ± 0.025	0.819 ± 0.015	0.882 ± 0.019	17 ± 7
	PSO	0.797 ± 0.004	0.790 ± 0.004	0.817 ± 0.010	0.876 ± 0.013	24 ± 3
	PSO-KDR	**0.801 ± 0.009**	**0.794 ± 0.010**	**0.823 ± 0.011**	**0.882 ± 0.013**	24 ± 4
Vehicle	Baseline	0.643 ± 0.012	0.633 ± 0.011	0.629 ± 0.012	0.857 ± 0.008	18 ± 0
	Filter (IG)	0.555 ± 0.044	0.550 ± 0.042	0.549 ± 0.040	0.795 ± 0.031	5 ± 2
	PSO	0.717 ± 0.011	0.711 ± 0.010	0.708 ± 0.010	0.898 ± 0.008	10 ± 1
	PSO-KDR	**0.731 ± 0.009**	**0.725 ± 0.008**	**0.724 ± 0.008**	**0.902 ± 0.005**	10 ± 1

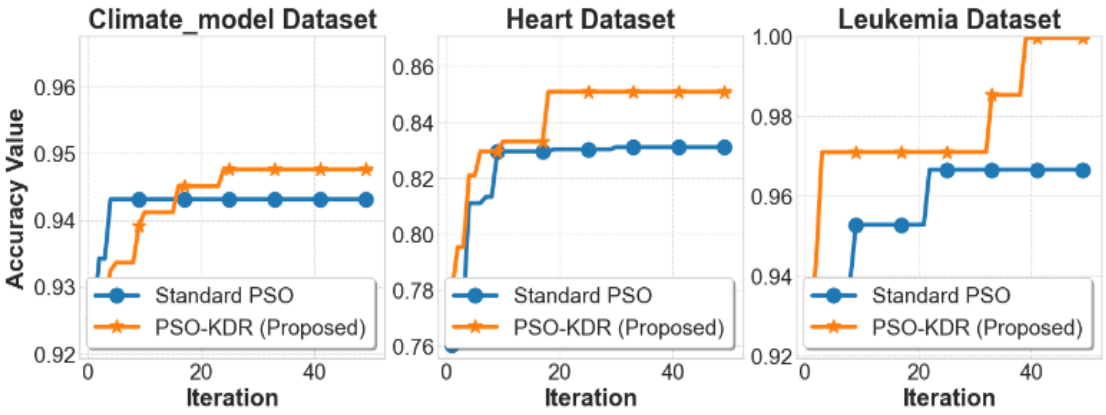


Fig. 2. Convergence curves of standard PSO vs. PSO-KDR.

The convergence curves show that PSO-KDR achieves faster and smoother fitness improvement over iterations that due to the guidance provided by the KDR that effectively balances global exploration and local refinement during the optimization process.

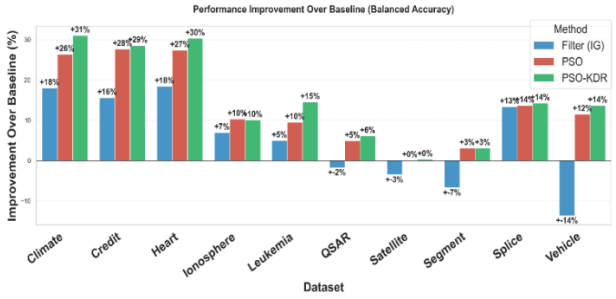


Fig. 3. Comparison of improvement over baseline.

As illustrated in Fig. 3, the comprehensive performance analysis across ten datasets shows the efficacy of various feature selection methods. Across the most tested datasets, all three evaluated feature selection techniques showed positive performance gains, with the most pronounced improvements observed in the Climate Model, Credit, and Heart datasets. The maximum performance enhancement reached +31.0% by PSO-KDR on the Climate_Model dataset.

PSO and its enhanced variant, PSO-KDR, show consistent superiority compared to conventional filter methods that achieved the maximum performance improvement across four datasets (Climate_model, Heart, Leukemia, and Vehicle), and the IG filter method exhibited inconsistent behavior, with performance degradation observed in certain datasets, such as Vehicle and Segment.

Fig. 4 shows the analysis of selected feature subset sizes across ten datasets. To handle high-dimensional datasets, the logarithmic scale is used. The minimal subsets across most of the datasets were selected by using the IG filter method, but its independence from classifier behavior sometimes caused performance unreliability, as shown in datasets such as Segment and Vehicle, which feature elimination causes less accuracy. The PSO and PSO-KDR wrapper methods gave more balanced feature selection behavior, keeping slightly larger but more discriminative subsets to maximize classification accuracy. This drift is usually evident in QSAR and Satellite, where keeping a moderate number of features gave higher results. The average computation time of the proposed KDR-PSO method ranged from approximately 3 to 8 seconds for low- and medium-dimensional datasets and from 2 to 6 minutes for high-dimensional gene expression datasets, depending on the number of features and optimization iterations.

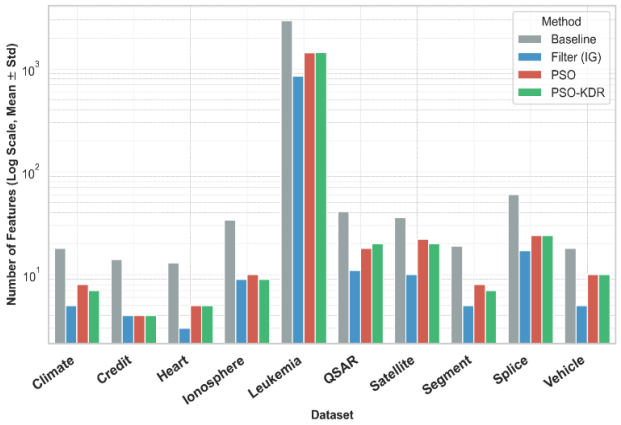


Fig. 4. Feature reduction comparison (Log scale).

PSO-KDR outperforms baseline, filter, and standard PSO methods by selecting compact, relevant feature subsets while improving classification performance. This shows that the KDR-based fitness function effectively balances feature relevance and predictive accuracy, especially on high-dimensional datasets. However, although effective, the proposed KDR-PSO method has some limitations. As a population-based optimization approach, its computational cost increases with data dimensionality and the number of PSO iterations.

V. Conclusion

This study proposed KDR-PSO, a new hybrid feature selection method that merges the global search capability of Binary Particle Swarm Optimization (BPSO) with a filter-based KNN Distance Ratio (KDR) objective function. The obtained results showed reaching the optimal balance between computational efficiency and feature selection performance in

the proposed algorithm KDR-PSO, that keeping high accuracy and clarity across various datasets.

In terms of classification accuracy and feature reduction, the proposed KDR-PSO method showed excellent performance, as shown by the values of the evaluation metrics F1-score, AUC, and precision. KDR-PSO joined filter-based techniques with a wrapper framework so it can handle strongly the computational limitations related to the wrapper techniques and make it practical for high-dimensional data. Furthermore, the proposed KDR-PSO got significant feature proximity while maintaining or improving the classification performance and selecting the minimum number of features. The logarithmic-scale comparisons of feature counts over datasets revealed and emphasized the wide variation in feature dimensions. The basic contribution for this work is building KNN Distance Ratio multi-Objective, that works as an effective mechanism for PSO search phases, accelerating in superior and low-cost computations for effective feature subset selection.

This study introduced successful implementation of KDR-PSO, that will be strong basis for a lot of future work. The expected research can include studying alternative distance metrics, expanding adaptive penalty terms, and executing the method to emerging domains that need efficient feature selection for high-dimensional data. This work introduces valuable advancement in terms of the feature selection literature, covering the gap between the strengths of filter and wrapper methods.

REFERENCES

[1] M. Alzaqebah and E. a. E. Ahmed, “Accelerated fuzzy min–max neural network and arithmetic optimization algorithm for optimizing hyper-boxes and feature selection,” Neural Computing and Applications, vol. 36, no. 4, pp. 1553–1568, Nov. 2023.

[2] C. Kuzudisli, B. Bakir-Gungor, N. Bulut, B. Qaqish, and M. Yousef, “Review of feature selection approaches based on grouping of features,” PeerJ, vol. 11, p. e15666, Jul. 2023.

[3] D. Patel and A. K. Saxena, “Feature Selection in High Dimension Datasets using Incremental Feature Clustering,” Indian Journal of Science and Technology, vol. 17, no. 32, pp. 3318–3326, Aug. 2024.

[4] M. Alzaqebah, N. Alrefai, E. a. E. Ahmed, S. Jawarneh, and M. K. Alsmadi, “Neighborhood search methods with Moth Optimization algorithm as a wrapper method for feature selection problems,” International Journal of Power Electronics and Drive Systems/International Journal of Electrical and Computer Engineering, vol. 10, no. 4, p. 3672, Mar. 2020.

[5] M. Alzaqebah et al., “Hybrid feature selection method based on particle swarm optimization and adaptive local search method,” International Journal of Power Electronics and Drive Systems/International Journal of Electrical and Computer Engineering, vol. 11, no. 3, p. 2414, Feb. 2021.

[6] F. Wang et al., “Navigating the microarray landscape: a comprehensive review of feature selection techniques and their applications,” Frontiers in Big Data, vol. 8, p. 1624507, Jul. 2025.

[7] L. Qu, W. He, J. Li, H. Zhang, C. Yang, and B. Xie, “Explicit and size-adaptive PSO-based feature selection for classification,” Swarm and Evolutionary Computation, vol. 77, p. 101249, Jan. 2023.

[8] A.-D. Li, B. Xue, and M. Zhang, “Multi-objective particle swarm optimization for key quality feature selection in complex manufacturing processes,” Information Sciences, vol. 641, p. 119062, May 2023.

[9] F. Ayeche and A. Alti, “Efficient feature selection in high dimensional data based on enhanced binary chimp optimization algorithms and machine learning,” Human-Centric Intelligent Systems, vol. 3, no. 4, pp. 558–587, Nov. 2023.

[10] M. K. Alsmadi et al., “An Enhanced particle swarm optimization for ITC2021 sports Timetabling,” Computers, Materials & Continua/Computers, Materials & Continua (Print), vol. 72, no. 1, pp. 1995–2014, Jan. 2022.

[11] K. Chen, W. Wang, F. Zhang, J. Liang, and K. Yu, “Correlation-Guided particle swarm optimization approach for feature selection in fault diagnosis,” IEEE/CAA Journal of Automatica Sinica, vol. 12, no. 11, pp. 2329–2341, May 2025.

[12] B. Ahadzadeh, M. Abdar, F. Safara, A. Khosravi, M. B. Menhaj, and P. N. Suganthan, “SFE: A simple, fast and efficient feature selection Algorithm for High-Dimensional Data,” arXiv (Cornell University), Mar. 2023.

[13] S. A. Al-Shalif et al., “A systematic literature review on meta-heuristic based feature selection techniques for text classification,” PeerJ Computer Science, vol. 10, p. e2084, Jun. 2024.

[14] O. O. Akinola, A. E. Ezugwu, J. O. Agushaka, R. A. Zitar, and L. Abualigah, “Multiclass feature selection with metaheuristic optimization algorithms: a review,” Neural Computing and Applications, vol. 34, no. 22, pp. 19751–19790, Aug. 2022.

[15] D. Bassi and H. Singh, “A comparative analysis of metaheuristic feature selection methods in software vulnerability prediction,” e-Informatica Software Engineering Journal, vol. 19, no. 1, p. 250103, Nov. 2024.

[16] M. Shafipour, A. Rashno, and S. Fadaei, “Particle distance rank feature selection by particle swarm optimization,” Expert Systems With Applications, vol. 185, p. 115620, Jul. 2021.

[17] M. Jureček and R. Lórencz, "Distance Metric Learning using Particle Swarm Optimization to Improve Static Malware Detection," in Proceedings of the 6th International Conference on Information Systems Security and Privacy (ICISSP 2020), Prague, Czech Republic, 2020, pp. 725-732.

[18] H. D. Sharma et al., “Sentiment classification via improved feature selection using Boolean operator-based particle swarm optimization,” Scientific Reports, vol. 15, no. 1, p. 38923, Nov. 2025.

[19] J. Kennedy and R. Eberhart, “Particle swarm optimization,” in Proc. ICNN'95-Int. Conf. Neural Networks, Nov. 1995, pp. 1942–1948.

[20] D. D. Lucas, R. Klein, J. Tannahill, D. Ivanova, S. Brandon, D. Domyancic, and Y. Zhang, “Failure analysis of parameter-induced simulation crashes in climate models,” Geosci. Model Dev., vol. 6, no. 4, pp. 1157–1171, Jul. 2013.

[21] R. Quinlan, “StatLog (Australian Credit Approval),” UC Irvine. Jan. 01, 1987.

[22] A. J. W. Steinbrunn, “Heart disease,” UC Irvine. Jan. 01, 1989.

[23] V. S. S. Wing, “Ionosphere,” UC Irvine. Jan. 01, 1989.

[24] Golub, T. R., Slonim, D. K., Tamayo, P., Huard, C., Gaasenbeek, M., Mesirov, J. P., ... & Lander, E. S. (1999). Molecular classification of cancer: class discovery and class prediction by gene expression monitoring. science, 286(5439), 531-537.

[25] K. M. T. Ringsted, “QSAR biodegradation,” UC Irvine. Jan. 01, 2013.

[26] A. Srinivasan, “Statlog (Landsat Satellite),” UC Irvine. Jan. 01, 1993.

[27] “Image segmentation,” UC Irvine. Jan. 01, 1990.

[28] UC Irvine, "Molecular Biology (Splice-junction Gene Sequences)," Jan. 01, 1991.

[29] P. Mowforth and B. Shepherd, "Statlog (Vehicle Silhouettes) [Dataset]," UCI Machine Learning Repository, 1990s (approx).

Dynamic Assessment and Goal Optimization of Corporate ESG Performance Based on DEA-CCR-GML and Inverse DEA Integration Framework

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***Abstract*—Since the Ministry of Ecology and Environment issued the "Reform Plan for the System of Environmental Information Disclosure in Accordance with the Law" in 2021, the nation has set forth new requirements for sustainable development. Against this backdrop, how enterprises enhance their value across all dimensions through ESG in compliance with national mandates holds significant implications for refining ESG management systems. This study employs DEA-CCR-GML and inverse DEA models to empirically examine how investments in specific dimensions of ESG's three pillars influence corporate value realization, using data from Shanghai to Shenzhen A-share listed companies from 2019 to 2024. Findings reveal that higher levels of scale efficiency and technical efficiency correlate with greater improvements in ESG scores, while mandatory enforcement of national policies exerts a highly effective driving force on enterprises. Mechanism analysis indicates that firms can enhance ESG score improvement efficiency by elevating scale and technical efficiency, thereby more effectively realizing their intrinsic value.**

***Keywords*—Corporate ESG performance; DEA; financing constraints; green innovation**

I. Introduction

Against the backdrop of the establishment of the National Social Responsibility Bureau (April 2022), policy initiatives by the China Securities Regulatory Commission, and the growing prevalence of ESG principles in China's capital markets, how companies can enhance their ESG ratings to improve governance standards has become a focal point [1]. While existing research predominantly examines the impact of ESG score changes on corporate performance volatility [2], firm value [3], and investor perspectives [4], it rarely explores how companies can more effectively improve their ESG scores by increasing investments in specific areas such as scale efficiency and technical efficiency. To address this gap, this study empirically examines the impact of corporate investments on key indicators and their underlying mechanisms using data from Chinese A-share listed companies from 2019 to 2024.

Zhang et al. demonstrate that corporate ESG measures enhance innovation performance through dual pathways: direct promotion and governance mediation (where strengthened environmental/social governance amplifies innovation). This process is moderated by institutional development levels, providing theoretical foundations and practical insights for sustainable innovation strategies in dynamic institutional environments [1].

Nguyen DT et al. based their study on data from 2,350 U.S. companies between 2018 and 2023, focusing on the heterogeneity of ESG risks (unmanaged risks versus management gaps). They revealed a significant negative correlation between total ESG risk and corporate performance, with the negative impact primarily driven by unmanaged risks (whose effect was approximately eight times that of management gaps). The negative impact of unmanaged ESG risks on performance is most pronounced in the first year and diminishes progressively thereafter. This conclusion holds even after controlling for endogeneity and undergoing multiple robustness tests [2].

Danny Zhao-Xiang Huang's theoretical analysis reveals a three-dimensional dilemma in shareholder ESG investment decisions: valuation conflict (ESG factors are difficult to quantify and integrate into earnings forecasts), the information paradox (ESG can reduce agency information asymmetry, but the validity of signals remains questionable), and the interest conflict (ESG embeds a multi-stakeholder interest game field). He proposes that future research should focus on the conditions under which ESG information triggers effective signals to bridge the cognitive gap in shareholders' long-term value assessment [3].

Avramov, D. et al. empirically demonstrated through the asset pricing equilibrium model and ESG rating discrepancies that ESG uncertainty elevates market premiums and reduces stock demand, driving simultaneous increases in CAPM alpha and effective beta while weakening the negative correlation between ESG and alpha. Supported by standard deviation data from six major rating providers, this study resolves the ESG-return relationship debate, demonstrating that ESG uncertainty distorts the risk-return tradeoff, thereby influencing sustainable investment decisions and social welfare [4].

A. Charnes et al. employed a nonlinear (nonconvex) programming model to address the challenge of efficiency evaluation in public programs for nonprofit entities. They developed a new definition of efficiency, an objective weighting method based on multiple observed output and input

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data, an equivalent computational relationship with standard linear programming models, and novel approaches for estimating extremes in dual models. Furthermore, they elucidated the connection between engineering and economics in efficiency assessment, offering fresh interpretations and applications for public project management [5].

Oh and Heshmati proposed a continuous Malmquist-Luenberger index combining a directional distance function with a continuous sequential production possibility set to address the challenge of measuring environmentally sensitive productivity growth, while excluding spurious technical regression from a macroeconomic perspective. They propose that this index exhibits trends similar to the traditional Malmquist-Luenberger index but with distinct decomposition components, and that efficiency changes dominate in the early stages while technological changes dominate in the later stages (based on empirical evidence from 26 OECD countries from 1970 to 2003) [6].

Chen et al. combined a novel counter-envelope analysis (DEA) model with undesirable outputs and a new inverse DEA model. By analyzing the relationships and differences among various objectives and their implementation pathways based on decision-makers' actual needs, they summarized valuable insights for advancing the achievement of China's road traffic safety goals [7, 8].

Lin explores the development prospects, economic benefits, and enabling environment of ESG investing within the context of carbon neutrality policy implementation and China's new development philosophy (green development). The study proposes that ESG has become a key factor in driving low-carbon transformation, assessing corporate performance, and influencing the economy. It aims to explore scientifically efficient methods for developing ESG to promote the transformation and upgrading of the carbon economy [9].

Wang et al. empirically examined the impact of performance-based budgeting (PBB) reforms on corporate ESG performance using quasi-natural experiments and multi-period DID models based on data from Chinese A-share listed companies from 2001 to 2020. Findings reveal that PBB reforms significantly enhance firms' economic and social contributions, with this effect being more pronounced in regions with high fiscal pressure and strong government audits. The impact is particularly significant for government-affiliated enterprises, firms with strong green innovation capabilities, or those facing high financing constraints. The mechanism operates by enhancing environmental governance through increased environmental subsidies and improved fiscal transparency, ultimately improving ESG performance and driving increases in return on assets, price-to-book ratios, and patent grants. This provides empirical evidence for deepening fiscal and tax system reforms and supporting the "dual carbon" strategy [10].

Weston and Nnadi et al. conducted research on the relationship between corporate social responsibility (CSR) and financial performance (CFP), establishing a framework for integrating CSR and environmental, social, and governance (ESG) principles into decision-making. By analyzing samples from the iShares MSCI KLD 400 Social ETF, the iShares Core S&P 500 ETF, and companies adhering to the Principles for Responsible Investment (PRI), the study found that ethical ETFs did not outperform traditional ETFs, but companies following PRI outperformed those not adhering to the principles [11].

Ye and Xu et al. examined the impact and mechanisms of ESG on carbon reduction (green innovation, efficiency, and managerial myopia) using data from China's listed manufacturing firms between 2010 and 2020. They found that ESG significantly reduces carbon emissions, with stronger effects observed in companies facing stricter environmental regulations, intense competition, and high capital intensity. Digital transformation plays a positive moderating role. This research provides new evidence for understanding ESG's emission reduction effects and offers insights for practical and policy approaches to achieving the" dual carbon" goals [12].

II. MODELING

This study employs the DEA-CCR model, the Globe-Malmquist-Luenberger index, and inverse DEA to conduct a scientific analysis of the profitability development efficiency of listed companies in China's A-share market.

A. DEA - CCR Model

There are n decision-making units (DMUs), each with m distinct input indicators and n output indicators. Let Xi denote the input vector for the i-th DMU, and Yi denote the output vector for the i-th DMU. When evaluating the efficiency of each DMU, the CCR model [5] is employed:

$$\begin{aligned} &\max\phi \\ &\text{s.t.} \quad \sum_{j=1}^{n}\lambda_j X_j \le X_0 \\ &\sum_{j=1}^{n}\lambda_j Y_j \ge \phi Y_0 \\ &\lambda_j \ge 0, \quad j=1,2,\ldots,n \end{aligned} \tag{1}$$

B. GML (Globe Malmquist-Luenberger Index) Model Construction

The GML index is constructed by integrating the Directional Distance Function (DDF) with the Global Production Technology Set (GPTS). It inherits the dynamic decomposition framework and relaxed measurement concept of the Malmquist index. By introducing a non-expected output constraint, it quantifies changes in Green Total Factor Productivity (Green TFP) within decision units, which balance expected output growth with reductions in non-expected output across intertemporal dynamics. Using the total production technology set across all study periods as the reference framework, it resolves shortcomings of the ML index such as lack of cyclical transitivity and unsolvability of linear programming [3], enabling more objective and accurate reflection of changes in the financial systems of listed companies. Let $\vec{D}_V^G(xt,yt,bt;g)$ denote the global directional distance function. Then the GML index from period t to period t+1 is defined as [6]:

$$GML^{t,t+1}=\frac{1+\vec{D}_V^G(x^t,y^t,b^t;g)}{1+\vec{D}_V^G(x^{t+1},y^{t+1},b^{t+1};g)} \tag{2}$$

The GML index can be decomposed into four interpretable components: Technical Efficiency Change (*EC*), Scale Efficiency Change (*SEC*), Pure Technical Change (*PTC*), and Scale-Technical Change (*STC*). The specific decomposition is as follows:

$$\begin{aligned}\mathrm{GML}^{t\to t+1} &= EC\times SEC\times PTC\times STC \\ &= \left(\frac{1+\vec{D}_V^{t}(\mathbf{x}^{t},\mathbf{y}^{t},\mathbf{b}^{t};\mathbf{g})}{1+\vec{D}_V^{t+1}(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{b}^{t+1};\mathbf{g})}\right)\times\left(\frac{\mathrm{SE}^{t+1}(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{b}^{t+1})}{\mathrm{SE}^{t}(\mathbf{x}^{t},\mathbf{y}^{t},\mathbf{b}^{t})}\right) \\ &\times\left(\frac{1+\vec{D}_V^{G}(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{b}^{t+1};\mathbf{g})}{1+\vec{D}_V^{t+1}(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{b}^{t+1};\mathbf{g})}\cdot\frac{1+\vec{D}_V^{t}(\mathbf{x}^{t},\mathbf{y}^{t},\mathbf{b}^{t};\mathbf{g})}{1+\vec{D}_V^{G}(\mathbf{x}^{t},\mathbf{y}^{t},\mathbf{b}^{t};\mathbf{g})}\right) \\ &\times\left(\frac{\left[\frac{1+\vec{D}_V^{G}(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{b}^{t+1};\mathbf{g})}{1+\vec{D}_V^{CRS,G}(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{b}^{t+1};\mathbf{g})}\right]/\left[\frac{1+\vec{D}_V^{G}(\mathbf{x}^{t},\mathbf{y}^{t},\mathbf{b}^{t};\mathbf{g})}{1+\vec{D}_V^{CRS,G}(\mathbf{x}^{t},\mathbf{y}^{t},\mathbf{b}^{t};\mathbf{g})}\right]}{\frac{\mathrm{SE}^{t+1}(\mathbf{x}^{t+1},\mathbf{y}^{t+1},\mathbf{b}^{t+1})}{\mathrm{SE}^{t}(\mathbf{x}^{t},\mathbf{y}^{t},\mathbf{b}^{t})}}\right)\end{aligned} \tag{3}$$

C. Inverse DEA Model Construction

Reverse DEA theory extends the boundaries of traditional Data Envelopment Analysis (DEA) through a reverse optimization framework. This approach translates abstract efficiency assessments into concrete action plans, making it suitable for resolving resource allocation disputes in public policy formulation [7]. The core value of Reverse DEA theory lies in addressing two critical issues: goal-oriented resource planning and short-term forecasting under constraints. This study focuses on short-term forecasting under constraints.

The inverse DEA of the output-oriented CRS super-efficiency DEA model is expressed as [8]:

$$\begin{aligned} &\max\varphi \\ &\textstyle\sum_{(j=1,\ j\neq k)}^{n}\lambda_j x_{ji}\le x_{ki}+\Delta x_{ki} \\ \text{s.t.}\quad &\textstyle\sum_{(j=1,\ j\neq k)}^{n}\lambda_j y_{jr}/\varphi_k^{*}\ge\gamma y_{kr} \\ &\lambda\ge 0 \\ &i=1,2,\ldots,p;r=1,2,\ldots,q;k=1,2,\ldots,n \end{aligned} \tag{4}$$

where, ϕ^{*}_{k} represents a known value, i.e., the optimal solution from the original DEA model or a manually set efficiency value; γ^{*}_{k} denotes the optimal solution from the inverse DEA model; $\gamma^{*}_{k}y_{kr}$ signifies the predicted output value; Δx indicates the increase in input quantity; and let Δy denote the increase in output quantity, then $\Delta y=\gamma^{*}_{k}y_{kr}-y_{kr}$.

III. Selection of the Indicator System

To evaluate the effectiveness of the efficiency assessment system, eight corresponding evaluation indicators were established based on the principles of scientific rigor, objectivity, and quantitative analysis, incorporating existing literature [9]. The data sources and their respective origins are detailed in Table I.

TABLE I. Variable Definitions and Data Sources

Indicator type	Indicators	Variant	Unit	Source
Input indicators	Market capitalization	X_1	Ten billion yuan	[8]
	Main revenue	X_2	Ten billion yuan	
	Operating cash flow	X_3	Ten billion yuan	/
	R&D expenditures	X_4	Hundred million yuan	
Output indicators	ESG score	Y_1	/	[8]
	Asset-liability ratio	Y_2	%	
	Total asset turnover ratio	Y_3	Times	/
	Return on total assets	Y_4	%	[8]

IV. Empirical Research

A. DEA Static Analysis

This study covers the period from 2019 to 2024, selecting 10 listed companies from five industries on the Shanghai and Shenzhen stock exchanges as research subjects, with data sourced from the Wind Database. By comparing and analyzing the scale efficiency, pure technical efficiency of technological innovation, and comprehensive efficiency of these 10 listed companies, the study dissects the internal factors influencing changes in corporate ESG scores and provides corresponding recommendations. Comprehensive efficiency values were calculated using the DEArun software, revealing the ESG improvement comprehensive efficiency for the 10 listed companies, as shown in Table II.

TABLE II. Comprehensive Efficiency of ESG Score Improvement for 10 A-Share Listed Companies

	2019	2020	2021	2022	2023	2024
Zijin Mining	0.464	0.266	0.623	0.362	0.228	0.316
China Northern Rare Earth	1.000	1.000	1.000	1.000	1.000	1.000
Beijing Capital Eco-environment	1.000	1.000	1.000	1.000	1.000	1.000
Originwater	1.000	1.000	1.000	1.000	1.000	1.000
Offshore Engineering	1.000	1.000	1.000	1.000	1.000	1.000
Hengli Petrochemical	0.317	0.367	0.602	0.668	0.620	0.579
Fuyao Glass	0.683	0.688	0.645	0.692	0.945	0.900
Conch Cement	1.000	0.737	0.500	0.284	0.329	0.288
999 Pharmaceutical	1.000	1.000	1.000	1.000	1.000	1.000
WuXi AppTec	1.000	0.811	0.737	0.723	1.000	0.936
Average value	0.846	0.787	0.811	0.773	0.812	0.802

Table II shows that the average comprehensive efficiency of ESG score improvement for the 10 A-share listed companies fluctuated between 2019 and 2024, peaking in 2019 before exhibiting an overall downward trend. Over the past six years, the mean comprehensive technical efficiency of the sample companies ranged between 0.773 and 0.846. Although

generally at a high level, it has been decreasing annually, reflecting that, under given resource input conditions, companies still have room for improvement in their comprehensive development in ESG-related areas. Specifically, five companies achieved a comprehensive efficiency score of 1 in each of 2020, 2021, 2022, and 2024, rising to six in 2023. In contrast, seven companies attained optimal comprehensive efficiency in 2019, further confirming the overall downward trend in the average efficiency score. This phenomenon is primarily linked to companies' relatively high debt-to-asset ratios during the period, insufficient R&D investment, and strong volatility in ESG scores. In particular, inadequate R&D expenditure significantly impacted companies' scores in the "ESG Technology R&D" category, thereby lowering their overall ESG scores and slowing the pace of improvement in their comprehensive ESG efficiency.

At the individual enterprise level, Zijin Mining, Hengli Petrochemical, and Fuyao Glass remained in a non-DEA efficient state throughout the review period. This indicates significant room for improvement in their overall efficiency across ESG resource allocation, environmental management (E), social responsibility (S), and corporate governance (G) dimensions. Their input factors have not achieved optimal allocation, necessitating urgent improvements through measures such as optimizing ESG strategic structures, increasing green R&D investments, and enhancing environmental information disclosure. Conch Cement achieved DEA efficiency only in 2019, remaining inefficient in other years. Fluctuations in environmental indicators like carbon emissions intensity and water resource utilization efficiency may have undermined its sustained high performance. WuXi AppTec failed to meet DEA efficiency in all years except 2019 and 2023, reflecting unstable input-output structures in S and G dimensions-including green R&D, employee rights, and business ethics. In contrast, China Northern Rare Earth, Beijing Capital Eco-environment, OriginWater, Offshore Engineering, and 999 Pharmaceutical maintained DEA validity throughout the six-year period. This demonstrates strong synergies across all three ESG dimensions-such as China Northern Rare Earth resource recycling, OriginWater's water environmental protection technologies, Offshore Engineering's low-carbon project investments, and 999 Pharmaceutical's health product responsibility management-along with rational resource allocation with both technical and scale efficiencies optimized simultaneously, demonstrating robust comprehensive ESG management capabilities. Notably, in observations of companies within the Greater Bay Area, years with a comprehensive efficiency value of 1 corresponded to significant improvements in the ESG technology R&D segment, indicating rational innovation resource structures and leading green technology output efficiency.

In summary, the overall efficiency of improving corporate ESG scores is not only constrained by financial structure and R&D investment levels but also closely tied to specific performance indicators in environmental outcomes, social responsibility fulfillment, and governance transparency. Moving forward, companies should address their ESG weaknesses by intensifying technological R&D efforts, optimizing capital structures, and enhancing the quality of ESG disclosures. This approach will enable simultaneous improvements in resource allocation efficiency and overall ESG ratings.

B. Dynamic Analysis of Global Malmquist-Luenberger Index

The Global Malmquist-Luenberger index dynamically and comprehensively reflects changes in the technological innovation efficiency of A-share listed companies. Applying this index to decompose the ESG score improvement rates of 10 A-share listed companies from 2019 to 2024 yields the following results:

TABLE III. AVERAGE GLOBAL MALMQUIST-LUENBERGER INDEX AND DECOMPOSITION FOR ESG SCORE IMPROVEMENT OF 10A-SHARE LISTED COMPANIES FROM 2019 TO 2024

	Effch	Rech	Pech	Sech	tfp
2019-2020	0.968	0.971	0.994	0.973	0.942
2020-2021	1.025	0.982	1.006	1.020	0.999
2021-2022	0.976	1.003	1.000	0.976	0.976
2022-2023	1.022	0.944	0.992	1.031	0.960
2023-2024	0.996	0.991	0.997	0.999	0.986
Average value	0.997	0.978	0.998	1.000	0.973

As shown in Table III, from the perspective of overall efficiency changes, the average ESG score improvement rate index for the 10 A-share listed companies from 2019 to 2024 was 0.978, while the Global Malmquist-Luenberger productivity decreased by 2.2%. Throughout the study period, the tfpch for 2019–2024 remained below 1, indicating that the ESG score improvement rate of these 10 listed companies showed a declining trend year by year. This suggests that inputs and outputs related to ESG score improvement have not been optimized. Further analysis of each company's ESG indicator performance reveals that the following factors directly impact ESG score improvement: within the Environmental (E) dimension-carbon emission intensity, energy efficiency, and waste management rate; within the Social (S) dimension-employee training investment, community welfare expenditure, and labor rights protection; and within the Governance (G) dimension-board independence, information disclosure transparency, and anti-corruption mechanism development. For instance, some companies fall short of industry benchmarks in environmental metrics, limiting overall efficiency. In social metrics, insufficient investment in employee training may weaken innovation momentum, thereby impacting total factor productivity.

Breaking down total factor productivity (TFP) further into scale effect and technological progress indices reveals: 1)TFP reached its lowest point between 2019 and 2020, primarily due to scale effect and technological progress indices falling below other indicators. This indicates that the synergistic interaction between technological progress and scale effects was the main factor driving the decline in TFP. Specifically regarding ESG indicators, insufficient R&D investment in the environmental dimension and reduced scale of public welfare projects in the social dimension jointly constrained efficiency gains. Enhancing corporate technological innovation efficiency can be achieved by encouraging enterprises to increase their investment and scale in ESG and R&D. 2) The TFP value

reached its peak in 2020-2021, at 0.999. Further analysis reveals that the primary drivers of this increase were higher values for the scale effect index and the pure technical efficiency index. This demonstrates that scale effects and technical efficiency are crucial factors in enhancing corporate innovation efficiency. During this period, companies' improved information disclosure in governance and expanded community investments in social dimensions effectively supported higher ESG scores. However, the lack of technological advancement hindered the efficiency gains in ESG scoring, particularly the lag in environmental indicators like carbon reduction technology adoption, which may further depress overall performance.

Overall, specific ESG metric performance-including environmental compliance, social responsibility fulfillment, and governance structure optimization-constitutes the key driver of total factor productivity (TFP) fluctuations. Enterprises must implement targeted adjustments across these dimensions to optimize resource allocation and enhance efficiency.

TABLE IV. GLOBAL MALMQUIST-LUENBERGER INDEX AND DECOMPOSITION FOR ESG SCORE IMPROVEMENT AMONG 10 A-SHARE LISTED COMPANIES

	Effch	Rech	Pech	Sech	tfp
Zijin Mining	0.992	0.979	1.000	0.992	0.955
China Northern Rare Earth	1.000	0.965	1.000	1.000	0.965
Beijing Capital Eco-environment	1.000	1.000	1.000	1.000	1.000
Originwater	1.000	1.001	1.000	1.000	1.001
Offshore Engineering	1.000	1.018	1.000	1.000	1.018
Hengli Petrochemical	1.039	0.974	1.000	1.039	1.009
Fuyao Glass	1.027	0.950	1.000	1.027	0.971
Conch Cement	0.918	0.992	0.978	0.943	0.911
999 Pharmaceutical	1.000	0.953	1.000	1.000	0.953
WuXi AppTec	0.997	0.949	1.000	0.997	0.942
Average value	0.997	0.978	0.998	1.000	0.973

As shown in Table IV, during the period from 2019 to 2024, only four of the ten sample companies-OriginWater, Offshore Engineering, Hengli Petrochemical, and Beijing Capital Eco-environment, achieved a total factor productivity (TFP) index greater than or equal to 1. This indicates that these companies demonstrated relatively strong efficiency in improving their ESG scores. The remaining six companies all had TFP indices below 1, reflecting that while the overall efficiency of ESG score improvement showed an upward trend, there remains significant room for improvement. Comparisons across companies and industries reveal both limited gradient-based differences and technology-driven structural disparities, particularly in the uneven integration of Environmental (E), Social (S), and Governance (G) dimensions. Analysis based on the Global Malmquist-Luenberger index categorizes these ten companies into the following three groups:

1) Companies with a technical efficiency score of 1 or higher include China Northern Rare Earth, Beijing Capital Eco-environment, OriginWater, Offshore Engineering, Hengli Petrochemical, Fuyao Glass, and 999 Pharmaceutical-seven companies in total. These enterprises positively contributed to their ESG scores through enhanced technical efficiency. For instance, OriginWater made significant investments in water resource management and environmental technology applications, demonstrating strong environmental metrics such as wastewater treatment efficiency and carbon reduction performance. Offshore Engineering has strengthened practices in marine environmental protection and safety production measures, with improvements in employee training and community engagement on the social dimension; Hengli Petrochemical reduced environmental impacts through process optimization and resource recycling, though governance transparency requires further enhancement; Beijing Capital Eco-environment demonstrated efficient governance in environmental project operations and board diversity; China Northern Rare Earth made progress in resource utilization efficiency and mine ecological restoration; Fuyao Glass performed well in employee welfare, safety production and product sustainability; 999 Pharmaceutical has continuously optimized drug accessibility, patient safety and corporate ethical governance. However, these companies generally exhibit low technological advancement scores, which have constrained further growth in their ESG score improvement rates. Particularly, there is a lag in applying innovative technologies to environmental and social risk management.

2) Conch Cement experienced the largest decline in ESG score growth rate among all companies, decreasing by 8.91%. Its decline in total factor productivity primarily stemmed from a 6.23% reduction in scale efficiency, reflecting potential neglect of environmental compliance and social responsibility integration during rapid expansion, leading to deteriorating ESG performance. Specifically, in the social dimension, weaknesses were observed in community relations and labor rights protection; in the governance dimension, insufficient internal controls and execution efficiency of sustainability strategies exacerbated the negative impacts stemming from scale effects.

3) Both Zijin Mining and WuXi AppTec experienced varying degrees of decline in their ESG score improvement rates, at 4.5% and 5.8%, respectively. Both companies exhibited unchanged pure technical efficiency indices, while technical efficiency, technological progress, and scale efficiency indices all decreased. The reduction in scale efficiency directly led to the decline in technical efficiency. Zijin Mining faces challenges in environmental restoration, biodiversity conservation, and labor safety within its mining operations. Social dimension issues, including local community conflicts and governance transparency, constrain its ESG improvement. WuXi AppTec exhibits deficiencies in governance areas such as R&D ethics, supply chain management, and data privacy protection. Its social responsibility practices-particularly regarding patient rights and employee diversity-require strengthening, as its scale expansion has failed to effectively align with ESG management demands.

Overall, the disparity in ESG score improvement efficiency among the ten companies highlights uneven development across environmental, social, and governance dimensions. Future efforts should focus on optimizing technical efficiency and economies of scale, while strengthening the integration of ESG metrics tailored to each industry's characteristics to drive sustainable enhancement of overall ESG performance.

V. Case Study

A. Performance Target Setting

The budget values for 2025 [10] for each unit are set at 80% of the 2024 increase, as shown in Table V.

TABLE V. Budgeted Investment Targets for each Unit in 2025

Subjects of evaluation	Company market capitalization (Tens of billions of dollars)	Main revenue (Tens of billions of dollars)	Operating cash flow (Tens of billions of dollars)	R&D expenditures (Billions of dollars)
Zijin Mining	70.151	54.655	59.620	28.482
China Northern Rare Earth	13.809	5.9339	5.1862	5.3982
Beijing Capital Eco-environment	4.3339	3.6090	3.0401	3.1888
Originwater	3.3009	1.5389	1.3163	6.1700
Offshore Engineering	4.3533	5.3900	5.9200	22.290
Hengli Petrochemical	19.449	42.529	50.997	30.650
Fuyao Glass	28.156	7.0653	7.0520	30.200
Conch Cement	21.427	16.385	18.823	22.627
999 Pharmaceutical	10.250	4.9710	5.2525	17.154
WuXi AppTec	28.423	7.0630	7.8237	22.290

Substituting the budgeted input values into the inverse DEA model yields an output value of 10 units, which represents the 2025 output indicator performance target. The results are shown in Table VI.

TABLE VI. Performance Targets for Output Indicators of each Unit in 2025

Subjects of evaluation	ESG score	Gearing ratio (%)	Total asset turnover (times)	Return on assets (%)
Zijin Mining	236.39	1891.14	5.837	169.27
China Northern Rare Earth	11.929	76.7852	0.800	7.783
Beijing Capital Eco-environment	10.871	87.7268	0.263	7.358
Originwater	9.5707	85.1268	0.162	2.058
Offshore Engineering	10.892	71.8277	0.700	5.600
Hengli Petrochemical	73.175	645.200	1.286	18.90
Fuyao Glass	23.776	189.324	00.700	13.80
Conch Cement	1153.59	1279.89	3.347	81.30
999 Pharmaceutical	13.718	93.2226	0.700	11.40
WuXi AppTec	20.429	163.663	0.502	14.50

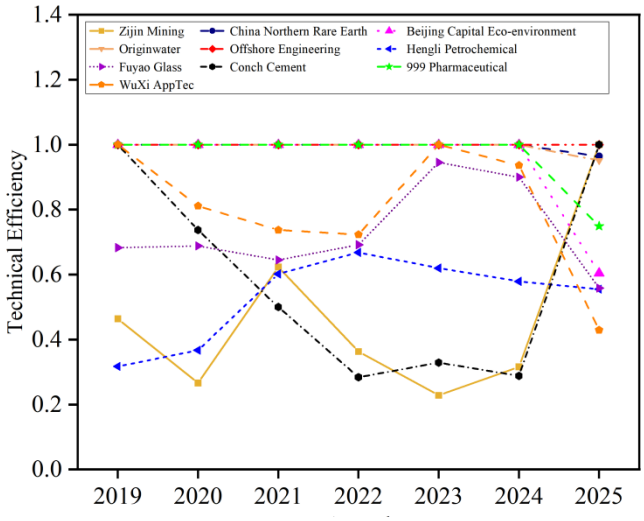


Fig. 1. Comprehensive technical efficiency of various units in 2019–2025.

Fig. 1 was created by plotting the comprehensive technical efficiency of each unit for the period 2019-2024 and their target comprehensive technical efficiency for 2025.

Conch Cement's comprehensive efficiency curve exhibits a V-shaped pattern with significant volatility. This trend of initial decline followed by recovery clearly demonstrates the effectiveness of resource allocation and technological application across different phases of Conch Cement's operations.

From the data characteristics, the decline phase from 2019 to 2022 indicates issues in certain input-output segments of enterprises, suggesting potential resource redundancy or misallocation. The recovery phase from 2023 to 2025 indicates improved efficiency following strategic adjustments. Notably, comprehensive technical efficiency saw a brief uptick in 2023 before declining again to the0.2-0.3range in 2024. A sharp upward trend is projected for 2025.

In summary, by 2025, Conch Cement should increase R&D investment to enhance automation levels and production efficiency, particularly by improving return on assets. This will help resolve the existing contradiction of high debt and low R&D investment, thereby boosting the ability to convert investments into profits. Additionally, in the realm of "circular economy", Conch Cement can increase the proportion of co-processing industrial solid wastes (such as steel slag and blast furnace slag) and construction waste, develop related products, reduce raw material costs, and simultaneously enhance resource recycling efficiency. Regarding suppliers, establish an ESG rating system for upstream suppliers (such as coal and sand/gravel enterprises), prioritizing collaboration with low-energy-consumption and compliant-emission suppliers. Promote the "green cement+low-carbon construction" integrated solution to downstream construction clients, driving overall ESG improvement across the supply chain while aligning with national policies and requirements. For governance structure, establish an ESG working group under the existing Board Strategy or Risk Control Committee, staffed by current executives to oversee ESG governance matters. Senior executives will leverage their management expertise

and resource advantages across respective domains to embed ESG requirements into core processes, including strategic planning, operational management, and risk control. This ensures ESG initiatives are integrated into the company's core business rather than treated as superficial formalities. The approach enhances brand reputation and credibility among investors, regulators, and the public, aligning with current ESG investment trends and policy directions. It simultaneously drives the company's green and low-carbon transformation and supply chain sustainability, laying the foundation for long-term high-quality development.

In analyzing corporate historical performance and forecasting future decisions, the core value of the reverse DEA model lies not only in its application as a tool but also in its methodological innovation for short-term ESG forecasting—an innovation that breaks through the limitations of traditional forecasting reliant on experiential judgment or linear extrapolation. By deeply integrating historical ESG efficiency characteristics, input budget constraints, and reverse optimization logic, it constructs a closed-loop forecasting framework that starts with efficiency attribution, proceeds through resource allocation optimization, and culminates in target quantification. This approach fills the gap where traditional methods struggle to precisely align efficiency assessments with specific ESG objectives. Specifically, enterprises can leverage this integrated model to precisely calculate ESG output targets based on input indicator budget values, enabling targeted forecasting and pathway planning for short-term ESG performance. For instance, Conch Cement leveraged this integrated approach to not only pinpoint redundant inputs underlying prior inefficiencies but also directly link optimization directions with short-term improvement targets across ESG dimensions through reverse DEA's backward-tracking capability. This provides quantitative grounds for setting stable and achievable ESG output goals, enabling enterprises to clearly define "which inputs to optimize, which ESG dimensions to enhance, and what targets to achieve". Compared to traditional performance goal-setting methods, reverse DEA emphasizes the dynamic alignment of performance evaluation outcomes with ESG objectives. It transforms static efficiency assessments into dynamic, actionable ESG improvement pathways, ensuring goal-setting aligns with both operational realities and core ESG development priorities. This significantly enhances the scientific rigor, precision, and operational feasibility of short-term ESG target setting.

VI. Conclusion and Recommendations

This study employs a methodological framework of "static evaluation—dynamic decomposition—reverse optimization," integrating the DEA-CCR model, Global Malmquist-Luenberger (GML) index, and reverse DEA methodology. It conducts a systematic analysis of ESG performance improvement efficiency across 10 representative listed companies from different sectors in China's A-share market during 2019–2024. Based on historical performance, it further establishes resource optimization pathways for 2025. DEA-CCR analysis reveals these companies exhibit overall decline with significant divergence. The core contradiction lies in the combined effects of insufficient R&D expenditure, high debt-to-asset ratios, and volatile ESG scores, which collectively suppress efficiency gains. Meanwhile, GML index decomposition indicates that overall efficiency is declining amid fluctuations, largely consistent with the preceding description. Despite heterogeneity among different enterprises, technology (tech) emerges as the primary driver of decline, revealing weak innovation momentum in the ESG domain. Finally, constrained short-term forecasts for input budgets and target efficiency values are generated using an inverse DEA model, providing quantitative guidance for budget allocation [10]. This reveals that under China's deliberate efforts to enhance corporate ESG integration and innovation, enterprises across different sectors can improve their ESG performance through management process optimization. However, it is noteworthy that scale efficiency and technological innovation may emerge as constraining factors in further elevating ESG performance.

At the corporate level, this study provides inefficient units with pathways for optimizing scale structures and identifies key areas for technological upgrading in declining units. At the policy level, it establishes an ESG budget performance management paradigm centered on "efficiency diagnosis-attribution analysis-target generation". The study proposes the following differentiated improvement strategies for enterprises: For non-DEA-efficient enterprises such as Zijin Mining and Hengli Petrochemical, the focus should be on optimizing scale structures and increasing R&D expenditures in line with reverse DEA budgets. Declining enterprises like Conch Cement should enhance scale efficiency through automation upgrades and capacity efficiency improvements. Overall, both domestic and international enterprises should focus on long-term capacity building, strengthen synergies between technological progress and economies of scale [11], particularly by enhancing ESG-related technological innovation capabilities and mitigating the negative impact of ESG score volatility on total factor productivity. Concurrently, the inverse DEA model can serve as a reference for budget allocation.

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References

[1] Zhang Q, Loh L, Wu W. (2020). How do environmental, social and governance initiatives affect innovative performance for corporate sustainability? Sustainability, 12(8): 1-18.

[2] Nguyen DT, Tran VT, Phan DHB, et al. (2025). Unmanaged ESG risks and corporate performance - The impact of management gaps. Finance Research Letters, 83: 107707. DOI: 10.1016/J.FRL.2025.107707.

[3] Huang D. (2022). Environmental, social and governance factors and assessing firm value: valuation, signaling and stakeholder perspectives. Accounting and Finance, 62, 1983-2010.

[4] Avramov D, Cheng S, Lioui A, et al. (2022). Sustainable investing with ESG rating uncertainty. Journal of Financial Economics, 145 (2): 642-667.

[5] Charnes A, Cooper WW, Rhodes E. (1978). Measuring the efficiency of decision making units. European Journal of Operational Research, 2(6): 429-444.

[6] Oh D-h, Heshmati A. (2010). A sequential Malmquist-Luenberger productivity index: environmentally sensitive productivity growth considering the progressive nature of technology. technology. Energy Economics, 32(6): 1345-1355.

[7] Chen L, Gao Y, Li M, et al. A new inverse data envelopment analysis approach to achieve China's road transportation safety objectives transportation safety objectives. Safety Science, 2021, 142: 105362.

[8] Wei, Q.L., Zhang, J., Zhang, X., 2000. An inverse DEA model for input/output estimate. Eur. J. Operat. Res. 121 (1), 151–163.

[9] Lin Z. Does ESG performance indicate corporate economic sustainability? Evidence based on the sustainable growth rate. Borsa Istanbul Review, 2024, 24(3): 485-493.

[10] Wang X, Hu S. Can performance-based budgeting reform improve corporate environment in ESG? Evidence from Chinese-listed firms. Frontiers in Environmental Science, 2022, 10: 982160. DOI: 10.3389/FENVS.2022.982160.

[11] Weston P, Nnadi M. (2023). Evaluation of strategic and financial variables of corporate sustainability and ESG policies on corporate finance performance. Journal of Sustainable Finance & Investment, 13(2): 1058-1074.

[12] Ye J, Xu W. (2023). Carbon reduction effect of ESG: empirical evidence from listed manufacturing companies in China. Frontiers in Ecology and Evolution, 11: 1311777.

Development and Evaluation of a Mobile-Based Local Food Information System for Elderly Nutrition Support

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***Abstract*—This research aimed to: 1) study information needs regarding local foods and information systems for the elderly, 2) develop a local food information system for the elderly, and 3) evaluate system effectiveness. The quantitative study included 235 senior caregivers selected via purposive sampling. The research tools were an interview form (IOC = 0.98) and a questionnaire (Cronbach's alpha = 0.953). The results indicated that there were three key information needs: 1) Comprehensive and reliable content that includes dietary data, food types, and disease categorization, daily meal search features, disease-specific recommendations, and presentation with large-font images and succinct language. The system was developed on the LINE Official Account platform and is based on a web application. 2) User evaluation from 235 participants showed strong agreement with overall system efficiency. Usefulness received the highest rating, followed by LINE OA usability and efficiency. A gender comparison showed that there were statistically significant differences ($p < .01$) between females and males in terms of content and efficiency. 3) Linear regression analysis identified efficiency as the primary factor influencing usefulness, followed by system usability and functionality. A one-way ANOVA showed that users accessing LINE once per week had significantly higher usefulness scores than those using it every 2 to 3 days ($p < .05$).**

Keywords*—*Information system; LINE OA; elderly care system; local food; elderly nutrition

I. Introduction

The change in population structure towards an aging society is an important phenomenon that is occurring worldwide and is becoming increasingly apparent. History recorded a significant event in 2018 when, for the first time, the world's population aged 65 and over exceeded that of children under 5 [1]. In addition, it is estimated that between 2015 and 2050, the proportion of the world's population aged 60 and over will tend to increase from 12.3 per cent to 21.5 per cent [2]. The region with the fastest rate of elderly growth is East and Southeast Asia, especially Japan, South Korea and China. Since 2005, Thailand has entered the aging society with more than 10 per cent of the population aged 60 and over [3], according to the definition of the United Nations. Thailand has entered the aging society completely in 2025 with the population aged 60 and over exceeding 20 per cent or approximately 14.4 million people [4-5]. In 2035, it is predicted that Thailand will enter the advanced aging society fully with the elderly increasing by 28.55 per cent [6]. Such changes in the population structure have resulted in the issue of caring for the elderly becoming a major policy challenge in terms of the economy, society, and public health system [7]. Effective care for the elderly must integrate both physical and mental health promotion, as well as support for the elderly to be able to participate in social activities to their full potential. The key components of caring for the elderly consist of 6 main factors: hygiene, exercise, air, emotion, safety, and food [8].

Elderly people experience physiological changes that affect digestion, nutrient absorption, and energy metabolism, making nutrition a crucial factor in their well-being [9]. Thus, each older adult's energy and nutritional needs vary based on age, weight, height, physical activity, and health [10]. Nutrition for the elderly must focus on getting complete nutrients according to the 9 nutritional principles developed by [11], which must be adjusted to suit changing physiological needs [12]. Appropriate nutrition management can reduce the risk and severity of non-communicable diseases (NCDs), which are common health problems in the elderly [13]. Dietary guidelines advocate for modifying nutrient intake by decreasing the consumption of complex carbohydrates and saturated fats while increasing high-quality protein. Furthermore, an emphasis is placed on consuming low-glycemic-index vegetables, legumes, grains, and fruits, in addition to ensuring adequate hydration [14-15]. However, current social and lifestyle changes often lead the elderly and their caregivers to have difficulty accessing accurate and appropriate nutritional information, lack reliable sources of information, or have limited access to digital information [16]. Local food is a cultural heritage that passes on nutritional wisdom from generation to generation, presenting local identity through the use of ingredients and cooking methods that are consistent with the local ecosystem and resources [17]. A study in Japan found that the elderly who continued to consume traditional local food had a lower incidence of cardiovascular disease than those who turned to Western food [18]. Local Thai food also has outstanding health benefits due to the combination of herbs and spices with pharmaconutrient properties that help fight free radicals and have anti-inflammatory properties [19].

Southern Thai foods made with turmeric, galangal, fingerroot, and pepper have antioxidant and anti-inflammatory properties that benefit the elderly [20-21]. In [22], the authors also found that local foods improve the mental health of the elderly by promoting positive memories, cultural identity, and social interactions. Surat Thani Province is a province with geographical and cultural diversity, which results in a unique combination of food identities [23]. Khlong Prab Subdistrict, Ban Na San District, Surat Thani Province is considered an area that still strongly preserves the traditional way of life and consumption culture. Local food in Khlong Prab Subdistrict is

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diverse in terms of ingredients, cooking processes, and flavors, with local resources being the main ingredients [24]. Prominent ingredients include Satho, which is highly nutritious, especially calcium, phosphorus, and vitamin C [25], as well as other local foods such as Southern-style Khanom Jeen Nam Ya, Yam Pla Meng, Sour Fish Curry with Raw Bamboo Shoots, and local desserts with high nutritional value [26-27]. In [28], the authors found that local foods in Surat Thani Province, especially in Khlong Prab Subdistrict, contain high amounts of antioxidants and phytochemicals with anti-inflammatory properties, which help reduce the risk of chronic diseases. This supports [29] the finding that southern spices and herbs lower blood sugar and diabetes risk. According to [30], southern local meals contain more local vegetables than other areas, which boosts dietary fiber and vitamin consumption. The preservation and promotion of local food culture is very important in preserving cultural identity and local wisdom [31]. In Khlong Prab Subdistrict, there are operations at many levels, such as establishing a local food learning center, organizing a local food festival, and integrating knowledge about local food into the local curriculum of local schools [32]. In addition, there is the development of gastronomy tourism, which helps create added economic value and promotes the preservation of local food culture [33].

Currently, information technology has played a significant role in taking care of the health and promoting the quality of life of the elderly (Elderly Health Technology) [34]. Thailand's entry into a complete aging society has stimulated the development of health innovations and information technology that meet the specific needs of the elderly [35]. However, although there are currently various platforms providing health information on the Internet and information systems related to the care of the elderly, the elderly and caregivers still have problems accessing and applying this information in their daily lives [36]. Health information systems are an important tool for improving the efficiency of population health care, as evidenced by the success of the "Health Connect" system in the Republic of Singapore, which achieved impressive results in reducing hospital readmission rates among the elderly population by 30 per cent through a mechanism for monitoring health status and providing personalized nutritional advice [37]. In [38], the authors found that integrating the "Healthy Aging" application into the care of the elderly in Chiang Mai Province reduced malnutrition risk by 18% and increased self-care literacy. LINE is a very popular platform in Thailand, especially among the elderly. A recent survey found that 86 per cent of Thai elderly people regularly use LINE [52], making the development of an information system through LINE Official Account (OA) having a high potential to reach the target group. In [39], the authors stated that LINE OA is an appropriate platform for developing a health knowledge system for the elderly because it has a familiar, uncomplicated user interface and can be easily accessed via mobile devices.

Despite studies on the nutritional content of Thai indigenous cuisines and the development of health information systems for the elderly, the literature study discovered some key research gaps. In [40], the authors noted that most nutrition information systems for the elderly in Thailand have not systematically employed local food data, despite local meals being culturally acceptable and nutritious for Thai seniors. Most existing nutrition information systems for the elderly provide general information that does not take into account the differences in local contexts and cultures. In [41], the authors observed that older people typically reject nutritional advice that conflicts with cultural context and local resources. The research of [42] indicated that most health information systems are not designed with the limitations of digital technology use in mind for the elderly and are often developed on platforms that the elderly are not familiar with, resulting in barriers to access and use. The study of [43] found that there is a lack of research that systematically assesses the impact of information systems on local food consumption behavior in the elderly, resulting in a lack of empirical data that will lead to the development of more effective systems. Each elderly person has different nutritional needs according to their health status, but most information systems still provide general information that cannot be tailored to individual needs [44].

This research aims to fill the research gaps mentioned above by developing a local food information system for the elderly in Khlong Prab Subdistrict, Ban Na San District, Surat Thani Province, developed through the LINE OA platform. The information system integrates local food knowledge with information technology, presenting context-specific information based on the area with an interface design suitable for the elderly on a familiar platform, and evaluating the usability of the information system for the elderly. The developed information system can also provide recommendations appropriate to the health status of each elderly person. The developed system consists of important functions, including a basic health assessment form, a healthy menu tailored to the elderly's condition, a health food shop, frequently asked questions about nutrition for the elderly, and a graph showing the results of the health assessment, which allows users to continuously monitor their health development.

This research is the first to combine specialized Thai food information with elderly-specific mobile health technologies. Regional culinary knowledge from Khlong Prab Subdistrict is operationalized via LINE Official Account, a medium known to Thai elders, unlike generic nutrition platforms. The research presents a replicable model for indigenous food systems and personalized health care for cultural preservation and clinical needs. Traditional meals, health profiles, and age-appropriate digital design enhance community-based health informatics for older individuals. Senior nutrition knowledge and health improved. Using regional cuisine-friendly technology, politicians and healthcare experts help older Thais.

This introduction is followed by Section II on digital health systems and research technology acceptance frameworks. Section III covers participatory design and LINE OA system development. Section IV details caregiver interviews and system evaluations. Section V compares outcomes to literature. Section VI summarizes findings and goals. It provides research contribution and concludes with rural strategy or research applications.

II. Literature Review

A. Ban Khlong Prap Local Food Information System Development

The Ban Khlong Prap Local Food LINE OA development has numerous significant research needs, notably in the integration of digital technology with local food knowledge, which most research has not yet investigated (see Table I). It involves creating a system that combines health assessment findings with local dietary recommendations and an elderly-friendly user interface with cultural context and local language.

TABLE I. Literature Review

Authors (Year)	Key Findings	Research Gaps
Kim et al. [45]	The Chatbot system made 89.3% correct suggestions, and 76.8% of senior participants followed them.	AI gives generic dietary recommendations without local expertise. Integration of AI to assess and deliver tailored local food suggestions may improve the future Khlong Prap LINE OA and change consumption habit.
Singh & Kaur [46]	Traditional culinary knowledge and digital technologies assist older people accept and eat healthy meals.	While the idea is similar, it was not established on the LINE OA platform and was developed in Singapore. Khlong Prap LINE OA will use this approach to Thai Ban Khlong Prap, a local dish with distinct qualities.
Johnson & Martínez [47]	It discovered that simple, local language-supported systems like LINE were more popular in East Asia.	Platform acceptability was studied macroscopically, not locally. Southern Thai terminology and idioms may help the future Khlong Prap LINE OA adopt local language.
Sangchan & Lekcharoen [48]	The device reduces emergency response time by 35% by monitoring vital indicators and sending notifications.	Vital sign monitoring and emergencies are prioritized above food and nourishment. The Khlong Prap LINE OA may relate health data to local dietary suggestions for certain health issues.
Harris & Brown [49]	Messaging services like LINE are as effective as conventional health monitoring approaches but 40% cheaper.	The research did not address cuisine or local culture. The Khlong Prap LINE OA may use messaging platform cost-effectiveness to create a low-cost, high-efficiency system.
Thepat-as et al. [50]	System satisfaction was 87.5% and suggestion compliance increased 42.8% for elderly users.	Lacks food consumption and local expertise, but the Khlong Prap LINE OA will integrate local food knowledge and current nutritional values connected to old health.
Decha-adisai &Makmee [51]	It found substantial improvements in health literacy ($p<0.01$) and habits among elderly individuals.	Health literacy, not local cuisine. To preserve and promote food culture, Khlong Prap LINE OA will combine health literacy with local food knowledge.
Rangkuat & Wongwiseskul [52]	senior system users had significantly lower blood sugar levels ($p<0.05$) than the control group.	It focuses on diabetes and utilizes broad nutritional ideas, whereas the Khlong Prap LINE OA will cover many health conditions and link them to local foods with specific nutritional qualities that may prevent sickness. It found substantial improvements in health literacy ($p<0.01$) and habits among elderly individuals.
Tanaka et al. [53]	The strategy increased senior health care cooperation by 68% and reduced unnecessary medical visits by 23%.	Not culturally informed or local. The Khlong Prap LINE OA's technology and traditional knowledge may improve healthcare cooperation due to users' lifestyle and culture.
Zhang & Wong [54]	LINE is simpler for seniors, while WeChat has more functions.	Platform comparative study is not food-related. Khlong Prap LINE OA will bring Thai-specific food features to LINE's simplicity.

B. System-Design and Testing Theories

Information system building and testing in this research employ human-computer interaction and information systems success theories. TAM by [69] and the IS Success Model by DeLone and McLean [70] are used to assess design concepts from Shneiderman [71] and Nielsen [72]. UI Design Guidelines Two primary concepts make the Information System (IS) simple to use, effective, and user-focused. Eight Golden Rules by Shneiderman emphasizes uniformity across interface components like buttons, colors, and typefaces and offering users relevant feedback that puts them in control in his 2005 book Eight Screen Design Guidelines. Structure encourages error avoidance and makes error management straightforward and adjustable. Other important considerations are system and real-world compatibility, user autonomy and freedom, and consistency and standards. Nielsen [72] also emphasizes error avoidance, recognition over recall (making information available rather than forcing people to remember it), flexibility and efficiency, and simple design. Finally, the system must provide clear guidance and documentation to aid users in identifying, diagnosing, and correcting errors.

C. System Evaluation Framework

This research uses a synthesized assessment approach to evaluate system effectiveness and adoption. The main assessment framework is DeLone and McLean [70] Model of Information Systems Success. This prominent methodology measures complete, multidimensional IS success. Information Quality, System Quality, and Service Quality separately and jointly affect User Satisfaction and Intent to Use (or reuse) the system.

D. Technology Acceptance Model (TAM)

The TAM [69] is used to assess usability and user acceptance within the IS success framework. The robust TAM hypothesis predicts and explains technology user behavior. It highlights two core ideas as system acceptance drivers:

The degree to which a person feels a system will improve their work performance is called perceived usefulness (PU).

This study defines PU as a system that offers useful information, speeds up work, and simplifies chores. PEOU: How easy a person thinks the system will be to use. The perceived system learning, comprehension, and operation ease is included.

Davis [69] found that PU and PEOU directly affect a user's system use attitude, which predicts their actual usage intentions.

E. Synthetic Assessment Model

This study combines the DeLone and McLean [70] model with the TAM core components [69]. To establish IS success, this study's assessment questionnaire assesses system, information, and service quality, perceived usefulness, and ease of use. Nielsen's [72] 10 usability principles are crucial for UI design if you wish to expand on these criteria. These algorithms provide system status to inform users. Another important thing is to keep the system and the real world compatible. Users should also have power and freedom, and there should be stability and standards. Nielsen [72] also puts an emphasis on not making mistakes, recognizing knowledge instead of forcing people to learn it (making it easy to find instead of hard to remember), being flexible and efficient, and making things that are simple. Last but not least, the system needs to have clear help and instructions to help users find, analyze, and fix problems.

III. Research Methodology

This is a mixed-method research between qualitative and quantitative research. It uses triangulation techniques consisting of collecting data from primary sources, interviewing and asking for opinions from real users, and confirming information from experts.

A. Population and Samples

The population in this study was the elderly caregivers in Khlong Prab Subdistrict, Ban Na San District, Surat Thani Province, which consisted of 598 people [55]. For qualitative research, a purposive sample was selected, consisting of 14 elderly caregivers, divided into 10 family members or relatives, 2 village health volunteers, and 2 elderly caregivers in the community. In addition, there were 3 experts: a local public health officer and two local food experts. For quantitative research, a purposive sample was also selected, selecting 235 elderly caregivers in Khlong Prab Subdistrict. This sample size was calculated using the formula of [56] at a 95 per cent confidence level and an error of ±5%.

B. Research Instruments

Both the interview and questionnaire were developed according to research methodologies accepted in the academic circle and went through a quality control process according to standards. The interview research instrument has been tested for reliability by a panel of 3 experts in information systems. The test results show an index of consistency between the questions and the research objectives (IOC) at 0.98. As for the questionnaire, it was tested to collect data with a group of 30 people with demographic characteristics and contexts similar to the actual sample group. The data was then analyzed for reliability using the alpha coefficient calculation process according to Cronbach's principle, which showed a reliability of the entire questionnaire at 0.953. Both the interview and questionnaire were approved by the Human Research Ethics Committee of the Suratthani Rajabhat University. According to the certification document number SRU-EC 2024/150, which has a certification period from 23 December 2024 to 22 December 2025.

C. Data Collection

Data collection by the interview process was conducted by face-to-face conversation, lasting 45-60 minutes per informant at Khlong Prab Subdistrict Health Promotion Hospital. Audio recordings were recorded with the informant's consent, and important points were noted during the interview. After the interview, the audio recordings were carefully transcribed and the interview summary was returned to the informant for verification of completeness and accuracy. A purposive sample of 14 senior caregivers was chosen for qualitative study, which included 10 family members or relatives, 2 village health volunteers, and 2 elderly caregivers from the community. In addition, three specialists were present: a local public health officer and two local food experts.

D. Data Analysis

Data analysis in this study used various statistical methods as follows. For the background information of the informants, such as gender characteristics, education level, and frequency of using LINE communication applications, statistical analysis was performed in the form of frequency and percentage. For the opinion data, the mean and standard deviation were analyzed to reflect the level of opinion both in general and in each issue. For the data from the open-ended questions, the content analysis was used to categorize and summarize important points, and the frequency of issues with similar content was counted.

E. Developing Tools

The Khlong Prab Subdistrict Local Food Information System for the Elderly was developed using the following tools. Visual Studio Code is used for coding, along with Laravel Herd, which manages the development environment on macOS. This system uses the Laravel Framework as the main base for development, and is connected to the front-end via Inertia.js, which enables the efficient development of SPA applications. The user interface is developed using React, which provides fast response, and the Ionic Framework, which allows the system to display on multiple platforms. This information system supports usage via the LINE application with LINE LIFF and LINE Official Account technologies, allowing caregivers of the elderly to access information conveniently. The design uses Figma to create an interface and a suitable user experience, and the code is managed using the Git version control system, which allows the development team to work together efficiently.

F. Steps in Developing the System

The steps in developing the local food information system for the elderly in Khlong Prab Subdistrict are as follows:

1) Develop an information system via the Line OA platform

2) Write a program to calculate the health assessment of non-communicable chronic diseases. The assessor answers 7 questions as follows: i) Have you ever smoked? ii) Do you have diabetes? iii) What is your blood pressure level? iv) What is

your waist size? v) How tall are you? vi) How much do you weigh? vii) Do you have a history of diabetes in your relatives?

3) Then use the data to calculate the risk of 4 diseases: diabetes, hypertension, cardiovascular disease, and overweight. These questions in the disease assessment and the formula for calculating non-communicable chronic diseases refer to [10].

4) Recommend appropriate menus for users by displaying health menus according to the risk of various diseases and by meal, namely breakfast, lunch, afternoon, and evening. The information can be displayed as food names, pictures, and nutrition. This step is considered new knowledge that the research team has developed.

5) The researcher has collected menus from health food restaurants in Surat Thani Province to pin a map showing health restaurants with a menu, and can be pressed to go through Google Maps to the restaurant. With distance indication.

6) The researcher has written a program to display a health assessment graph, gender, age, risk group, and the most recommended food.

7) The researcher has developed a FAQ section with Line Liff. Displaying the menu in Rich Menu for users to use conveniently.

8) The researcher has developed a recipe for a local health food menu of Ban Khlong Prab Subdistrict, consisting of information on the name of the food, pictures, nutrition, and how to make it. This step is considered new knowledge that the research team has developed.

9) The researcher has collected recommended health menus for the elderly, separated by food type, consisting of information on the name of the food, pictures, restaurant address, and nutrition.

G. The usage of the Local Food Information System

The usage of the local food information system for the elderly in Ban Khlong Prab involves the following steps:

1) Logging in via Line (see Fig. 1).

a) Access the Line application and add friends by adding the ID: @*642*kxqcn.

b) Select the Home menu, then select the "Add Friends" menu, then select the "Search" menu.

c) The Line OA Elderly Food name appears

d) Line OA Elderly Food, a local food information system for elderly health care, consists of a login menu (https://elderlyfood.baanthammawat.com/?openExternalBrower=*1)*, a health assessment menu, a health menu, FAQs, and a graph of assessment results.

e) Click the menu link to start using the system. This will take you to the main page of the system, which has three main menus: Home, Overview, and Profile.

2) Health assessment (see Fig. 2): Health Assessment Users must complete seven health information questions. This assessment will be conducted using a series of questions for users to choose from. Once all information is complete, the system will assess the user's risk of various diseases.

3) Calculate the risk score for four diseases: i) Diabetes, ii) Hypertension, iii) Cardiovascular Disease, iv) Overweight (see Fig. 3)

4) Recommended healthy menus: After assessing, the system will recommend healthy menus, including foods to avoid, examples of appropriate menus to choose for breakfast, lunch, afternoon, and dinner.

5) Use the system by clicking the menu link. This opens the system's home page with three menus: Home, Overview, and Profile.

6) Health check: Health Checkup of Seven health details are required as mentioned above. Users will pick from a series of questions for this evaluation. Once all information is entered, the system will calculate illness risk.

7) Calculate four disease risk scores: i) Diabetes, ii) Hypertension, iii) cardiovascular disease, iv) Heavy weight, v) Healthy Menu Ideas.

8) After reviewing, the system will suggest healthy breakfast, lunch, afternoon, and supper meals, including items to avoid (see Fig. 4).

9) Khlong prab local cuisine: Learn about five local Khlong Prab menus: Yam Bai Mai/Khao Yam Bai Mai, Budu Nam with Butterfly Pea Rice, Ua Tai Pla, Kua Curry Paste, and Salak Loi Kaew. Details on each menu item, including ingredients and cooking processes, are shown (see Fig. 5).

*10)*Healthy food restaurant display: The Surat Thani Health Food Restaurant menu lists restaurants. Restaurants provide salads, appetizers, single meals, rice, noodles, and beverage options (see Fig. 6). A map, retail details, and contact information are also shown for the eatery. For navigation, users may connect to the restaurant (see Fig. 7).

*11)*Health assessment responses by gender, age, and risk are graphed (see Fig. 8).

*12)*FAQs—Frequently asked questions and answers.

IV. Results

A. The Need for Local Food Information and an Information System for Elderly Health Care

Analysis of the results of interviews with elderly caregivers to develop a local food information system in Khlong Prab Subdistrict, Ban Na San District, Surat Thani Province, is detailed as follows: A qualitative study interviewed 14 elderly caregivers in Khlong Prab Subdistrict, consisting of 10 family members/relatives (71.43%), 2 village health volunteers (VHV) (14.29%), and 2 community caregivers (14.29%). The survey by the authors identified the needs and challenges in preparing local food that is appropriate for the health of the elderly, as well as expectations for the development of an information system that will enhance knowledge and skills in caring for the elderly through local food.

B. Food Preparation Characteristics and Challenges

From the data analysis, it was found that most caregivers (12 people, 85.71%) emphasized the use of natural and local ingredients in cooking, especially local vegetables that are grown by themselves or found in the community. Interviewee

No. 1 said, "Mostly, I cook food that my mother likes and is easy to eat because my mother has a dental problem. I focus on soft meats, tom yum, sour curry, galangal curry, anything with lots of vegetables."

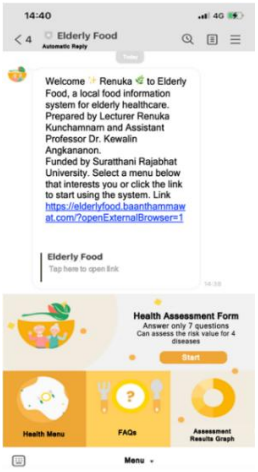


Fig. 1. Home.

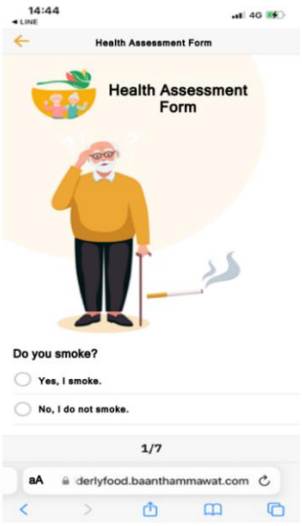


Fig. 2. Assessment form.

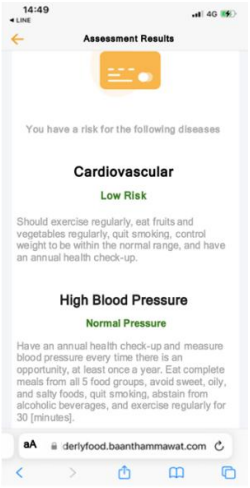


Fig. 3. Calculate results.

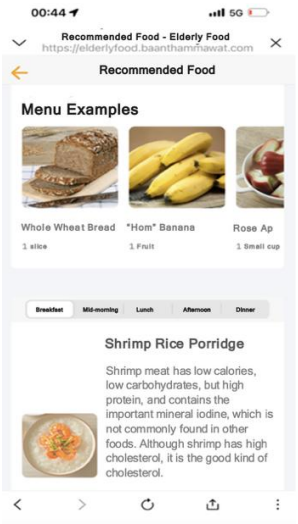


Fig. 4. Recommended menu.

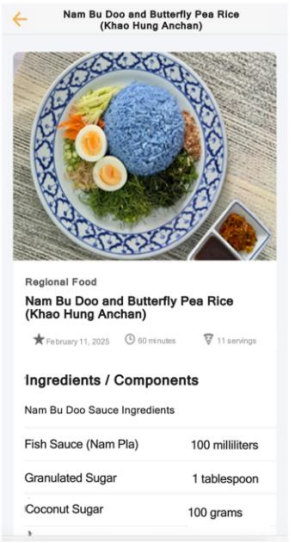


Fig. 5. Local menu.

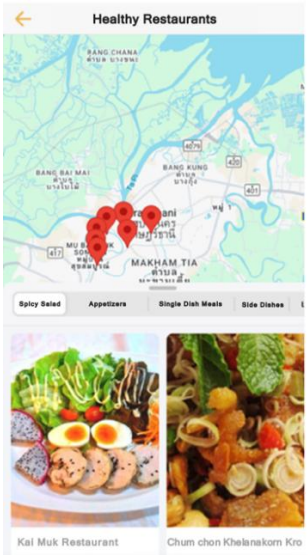


Fig. 6. Searching restaurant.

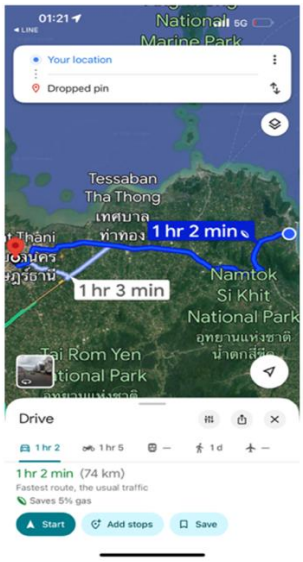


Fig. 7. Navigation.

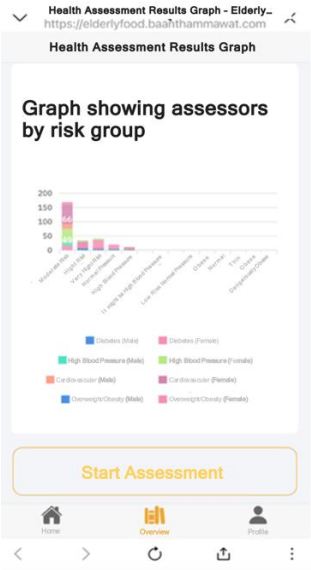


Fig. 8. Graph.

Almost all caregivers (13 people, 92.86%) adjusted their diet to suit the elderly's underlying diseases. Interviewee No. 9 added, "My mother has high blood pressure and diabetes, so I try to reduce sugar, salt, and oil, and season it lightly." Similarly, Interviewee No. 2 said, "My father likes to eat spicy food, but he has kidney disease. He has to be careful about salt, which makes the food bland and tasteless. He doesn't want to eat it, so he has to try to find ways to make it more appealing without using seasonings high in sodium."

Ten interviewees (71.43%) used local herbs in their cooking. Interviewee No. 3 said, "Most of them learned from listening to the elders in the community, learning from their mothers, and sometimes from the village health volunteers when they came to share knowledge in the village, such as using turmeric, ginger, galangal, and moringa leaves in cooking."

In terms of challenges, most caregivers (11 people, 78.57%) were unsure about interactions between food and medicines that the elderly were taking. Interviewee No. 6 said, "I am not sure if some foods are suitable for my mother's disease, such as sugar in some fruits, will affect my mother's diabetes, or some foods may be high in potassium, which is not good for the kidneys that are starting to have problems."

Nine caregivers (64.29%) faced problems with seasons and finding ingredients. Interviewee No. 6 said, "Some seasons it is difficult to find some local vegetables, such as during the dry season, sweet vegetables are hard to find. We have to buy vegetables from the market instead, but we are not sure about the chemicals."

C. Knowledge Sources and Limitations in Accessing Information

Almost all caregivers (13 people, 92.86%) received knowledge about local food from the wisdom passed down from their ancestors. Interviewee No. 11 said, "Khlong Prab's local food is very nutritious because most of it is natural and free of chemicals. Our local vegetables have bitter, sour, and astringent tastes, which have medicinal properties."

In addition, caregivers also received knowledge from village health volunteers (10 people, 71.43%), medical personnel (8 people, 57.14%), online media and social media (7 people, 50.00%), and television programs (5 people, 35.71%). However, all caregivers (14 people, 100%) had problems accessing information about local foods. Interviewee No.12 said, "Most of the information is knowledge that has been passed down from generation to generation. There are no clear records. Sometimes we don't know how reliable it is. There is no medical evidence to confirm it. When we want to search for more information, it's difficult."

Common problems included scattered information (14 people, 100%), conflicting information (12 people, 85.71%), different local names (11 people, 78.57%), lack of scientific evidence (10 people, 71.43%), and information not specific to the locality (9 people, 64.29%).

D. Need for Information on Local Food

All caregivers (14 people, 100%) wanted information on the medicinal properties and nutritional value of local food. Interviewee No. 9 said, "I want to know what benefits each local vegetable has, especially for diseases that are common among the elderly, such as diabetes, blood pressure, and high cholesterol. I also want to know which local foods are high in calcium, help with bones, and which foods help with the excretory and digestive systems."

In terms of the relationship with various diseases, almost all caregivers (13 people, 92.86%) wanted to know which local foods help prevent or alleviate which diseases; While 12 caregivers (85.71%) wanted information on appropriate cooking methods, and 11 caregivers (78.57%) wanted information on the amount and frequency of consumption, as well as precautions and interactions with medications. In terms of data classification, Interviewee No. 4 suggested that "It should be divided by type of food, such as local vegetables, pickled food, local curry, and it might also be divided by benefits for various

diseases. For example, food for diabetics, food for people with high blood pressure, or divided by season, because some things are only available during certain times."

The data classification that caregivers wanted the most was by type of food (14 people, 100 per cent), by properties (13 people, 92.86%), by disease (12 people, 85.7%), by season (10 people, 71.43%), and by cooking method (9 people, 64.29%).

All caregivers (14 people, 100 per cent) wanted information linking local food to disease care. Interviewee No. 3 said, "I really want it. I want information about what to eat for this disease, what to avoid, such as diabetes, what vegetables to eat to reduce sugar, or blood pressure, and what to eat to reduce blood pressure." In addition, all 14 caregivers (100%) wanted information on how to cook or modify local food to suit their underlying diseases. Interviewee No. 5 said, "I want it. I want local recipes that are modified to suit the elderly, such as reducing saltiness, but still having good taste, or using alternative ingredients that are more beneficial, such as using coconut sugar instead of granulated sugar, or using herbal salt instead of regular salt."

E. Information System for Elderly Food Development Needs

In terms of appropriate data presentation formats, most administrators (13 people, 92.86%) like images with short text. Interviewee No.10 said, "I like images with short text that are easy to understand. If it's a video, it should not be too long; 1-2 minutes is enough. If you want to know more, just click to read the details. I also like having pictures showing the cooking steps clearly." In addition, caregivers also preferred short videos (10 people, 71.43%), large text (9 people, 64.29%), audio commentary (8 people, 57.14%), and local languages (7 people, 50%). As for the features they wanted in LINE OA, all caregivers (14 people, 100%) wanted to search by disease and daily recommended menus. Interviewee 1 suggested that, "I want to have a daily recommended menu that is appropriate for the disease and ingredients that are easy to find in the local area." Other features that caregivers wanted included searching by food type (13 people, 92.86%) and FAQs (12 people, 85.7%). Analysis of the interview results of elderly caregivers in Khlong Prab Subdistrict revealed the need for a local food information system that meets the specific needs of the community. Such a system should emphasize ease of use, provide reliable data, have clear illustrations, and link local food to the care of elderly people with various chronic diseases.

1) Results of interviews with local health personnel and local food experts

The results of interviews with 3 experts: 1 local health personnel and 2 local food experts are as follows. From the analysis of the interview content, 8 main issues were found. All 3 experts (100%) agreed that the local food of Khlong Prab Subdistrict has high nutritional value. This is because it uses fresh, natural ingredients that are not stored for long periods of time, uses local herbs for seasoning, and has cooking methods that emphasize boiling, steaming, and grilling more than frying.

All experts (100%) offered five different forms of data classification: According to food type, the options are: 1) salad, 2) snacks, 3) one-dish dinners, 4) side dishes, and 5) noodle dishes. All experts (100%) desired the Information System for Elderly Local Food to include the following five features: 1) Food search by ailment, 2) Food search by type, 3) Daily suggested meal, 4) Frequently asked questions, and 5) Personalized guidance system. In terms of local food information needs, all experts (100%) wanted five types of information: 1) in-depth information on nutrients in local vegetables, 2) the relationship between local food and NCDs, 3) flavor modification to suit the elderly with various diseases, 4) medicinal properties of herbs, and 5) methods of storing ingredients. All experts (100%) identified five problems in finding information about local food: 1) Most information is transmitted by word of mouth, 2) Scientific information is difficult to access, 3) Information on the Internet has different reliability, 4) Lack of knowledge transfer, and 5) Lack of information on food modification to accommodate modern diseases.

In terms of data classification, all experts (100%) proposed five types of classification: 1) Salad, 2) Snacks, 3) One-dish meals, 4) Side dishes, and 5) Noodle dishes, according to food types. For the development needs of the Information System for Elderly Local Food, all experts (100%) wanted the system to have five features: 1) food search by disease, 2) search by type of food, 3) daily recommended menu, 4) frequently asked questions, and 5) personalized advice system. In terms of appropriate data presentation formats, all experts (100%) suggested using images with short text, 1–2-minute videos, explanatory audio, infographics, and using easy-to-understand language, including some local dialects. The interview results reflect a clear need to develop a local food information system for the elderly. The focus is on providing useful, easily accessible information that meets the specific needs of the elderly with various chronic diseases. Using this information to develop the system will help preserve local food wisdom and effectively promote the health of the elderly in the community.

2) Evaluation of the efficiency of the local food information system for elderly health care.

F. General Information of the Respondents

From Table II and Fig. 9, it was found that most respondents were male, accounting for 26.39 per cent, followed by female, accounting for 35.70 per cent.

TABLE II. GENDER

Gender	Frequency	Percentage
Male	62	26.38
Female	173	73.62
Total	**235**	**100**

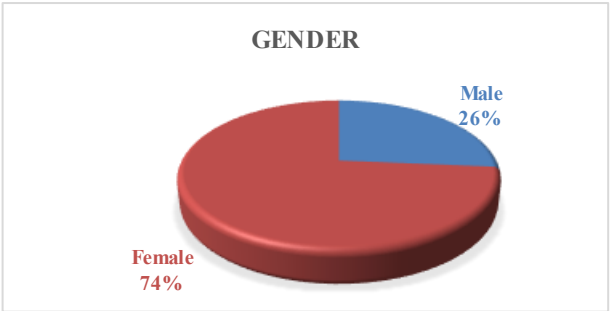


Fig. 9. Gender.

From Table III and Fig. 10, it was found that the respondents in the 18-30 age group had the highest proportion, accounting for 43 per cent, followed by the 51-60 age group, accounting for 35.70 per cent, while the 31-40 and 41-50 age groups had similar proportions at 11.10 and 10.20 per cent, respectively.

TABLE III. AGE

Age	Frequency	Percentage
18-30 years	101	43.00
31-40 years	26	11.10
41-50 years	24	10.20
51-60 years	84	35.70
Total	**235**	**100.00**

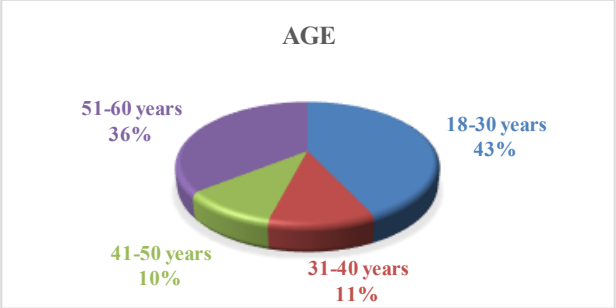


Fig. 10. Percentage of age.

TABLE IV. EDUCATION LEVEL

Education Level	Frequency	Percentage
Below Bachelor's Degree	110	46.81
Bachelor's Degree	123	52.34
Above Bachelor's Degree	2	0.85
Total	**235**	**100.00**

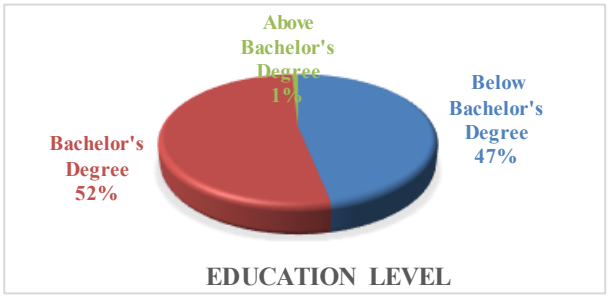


Fig. 11. Percentage of education level.

From Table IV and Fig. 11, it was found that most of the respondents had a bachelor's degree, accounting for 46.81 per cent, followed by those with lower than a bachelor's degree, accounting for 46.81 per cent, and the least was those with higher than a master's degree, accounting for 0.85 per cent.

From Table V and Fig. 12, it was found that most of the respondents used the LINE application every day, accounting for 54.47 per cent, followed by using the LINE application 2-3 days/time, accounting for 21.70 per cent, and using the LINE application once a week, accounting for 21.70 per cent, and the least used others, accounting for 2.13 per cent (rarely 1.40%, rarely used 0.73%).

TABLE V. INFORMATION SYSTEM FOR ELDERLY USAGE FREQUENCY

Line usage frequency	Frequency	Percentage
Every day	128	54.47
2-3 days/time	51	21.70
Once a week	51	21.70
Other	5	2.13
Total	**235**	**100.00**

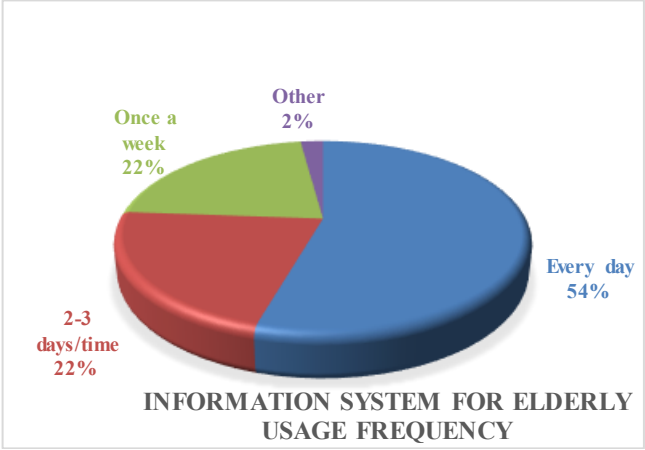


Fig. 12. Information system for elderly usage frequency.

G. System Performance Evaluation and Utilization

TABLE VI. OVERVIEW OF SYSTEM PERFORMANCE EVALUATION AND UTILIZATION

Aspect	Mean	S.D.	Opinion level
1. Content	4.41	0.72	Strongly agree
2. Functionality	4.40	0.68	Strongly agree
3. Usability of Healthy Food LINE OA	4.49	0.68	Strongly agree
4. Efficiency	4.46	0.64	Strongly agree
5. Utilization	4.60	0.57	Strongly agree
Total	**4.47**	**0.66**	**Strongly agree**

Table VI shows that most respondents rated their overall opinion on each aspect at the strongly agree level ($\bar{x}$ = 4.47). When considering each aspect individually, it was found that most respondents believed that the Healthy Food LINE could be utilized the most ($\bar{x}$ = 4.60), followed by the usability aspect of Healthy Food LINE OA ($\bar{x}$ = 4.49), and the least was the functionality aspect ($\bar{x}$ = 4.40).

Table VII revealed that the majority of respondents strongly agreed with all items ($\bar{x}$ = 4.41). When considering each item individually, most respondents believed that the Healthy Food LINE contains essential content for comprehensive elderly care ($\bar{x}$ = 4.50). This was followed by their belief that the Healthy Food LINE provides menu information suitable for elderly health and offers nutritional information on local food appropriate for elderly health care ($\bar{x}$ = 4.43). The least agreement was with the statement that the Healthy Food LINE has comprehensive information on local food ($\bar{x}$ = 4.32).

TABLE VII. CONTENT

Content	Mean	S.D.	Opinion level
1. The Healthy Food LINE contains complete local food information.	4.32	0.719	Strongly agree
2. The Healthy Food LINE provides food menus appropriate for elderly well-being.	4.43	0.745	Strongly agree
3. The Healthy Food LINE provides nutritional information on local cuisine suitable for elderly health management.	4.43	0.715	Strongly agree
4. The Healthy Food LINE content is appropriately written, easy to comprehend, and suitable for elderly users.	4.35	0.767	Strongly agree
5. Healthy Food LINE includes all necessary content for holistic elderly care.	4.50	0.669	Strongly agree
Total	**4.41**	**0.72**	**Strongly agree**

TABLE VIII. FUNCTIONALITY

Functionality	Mean	S.D.	Opinion level
1. The Healthy Food Information System is capable of managing local food data categories.	4.37	0.650	Strongly agree
2. The Healthy Food LINE allows adding, deleting, and modifying local food data.	4.28	0.760	Strongly agree
3. The Healthy Food LINE enables searching for local food information.	4.37	0.676	Strongly agree
4. The Healthy Food LINE can display information in a suitable format.	4.47	0.662	Strongly agree
5. The database system operates accurately.	4.50	0.669	Strongly agree
Total	**4.40**	**0.68**	Strongly agree

Table VIII revealed that the majority of respondents strongly agreed with all items ($\bar{x}$ = 4.40). When considering each item individually, it was found that most respondents believed that the Healthy Food LINE database system functions correctly ($\bar{x}$ = 4.50), followed by the Healthy Food LINE can present information in an appropriate format ($\bar{x}$ = 4.47), and the least was the Healthy Food LINE can add, delete, and modifying local food information ($\bar{x}$ = 4.28).

Table IX revealed that the majority of respondents strongly agreed with all items. When considering each item individually, it was found that most respondents believed that the Healthy Food LINE has clarity of text, colors, and background displayed on the screen ($\bar{x}$ = 4.57), followed by clarity of text, colors, and background displayed on the screen ($\bar{x}$ = 4.53), and the least was the navigation system design allows easy access to information ($\bar{x}$ = 4.41).

Table X revealed that the majority of respondents strongly agreed with all items. When considering each item individually, most respondents believed that retrieving various information can be done efficiently ($\bar{x}$ = 4.51). This was followed by their belief that the Healthy Food LINE can be used continuously for extended periods and can support multiple users simultaneously ($\bar{x}$ = 4.48). The least favorable opinion was regarding the accuracy of the display results from linking each page ($\bar{x}$ = 4.37).

TABLE IX. USABILITY OF HEALTHY FOOD LINE OA

Usability of Healthy Food LINE OA	Mean	S.D.	Opinion level
1. Screen design is easily accessible.	4.43	0.715	Strongly agree
2. Clarity of text, colors, and background displayed on the screen	4.53	0.668	Strongly agree
3. Menus are easy to understand and convey clear meanings.	4.57	0.646	Strongly agree
4. Navigation system design allows easy access to information.	4.41	0.707	Strongly agree
Total	**4.49**	**0.68**	Strongly agree

TABLE X. EFFICIENCY

Efficiency	Mean	S.D.	Opinion level
1. Page navigation and linking display correctly.	4.37	0.664	Strongly agree
2. Data retrieval is performed efficiently.	4.51	0.587	Strongly agree
3. The Healthy Food LINE supports continuous long-term usage.	4.48	0.649	Strongly agree
4. The Healthy Food LINE accommodates concurrent multi-user access.	4.48	0.669	Strongly agree
Total	**4.46**	**0.64**	Strongly agree

TABLE XI. UTILIZATION

Utilization	Mean	S.D.	Opinion level
1. System information is useful for elderly care.	4.61	0.530	Strongly agree
2. Elderly individuals can utilize system information in their daily routines.	4.58	0.567	Strongly agree
3. Food information in the system benefits elderly health management.	4.60	0.556	Strongly agree
4. The Health LINE system encourages using local ingredients in elderly cooking.	4.56	0.599	Strongly agree
5. The elderly can use various system information for healthy food preparation.	4.65	0.576	Strongly agree
Total	**4.60**	**0.57**	Strongly agree

Table XI revealed that the majority of respondents strongly agreed with all items. When considering each item individually, most respondents believed that the elderly can use various information from the system to prepare healthy meals ($\bar{x}$ = 4.65). This was followed by the belief that the information in the system is beneficial for elderly care ($\bar{x}$ = 4.61), while the least agreement was with the Healthy LINE system promoting the use of local food ingredients in elderly meal preparation ($\bar{x}$ = 4.56).

As shown by the majority of respondents (52.6%) who responded "the system is already good" or "excellent", the program is effective. Favorable comments like "the system is already good" and "excellent", which were provided by the majority of respondents (52.6%), imply that the program is successful. With 21.05% of replies, the food menu categories got positive comments and suggestions for growth, such as local item menus, vegetarian and vegan options, and various meals to

pique senior appetites. The least common proposals were for system and feature enhancements (5.26%), stating that LINE OA is most suited for elderly citizens, and for use in a variety of locations (5.26%), where users asked to expand use and data coverage to all provinces. Positive responses to its benefits indicate that the development satisfies the needs of the elderly. Positive responses to its advantages indicate that the innovation meets the demands of the elderly.

1) Comparison of differences between genders influencing opinions on various aspects.

TABLE XII. ANALYSIS OF T-TEST RESULTS COMPARING FEMALES AND MALES ON VARIOUS ISSUES

Independent Samples T-Test		Statistic	df	p
Content	Welch's t	3.391	146	<.001
Functionality	Welch's t	1.286	116	0.201
Usability of Healthy Food LINE OA	Welch's t	1.711	132	0.090
Efficiency	Welch's t	2.845	125	0.005
Utilization	Welch's t	0.903	113	0.368
Note. H_a $\mu_1 \neq \mu_2$				

From Table XII, the data analysis results using Welch's t-test, which is an appropriate test for cases where the variances of two groups are unequal, can be summarized as follows for the comparison between females and males on various issues. This study found statistically significant differences at the .01 level between females and males in the content aspect and the performance aspect. However, no significant differences were found in the functionality aspect, the usability aspect of Healthy Food LINE OA, or the utilization aspect.

2) Linear regression analysis results: From Table XIII, it was found that the model is statistically significant in predicting the dependent variable ($F = 104, p < .001$). All four independent variables have a high correlation with the dependent variable ($R = 0.803$). The model can explain 64.5% of the variance in the dependent variable (utilization) ($R^2 = 0.645$).

TABLE XIII. MODEL FIT MEASURES

			Overall Model Test			
Model	R	R^2	F	df1	df2	p
1	0.803	0.645	104	4	230	<.001

Note. Models estimated using sample size of N=235

3) Factors influencing LINE OA utilization: From Table XIV, it was found that the factor with the greatest impact on utilization is system performance efficiency ($\beta = 0.4377$), followed by system functionality ($\beta = 0.1255$) and Healthy Food LINE OA usability ($\beta = 0.1183$), respectively. Meanwhile, content design does not have a significant effect on LINE OA utilization.

4) One-Way ANOVA analysis: From Table XV, the test results showed a p-value of 0.042, which is below the 0.05 significance level, indicating a statistically significant difference in the mean utilization values between at least one pair of groups.

TABLE XIV. MODEL COEFFICIENTS – UTILIZATION

Predictor	Estimate	SE	t	p
Intercept	1.3690	0.1613	8.488	<.001
Content	0.0442	0.0477	0.929	0.354
Functionality	0.1183	0.0588	2.013	0.045
Usability of Healthy Food LINE OA	0.1255	0.0517	2.429	0.016
Efficiency	0.4377	0.0638	6.861	<.001

TABLE XV. ONE-WAY ANOVA (WELCH'S)

	F	df1	df2	p
Utilization	3.28	3	20.1	0.042

5) Post-Hoc test analysis: Once the overall differences were found in the ANOVA, a Tukey post-hoc test was performed to determine which frequency groups differed in the LINE application usage. The Tukey post-hoc analysis of the differences in the mean utilization values between LINE application usage groups using the Tukey post-hoc method revealed that only one pair showed a statistically significant difference: the 2-3 day/use group and the once-weekly group ($p = 0.008$). The once-weekly group had a higher mean utilization score than the 2-3 day/use group by 0.278 units. Comparisons between the other groups did not reveal any statistically significant differences ($p > 0.05$), indicating that utilization was not different between the dailyuser group and the other groups, nor between the infrequent user group and the other groups. This study suggests that frequency of LINE usage may not be the primary factor directly influencing utilization, except for those who use LINE 2-3 times per day and those who use it once per week. Other factors, such as usage patterns, purpose of use, or quality of content accessed, may influence utilization in the once-a-week group, rather than just frequency of use.

V. DISCUSSION

A. Discussion of Interview Results with Elderly Caregivers and Experts in Khlong Prap Subdistrict

Based on the analysis of interview data with elderly caregivers and experts in Khlong Prap Subdistrict, the research findings can be discussed in relation to relevant concepts and theories as follows:

B. Needs for Local Food Information for Elderly Health Care

The results of the study revealed that the majority of elderly caregivers prioritize the use of natural and local ingredients in cooking. This is consistent with the findings of [57] who examined the nutritional value of Thai local foods and discovered that many of them contain components beneficial to the health of the elderly, particularly the variety of local vegetables, the use of herbs and spices, and high-quality protein sources derived from fish. This point is a key strength of this research when compared to previous studies, such as the Chatbot

system by [45] or system by [50]. Local food context recommendations are limited by these algorithms, but accuracy and pleasure are high. The fact that caregivers in the area require local food information thus confirms the importance of developing a system that integrates local-specific knowledge. The researchers discovered and verified culturally unique dietary requirements via participatory design with caregivers, a crucial methodological addition.

C. Local Elderly Food and Health Promotion

All researchers agreed that Khlong Prab Subdistrict's local food is nutritious and contains five dishes with special properties for the elderly: local vegetable curry, turmeric fried fish/herb fried fish, shrimp paste chili dip with boiled vegetables, rice salad, and herbal tea. The research by [58] found that Khlong Prab Subdistrict's traditional diet is healthy and helps prevent and cure chronic illnesses in the elderly. Moreover, [59] revealed that 78.6% of the elderly in Khlong Prab Subdistrict routinely eat local cuisine, supporting the expert interview findings. Sour fish curry with raw bamboo shoots, shrimp paste chili dip with local vegetables, and stir-fried stink beans with shrimp were the most popular local dishes among the elderly. These nutritious and medicinal dishes provide health benefits. Other health systems prioritize vital sign monitoring, like [48], or diabetes management using broad nutritional ideas, like [52]. This focus on local foods with specific properties (e.g., local vegetable curry, turmeric fried fish) addresses a different need. Vital sign monitoring systems only collect physiological data. This system, on the other hand, gives actionable, culturally relevant dietary recommendations that can be used to make healthy meals every day, getting a utilization score of $\underline{x} = 4.65$ for "elderly people can prepare healthy meals". Thus, health data may be linked to local dietary recommendations in this study.

D. Integrating Local Wisdom with Modern Medical Knowledge

Science-based information is needed to blend local wisdom with contemporary medicine. This supports [60], who found that traditional Thai dietary patterns, which align with the Nine Nutritional Commandments (rich in fish, vegetables, fruits, whole grains, and herbs), were associated with a significantly reduced risk of noncommunicable diseases (NCDs). Furthermore, the research results align with the World Health Organization's [61] concept of active aging, which emphasizes holistic health promotion for the elderly, emphasizing optimal health, social participation, and security. This integration approach represents a theoretical contribution, advancing the TAM by demonstrating its applicability in integrating traditional food wisdom with digital health systems for elderly care in rural contexts. Developing a local food information system that meets the needs of caregivers and the elderly will promote access to accurate and useful information, a key factor in promoting activeness in communities. This integration approach is supported by [46], who found that using traditional culinary knowledge with digital technologies helps older people accept healthy meals. Furthermore, the Khlong Prap LINE OA system integrates local food knowledge with health literacy, filling a gap identified by [51], whose research noted that previous work often focused only on health literacy while lacking the dimension of local cuisine.

E. Development of an Information System that Meets the Specific Needs of the Community

All caregivers had trouble finding local food information, in the study. Information scattering and data conflicts the key issues. The participatory design framework systematically addressed these challenges through ethnographic interviews with elderly caregivers and local experts. A systematic data collection and organization method is needed to address these issues. This supports [62] suggestion that an information system that integrates local food and nutrition information for the elderly will connect local wisdom with modern technology, preserving food culture and promoting sustainable health. The Nine Nutrition Commandments for the Elderly by [63] emphasize adapting foods to the physiological changes and specific needs of the elderly and chronic non-communicable diseases of the elderly.

F. User-Friendly Information System Design

Most caregivers (92.86%) preferred pictures with brief text, followed by short films (71.43%) and big typefaces (64.29%). An information system design that is easy to use and appropriate for many users is needed. This is consistent with [64], who found that older adults in Khlong Prab Subdistrict used technology due to child support, family communication, health information, and local wisdom. This finding supports the decision to use the LINE platform, which aligns with [47], who found that simple, local language-supported systems like LINE were more popular in East Asia. It also corresponds with [54], who concluded that LINE is simpler for seniors. As a design contribution, the system provides a replicable model using accessible platforms (LINE OA) with user-centered design principles (pictorial content, large fonts, local language), achieving high satisfaction scores. The design of this system, therefore, directly meets user needs.

G. The Key Features of a Local Food Information System

Disease-specific foods (100%), daily dietary guidelines (92.86%), and often asked questions (85.71%) were the caregivers' search requests. According to the holistic approach to nutrition in the Thai old, a system that provides tailored recommendations and suitable options for the elderly's health state is needed. In [65], the authors promoted local food wisdom, nutritional knowledge and skills, and health care integration. In contrast to broad diabetes management systems that use general food guidelines, this method uses popular local food to give personalized advice for particular situations. This helps all the workers who want to focus on things that are good for people with certain diseases. This demand reiterates that a good system should not merely stop at vital sign monitoring or provide broad recommendations, but must be able to provide “tailored recommendations” according to the specific health conditions of the elderly.

6) Discussion of evaluation and development of the local food information system for elderly health: The local food information system for health care for the elderly at Ban Khlong Prab was established appropriately and met its aims, according to growth statistics. Its performance and usability were rated "strongly agree," indicating that the system satisfies consumers' requirements. These empirical findings provide quantitative

evidence demonstrating the effectiveness of the approach for researchers, policymakers, and system developers.

A. System Development based on the TAM

The TAM model was used throughout system development [66]. This approach assessed perceived functionality and usability. Evaluation shows "easy-to-understand menu" as key factor in high user satisfaction. "Clear communication" and "Clarity of text, colors, and background" indicate a clear, straightforward, accessible, and age-friendly user interface design. This validates the design contribution in developing elderly-accessible interfaces for resource-limited settings. The literature review found that people in this setting prefer LINE and accessible language.

B. System Efficiency and Utilization

The evaluation results for efficiency and utilization were high, particularly for "Elderly people can use the information from the system to prepare healthy meals" and "Information in the system is useful for caring for the elderly". This is consistent with [67] concept of local food being important to the health and culture of the community. This study extends on [49], which found messaging services successful and affordable. The LINE-based method works well in rural areas with few resources because it gets the same level of culture blending and user acceptance without the need for custom application creation. It demonstrates that this cost-effectiveness can be combined with the integration of 'local culture and cuisine' (a gap identified in [49]). This cultural integration may also be a factor in improving health care cooperation, which [53] identified as a limitation of systems that are not culturally informed.

C. Factors Influencing Utilization

The linear regression analysis revealed that the factor that had the highest influence on the utilization was system performance, followed by system functionality and the use of the healthy food OA line. These empirical findings provide quantitative evidence for prioritizing technical performance in elderly-focused digital health interventions, serving as a practical guideline for system developers. This finding is consistent with the research of [68] that indicated that system performance and ease of use are important factors in the acceptance and utilization of technology among the elderly.

VI. Conclusion and Future Work

This research is exclusive to Khlong Prab Subdistrict; however, the technique applies to other rural areas in Thailand with traditional food cultures. The framework bridges generic health literacy systems and culturally informed interventions by giving researchers a replicable method for integrating local food wisdom with evidence-based nutrition science, policymakers a cost-effective digital health solution using existing platforms, and system developers validated design specifications for elderly-accessible interfaces in resource-limited settings. The system uniquely combines: 1) evidence-based nutrition aligned with WHO active aging principles and the Thai Nine Nutritional Commandments, 2) preservation of local food wisdom validated by 78.6% elderly consumption rates, and 3) accessible delivery through a platform already familiar to users, resulting in significantly higher practical utilization than systems without cultural grounding. To gain acceptance and lasting influence, future work should spread this notion throughout Thailand, analyze health advantages, and integrate with established medical systems.

Contribution

1) Theoretically, the study shows how digital health solutions may respect cultural settings by making technology that is easy for seniors to use and preserving traditional knowledge. These tools could help people and keep culture alive.

2) The project uses food information made by the community and a study of older people's habits to come up with a new way to do things that uses the digital tools they already have. This plan could be used for similar projects in Southeast Asia.

3) The study shows how to make health information systems that work for Thailand's older people who are comfortable with technology, who have cultural standards, and who want preventive health care.

4) The results show that older people are more likely to use and connect with platforms that have useful information that is relevant to their area. This is beneficial for their health and helps keep traditional knowledge alive.

Research Applications

A. Benefits to Elderly Persons and Caregivers

1) Elderly persons and caregivers will benefit from access to reliable information on local foods that are beneficial to their health, which can be applied to meal planning appropriate for their health status.

2) Local food information systems will help build confidence among elderly persons and caregivers in self-management of their health through appropriate food selection and the preservation of familiar food cultures.

B. Benefits to Communities and Local Areas

1) Communities will benefit from collecting, organizing, and disseminating local food wisdom, which will preserve and revitalize the food culture that is a community identity.

2) Disseminating information on the nutritional value and health properties of local foods will foster pride in local culture and promote the continuation of knowledge from generation to generation.

C. Government Agency and Related Organization Benefits

1) To improve aged care, public health organizations and health-promoting hospitals may include local culinary knowledge in their health service systems.

2) Related organizations may reuse the local food information system development for health information systems.

D. Benefits to the Academic Community

1) This research will help build a collaborative network among researchers, academics, and practitioners in various

fields, such as nutrition, information technology, geriatric nursing, and community development.

2) The developed local food information system will serve as an important source of information for future research on local foods and their application to promoting the health of the elderly.

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REFERENCES

[1] World Health Organization, “Global Report on Ageism,” Geneva: World Health Organization, 2021.

[2] United Nations, “World Population Ageing 2020: Highlights, Dept. of Economic and Social Affairs,” Population Division. New York: United Nations, 2020.

[3] World Bank, “Global Economic Prospects: Aging Societies and Productivity,” Washington, DC: World Bank, 2022.

[4] Office of the National Economic and Social Development Council, “Report on the population situation of Thailand, 2022,” Bangkok: Office of the National Economic and Social Development Council, 2022.

[5] Foundation of the Thai Gerontology Research and Development Institute, “Situation of Thai older persons 2023,” Bangkok: Printery Co., Ltd., 2023.

[6] National Economic and Social Development Council, “The 3rd National Plan for Older Persons (2023-2037),” Ministry of Social Development and Human Security, 2023.

[7] W. Prachuapmoh and C. Atsawanirandorn, "Challenges of Thai aging society: Policy recommendations," Journal of Social Science and Buddhist Anthropology, vol. 6, no. 8, pp. 13–29, 2021.

[8] R. Petchsungnoen *et al*., "Key components in holistic health care for the elderly," Journal of Public Health Nursing, vol. 35, no. 2, pp. 57–74, 2021.

[9] S. Satsatranurak and K. Pholsen, "Nutrition for Thai elderly: Current situation and promotion guidelines," Journal of Nutrition, vol. 56, no. 2, pp. 42–57, 2021.

[10] Department of Health, Ministry of Public Health, “Nutrition management guidelines for the elderly,” Bangkok: Bureau of Nutrition, Department of Health, 2022.

[11] Nutrition Association of Thailand, “Nutrition promotion guidelines for the elderly,” Bangkok: Nutrition Association of Thailand, 2023.

[12] P. Thapthani, S. Sangthong, and A. Vongpiriyayotha, "Development of a care model for older persons with depression in the community," Journal of Public Health Nursing, vol. 36, no. 1, pp. 161–175, 2022.

[13] D. Wilson, K. Shah, and D. Brenner, "Nutrition in aging and noncommunicable disease prevention: Current evidence and future directions," *The Journals of Gerontology: Series A*, vol. 78, no. 4, pp. 656–662, 2023.

[14] Department of Health, Ministry of Public Health, “Nutrition management guidelines for the elderly,” Bangkok: Bureau of Nutrition, Department of Health, 2022.

[15] S. Amarya, K. Singh, and M. Sabharwal, "Changes during aging and their association with malnutrition," *Journal of Clinical Gerontology & Geriatrics*, vol. 12, no. 1, pp. 78–84, 2021.

[16] W. Banpuan and N. Singhwiratham, "Barriers to accessing nutrition information for Thai elderly," Journal of Nutrition, vol. 57, no. 2, pp. 98–112, 2022.

[17] P. Tansakun, "Local food: Cultural heritage and Thai wisdom," Journal of Humanities and Social Sciences, vol. 12, no. 1, pp. 71–89, 2020.

[18] K. Mori, A. Takada, and Y. Sato, "Traditional Japanese diet and cardiovascular health in elderly: A prospective cohort study," Journal of Nutrition, Health & Aging, vol. 26, no. 4, pp. 412–420, 2022.

[19] N. Sirisuwat, W. Jarisarapurin, and K. Chakree, "Pharmaconutrients in Thai cuisine and their potential health benefits for aging population," *Journal of Ethnic Foods*, vol. 10, p. 6, 2023.

[20] T. Songnok *et al*., "Nutritional value and antioxidant activity of Southern local food," Journal of Science and Technology, vol. 29, no. 4, pp. 698–712, 2021.

[21] P. Wongprayoon and M. Sukprasansap, "Anti-inflammatory properties of southern Thai food ingredients: An *in vitro* and animal model investigation," Food & Function, vol. 13, no. 5, pp. 2840–2851, 2022.

[22] N. Vatanasuchart, K. Chamroonsawasdi, and R. Phuphaibul, "Traditional foods and psychological well-being among Thai elderly: A qualitative study," *Journal of Ethnic Foods*, vol. 8, p. 16, 2021.

[23] N. Arunothai, "Southern Food Identity: A Case Study of Surat Thani Province," Journal of Buddhist Social Sciences and Anthropology, vol. 5, no. 12, pp. 486–498, 2020.

[24] P. Wongchan, "A Survey of Local Food in Khlong Prap Subdistrict, Ban Na San District, Surat Thani Province," Journal of Liberal Arts, vol. 22, no. 2, pp. 415–437, 2022.

[25] S. Chansangchot *et al*., "Nutritional Value and Utilization of Sato (*Parkia Speciosa*) in Southern Thai Local Food," Journal of Nutrition, vol. 56, no. 3, pp. 77–91, 2021.

[26] D. Suwanwong, "Local Wisdom in Preparing Southern Thai Rice Noodle Curry (Namya Pak Tai) and Dried Fish Kidney Curry (Tai Pla Haeng) of Khlong Prap Subdistrict, Surat Thani Province," Journal of the Ways of Human Society, vol. 10, no. 1, pp. 105–123, 2023.

[27] U. Santiwattanatham *et al*., "A Study of the Nutritional Value of Local Desserts in Surat Thani Province," *Journal of Food Science*, vol. 41, no. 4, pp. 143–158, 2021.

[28] W. Charoentanang *et al*., "A Study of Antioxidants and Phytochemicals in Local Food of Surat Thani Province," Journal of Science and Technology, vol. 33, no. 6, pp. 814–825, 2022.

[29] P. Pongthep, S. Supaporn, and L. Chaval, "Effects of southern Thai spices and herbs on glycemic control in elderly with type 2 diabetes: A randomized controlled trial," Asia Pacific Journal of Clinical Nutrition, vol. 31, no. 1, pp. 88–97, 2022.

[30] J. Suphunnee, P. Wanwimolruk, and S. Jaroenporn, "Nutritional composition and antioxidant properties of indigenous vegetables in Southern Thai cuisine," Food Chemistry, vol. 410, p. 135132, 2023.

[31] R. Phongsawatmanit, "Conservation and Promotion of Thai Local Food: Approaches and Challenges," Journal of Humanities and Social Sciences, vol. 13, no. 2, pp. 67–84, 2021.

[32] N. Suwansucharit, "Conservation and Promotion of Local Food Culture in Khlong Prap Subdistrict, Ban Na San District, Surat Thani Province," Journal of Buddhist Social Sciences and Anthropology, vol. 8, no. 2, pp. 226–241, 2023.

[33] S. Soithong, "Development of Gastronomy Tourism of Khlong Prap Subdistrict, Ban Na San District, Surat Thani Province," Journal of Sustainable Tourism Management, vol. 7, no. 2, pp. 76–93, 2022.

[34] Institute for Population and Social Research, “Technology and the Promotion of Quality of Life for the Elderly,” Nakhon Pathom: Institute for Population and Social Research, Mahidol University, 2022.

[35] W. Rangkawat, P. Honghin, T. Chanpen, S. Chumum, K. Katunyu, and S. Wiwat, "Technological Innovations for the Elderly in Thailand: Current Situation and Future Directions," Journal of Health Systems Research, vol. 15, no. 3, pp. 329–345, 2021.

[36] T. Suwattanakul and P. Nantakarat, "Challenges in Accessing Digital Health Information among Thai Elderly," Journal of Integrated Social Sciences, vol. 10, no. 1, pp. 24–46, 2023.

[37] J. Tan, A. Wong, and G. Koh, "Health Connect: Leveraging digital technology to improve health outcomes among older adults in Singapore," Journal of the American Medical Informatics Association, vol. 30, no. 3, pp. 510–517, 2023.

[38] C. Thianchai *et al.*, "Effect of the 'Sungwai Sukkhaphap Di' Application on Reducing Malnutrition Risk in the Elderly: A Quasi-Experimental Study," Journal of Public Health Nursing, vol. 37, no. 2, pp. 75–91, 2023.

[39] P. Wongsaroj, S. Tabtimsuwan, and K. Chancharoen, "LINE Official Account as a platform for health education delivery to Thai elderly: A mixed-methods evaluation," Journal of Medical Internet Research, vol. 25, no. 4, p. e41752, 2023.

[40] A. Chaikoolvatana, W. Phongphaew, and N. Kaewpitoon, "Digital health literacy and health knowledge among Thai elderly: A community-based study," Journal of Health Research, vol. 37, no. 2, pp. 131–142, 2023.

[41] T. Songprasert, S. Wibulpolprasert, and S. Tantivess, "Cultural appropriateness in nutritional interventions for elderly in Thailand: A qualitative study," *BMC Health Services Research*, vol. 21, p. 584, 2021.

[42] A. Puri, B. Kim, O. Nguyen, P. Stolee, J. Tung, and J. Lee, "Digital literacy among older adults: Barriers to adoption of health information technology," International Journal of Medical Informatics, vol. 158, p. 104665, 2022.

[43] T. Wattanachai, S. Promthet, and P. Thammawijaya, "Dietary patterns of Thai elderly and associations with health outcomes: A systematic review," Asia Pacific Journal of Clinical Nutrition, vol. 30, no. 4, pp. 527–541, 2021.

[44] S. Charoenkiatkul, S. Isaramalai, S. Srisurapran, W. Wimonpeerapattana, and R. Phromsuth, "Food and Nutrition Literacy Questionnaire for Thai Older Adults: A Development and Validation Study," Journal of Health Research, vol. 36, no. 6, pp. 1109–1121, 2022, doi: 10.1108/JHR-08-2020-0381.

[45] S. Kim, J. Park, and H. Lee, "Chatbot-based nutritional guidance for elderly via LINE application: Development and evaluation," Journal of Nutrition and Health Aging, vol. 27, no. 3, pp. 324–333, 2023.

[46] A. Singh and B. Kaur, "Integration of traditional food knowledge into digital health platforms for elderly care," Journal of Food and Culture, vol. 18, no. 4, pp. 289–305, 2022.

[47] C. Johnson and E. Martínez, "Cross-cultural adoption of messaging platforms for elderly health management," Journal of Global Health Technology, vol. 12, no. 1, pp. 45–62, 2024.

[48] A. Sangchan and S. Lekcharoen, "Development of a Health Monitoring and Assessment System for the Elderly Using LINE OA and IoT," Journal of Biomedical Engineering, vol. 15, no. 2, pp. 65–78, 2023.

[49] M. Harris and J. Brown, "Messaging applications for remote health monitoring in elderly population: A systematic review," International Journal of Digital Health, vol. 5, no. 2, pp. 167–185, 2023.

[50] J. Thepard, S. Pattanasiriphakdi, and W. Kongnu, "Development of a Medication Reminder and Medical Appointment System for the Elderly via the LINE OA Application," Journal of Information Technology, vol. 18, no. 2, pp. 45–57, 2022.

[51] S. Dechadisai and P. Makmee, "Development of a LINE OA Platform to Promote Health Literacy in the Elderly," Journal of Public Health, vol. 53, no. 1, pp. 78–92, 2023.

[52] W. Rangkawat and S. Wongwiseskul, "Application of LINE OA for Nutritional Counseling in Elderly Patients with Diabetes," Journal of Nutrition, vol. 57, no. 3, pp. 112–125, 2022.

[53] Y. Tanaka, A. Suzuki, and K. Nakamura, "Development and evaluation of LINE-based health management system for elderly," Journal of Medical Informatics, vol. 45, no. 2, pp. 213–225, 2023.

[54] L. Zhang and T. Wong, "WeChat and LINE: Comparative analysis for elderly care in Asian digital healthcare ecosystem," Asian Journal of Health Technology, vol. 9, no. 1, pp. 76–91, 2024.

[55] Electronic Transactions Development Agency, "Report on the Survey of Internet User Behavior in Thailand 2023," Bangkok: Electronic Transactions Development Agency, 2023.

[56] R. V. Krejcie and D. W. Morgan, "Determining sample size for research activities," Educational and Psychological Measurement, vol. 30, no. 3, pp. 607–610, 1970, doi: 10.1177/001316447003000308.

[57] N. Sinthispong, "Technology Acceptance Affecting Online Purchasing Decisions of the Elderly," M.S. thesis, Naresuan Univ., 2021.

[58] D. Simatupang and N. I. Ischak, "Functional properties of local food in Klong Prab sub-district," 2022.

[59] W. Yongpisanphob, "Industry Outlook 2022-2024: Beverage Industry," Krungsri Research, Feb. 1, 2022. [Online]. Available: https://www.krungsri.com/en/research/industry/industry-outlook/food-beverage/beverage/io/io-beverage-2022.

[60] W. Jiamjarasrangsi, C. Kaewanuchit, and P. Puthvinit, "Development of a Nutrition Literacy Questionnaire for Older Adults in Urban Communities," Journal of Health Systems Research, vol. 17, no. 1, pp. 62–75, 2023.

[61] World Health Organization, "Decade of healthy ageing: 2020-2030," 2020. [Online]. Available: https://www.who.int/initiatives/decade-of-healthy-ageing.

[62] M. Chaisawat, P. Kessomboon, R. Kamsom, K. Thavorn, and W. Aekplakorn, "Development and validation of a simple nutritional screening tool for community-dwelling older adults: A cross-sectional study," BMC Geriatrics, vol. 22, no. 1, p. 329, 2022, doi: 10.1186/s12877-022-03006-z.

[63] P. P. Sirichakwal, K. Sranacharoenpong, and K. Tontisirin, "Food based dietary guidelines (FBDGs) development and promotion in Thailand," Asia Pacific Journal of Clinical Nutrition, vol. 20, no. 3, pp. 477–483, 2011.

[64] K. Lephilibert and A. Pongvitayapanu, "Digital technology usage among elderly in Klong Prab sub-district," 2023.

[65] P. Srinonprasert, P. Srisvatsut, C. Chalermsri, and W. Aekplakorn, "Validation of the Mini Nutritional Assessment-Short Form (MNA®-SF) for nutritional screening among older adults in Thailand," Proceedings of the Nutrition Society, vol. 81, no. OCE1, p. E115, 2022, doi: 10.1017/S002966512100411X.

[66] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," MIS Quarterly, vol. 13, no. 3, pp. 319–340, 1989.

[67] H. V. Kuhnlein and O. Receveur, "Dietary change and traditional food systems of indigenous peoples," Annual Review of Nutrition, vol. 16, pp. 417–442, 1996.

[68] C. Machara, J. Viboonwattanakit, and S. Yanakomud, "Factors Affecting Technology Acceptance in Thai Elderly," Journal of Academic Information Technology, vol. 18, no. 1, pp. 45–58, 2022.

[69] F. Davis, "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," *MIS Quarterly*, vol. 13, no. 3, pp. 319-340, 1989. doi: 10.2307/249008.

[70] W. H. DeLone and E. R. McLean, "The DeLone and McLean Model of Information Systems Success: A Ten-Year Update," *Journal of Management Information Systems*, vol. 19, no. 4, pp. 9-30, 2003. doi: 10.1080/07421222.2003.11045748.

[71] B. Shneiderman, C. Plaisant, M. Cohen, S. Jacobs, and N. Elmqvist, *Designing the User Interface: Strategies for Effective Human-Computer Interaction*, 6th ed. Pearson, 2016. [Online]. Available: http://www.cs.umd.edu/hcil/DTUI6.

[72] J. Nielsen, "Heuristic Evaluation," in *Usability Inspection Methods*, J. Nielsen and R. L. Mack, Eds. New York: John Wiley & Sons, 1994, pp. 25-62.

Human-Centered Behavioral Analysis of Window Operation Using AI-Based Skeletal Recognition

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***Abstract*—This study presents a quantitative approach to analyzing window opening and closing behaviors using skeletal recognition technology. Video data of five participants performing these actions were captured and processed using the Openpose model, which detects 25 human joints. Focusing on the shoulder, elbow, and wrist, the study analyzed time-series joint coordinates to identify motion patterns and behavioral characteristics. The results revealed consistent relationships among joint movements and enabled accurate distinction between left- and right-hand operations. In addition, behavioral distribution characteristics were examined by visualizing horizontal and vertical skeletal displacements. The results showed that stationary postures are concentrated near a reference origin, whereas window operation actions produce distinct spatial shifts in the coordinate space, indicating that occupant behavior can be interpreted as a sequence of state transitions composed of distinct behavioral phases. The findings confirm that skeletal data can effectively represent occupant behavior without intrusive sensors, providing a non-contact and privacy-preserving monitoring method. This approach contributes to the development of human-centered intelligent building systems that can adapt indoor environments in real time based on occupant actions, thereby improving both thermal comfort and energy efficiency. Future research will expand behavioral categories and explore real-time implementation in smart building applications.**

Keywords*—Image processing; skeletal recognition; behavioral analysis; Openpose

I. Introduction

In recent years, the rapid advancement of digital technologies such as the Internet of Things (IoT) and Artificial Intelligence (AI) has significantly influenced the architecture and construction industries. These emerging technologies have enabled the development of intelligent, responsive environments that can adapt to human behaviors and preferences in real time [1]. Buildings are no longer static structures; they are evolving into dynamic systems capable of sensing, interpreting, and responding to occupants' needs. Among the many applications of IoT and AI in architecture, the creation of human-centered thermal environments has become an area of growing research interest [2].

Traditional environmental control systems, such as heating, ventilation, and air conditioning (HVAC), rely primarily on temperature, humidity, and occupancy sensors to regulate indoor conditions. However, such systems often neglect the diversity and variability of human behavior, which plays a critical role in determining comfort levels. For instance, an occupant's decision to open or close a window can significantly affect indoor temperature, air quality, and energy consumption. Understanding and predicting these behavioral patterns are essential for designing energy-efficient buildings that maintain comfort without excessive energy use [3, 4].

Recent studies have demonstrated that IoT-based monitoring systems can capture and analyze occupant behavior with high temporal and spatial resolution. By connecting sensors, cameras, and data analytics platforms, researchers can model the relationship between human actions and environmental parameters [5]. At the same time, AI technologies, including machine learning and computer vision, have made it possible to interpret complex human motions automatically. For example, deep learning-based image recognition models can detect gestures, postures, and movements that correspond to specific behaviors such as window operation, light switching, or adjusting clothing layers [6, 7].

Despite these advancements, challenges remain in achieving reliable and context-aware recognition of occupant behaviors. Many existing studies rely on wearable sensors or environmental data, which may not fully capture the physical actions associated with comfort regulation. Moreover, privacy concerns often limit the use of conventional video data in indoor monitoring applications [8]. To address these challenges, recent research has explored the use of skeletal recognition and pose estimation techniques, which analyze the positions of human joints rather than identifiable facial features. Such approaches provide a balance between behavioral accuracy and privacy protection [9, 10].

In this context, the present study investigates window-opening and closing as a form of architectural and environmental behavior using skeletal recognition technology. Rather than treating window operation as a simple motion detection task, this study interprets it as an occupant-driven behavioral process that influences indoor thermal conditions and energy performance. By capturing and modeling these behaviors, the research aims to support the development of intelligent, privacy-preserving, and human-centered building control strategies.

II. Literature Review

Many researchers have used the Internet of Things (IoT) and artificial intelligence (AI) technologies to study various issues in the architectural field. In recent years, research on human-centered thermal environments has attracted considerable attention [11, 12].

Henning Metzmacher et al. [13], Bin Yang et al. [14], and Yeyu Wu et al. [15] used thermal imaging camera images and skin sensors to analyze the thermal sensation of occupants in real-time and to control the indoor thermal environment according to the number of occupants. Mateus Vinícius Bavaresco et al. [16] and Muhammad Aftab et al. [17] monitored IoT-based buildings to provide an optimal thermal environment for behavioral changes of occupants. Miao Zang et al. [18] investigated human-centered indoor environment control methods based on image data collected using IoT technology.

Wenjun Duan et al. [19] investigated a method for detecting the behavior of changing the amount of clothing in real-time using video data. Kailai Sun et al. [20] used AI technology to classify the standing and sitting positions of occupants and attempted a human flow line analysis.

AI technology has also been used in many other fields to solve a variety of problems. Table I shows previous studies that used AI.

TABLE I Summary of Previous Studies

Field	Authors	Year	Main contributions
Behavior modification	Tomoya Tamei et al. [21]	2015	AI technology was used to analyze human movement behavior
	Teruhiro Mizumoto et al. [9]	2018	Behavioral pattern analysis of kitchen occupants
	Zhu Bin et al. [5]	2020	Detection and recognition of abnormal pedestrian behavior
Arts	Yan Wang et al. [22]	2023	Algorithm development to detect dance poses using AI technology
	Amir Irfan Mazian et al. [23]	2023	AI technology was used to detect the dance poses
Medical	Thanh-Hai Tran et al. [24]	2017	Development of a behavior detection system for inpatients falling out of bed
	Ramesh Balaji et al. [25]	2018	Development of a health management system for the elderly using AI remote control monitoring
	Nur Khalidah Zakaria et al. [26]	2021	Development of a method for detecting the behavior of people with disabilities
Safety	Manoj Kurien et al. [27]	2017	Development of a safety behavior detection system using 3D model simulation
	Paige Wenbin Tien et al. [4]	2020	Detection of work behavior of occupants in office buildings
	Chengle Fang et al. [28]	2022	Development of a safety action detection system for construction sites
	Zhe Sun et al. [29]	2023	Detection of clothing at construction sites using AI detection systems
	Xiangang Cao et al. [30]	2023	Investigation of a method for detecting safe behavior using skeletal recognition
Education	Guy Gaziv et al. [31]	2017	Development of a conversational behavior support system using 3D models and AI technology
	Soohyun Choi et al. [32]	2020	Development of a child behavior pattern analysis and facial expression recognition system using AI application technology

III. Methodology

A. Experiments Summary

Window opening and closing detection is made more efficient by directly analyzing the behavior of occupants. In addition, quantitative analysis methods must be considered to realize a human-centered built environment. In this study, cameras were installed in the room to collect video data of five occupants opening and closing windows. The camera was set to FPS 30, and the video data were saved on an SD card. The format of the data is *.mp4, 3840(px) × 2160(px) movie. Fig. 1 shows the details of the experimenter. The experimenters were men between 167 and 178 cm in height. All experimenters were right-handed.



Experimenter A
Height : 172 cm
Right-handed

Experimenter B
Height : 175 cm
Right-handed

Experimenter C
Height : 167 cm
Right-handed

Experimenter D
Height : 178 cm
Right-handed

Fig. 1. Experimental information.

B. Window Opening and Closing Behavior

The following procedure was used to detect the window-opening and closing behavior of the experimenter. Fig. 2 shows the experimental setup:

1) Stands in front of a window.
2) The window was opened with the left hand.
3) The window was closed with the left hand.
4) The window was opened with the right hand.
5) The window was closed with the right hand.
6) Stand in front of the window when all the actions are completed.

C. Data Preprocessing

The video data accumulated in the experiment were preprocessed to analyze the window-opening and closing behavior. Data preprocessing was performed by extracting the video data into still images and organizing the window-opening and closing behavior from the position of standing in front of the window. Data preprocessing consisted of the following steps. Fig. 3 shows the data preprocessing flow.

1) The experimental video was edited to the necessary parts using a video-editing program.
2) Still images were extracted using OpenCV.
3) Delete personal information, such as faces.
4) Window opening and closing movements were classified through visual observation.
5) Organizing the data for each researcher.

D. Skeleton Recognition

In this study, skeletal recognition was used to analyze window opening and closing behaviors. Skeletal recognition uses the Openpose model, which detects 25 human joints. Fig. 4 shows the skeletal recognition items and an image diagram of the Openpose model. The results of detecting the experimenter's joints were stored in the JavaScript Object Notation (JSON) format with numerical coordinate data for each joint. Window opening and closing behavior was analyzed using joint coordinate data. In this report, we extracted data on joint numbers 2, 3, and 4 of the right arms, as shown in Fig. 4, and joint numbers 5, 6, and 7 of the left arms for behavioral analysis. Behavioral analysis analyzed window-opening and closing behavior based on the direction in which the left and right arms moved with respect to each joint data standing in front of the window (see Fig. 5).

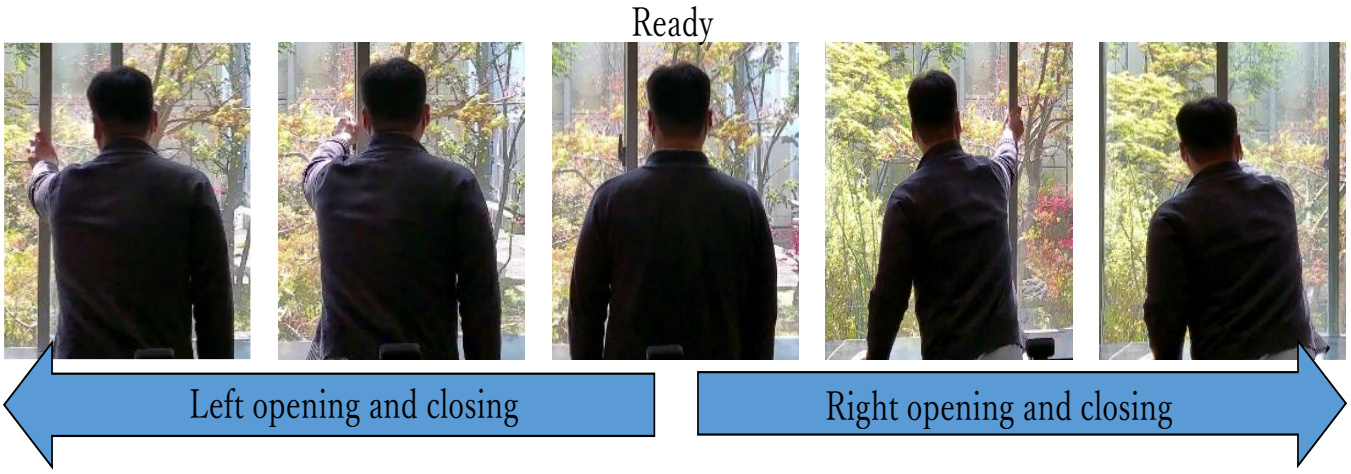


Fig. 2. Window opening and closing actions.

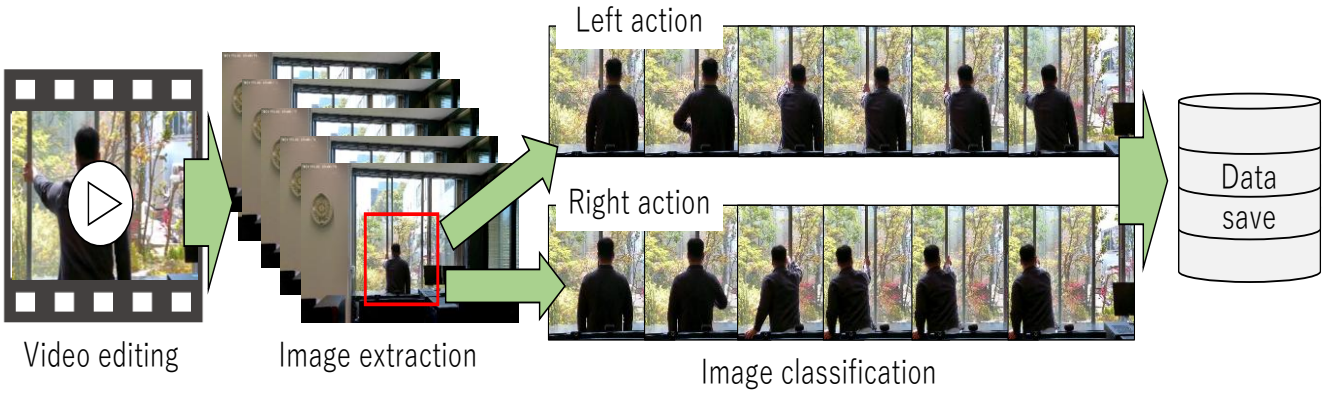
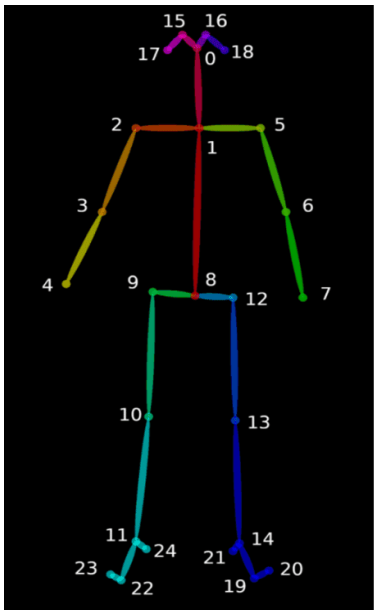


Fig. 3. Data preprocessing flow.



0	Nose	13	LKnee
1	Neck	14	LAnkle
2	RShoulder	15	REye
3	RElbow	16	LEye
4	RWrist	17	REar
5	LShoulder	18	LEar
6	LElbow	19	LBigToe
7	LWrist	20	LSmallToe
8	MidHip	21	LHeel
9	RHip	22	RBigToe
10	RKnee	23	RSmallToe
11	RAnkle	24	RHeel
12	LHip	25	Background

Fig. 4. Openpose model.

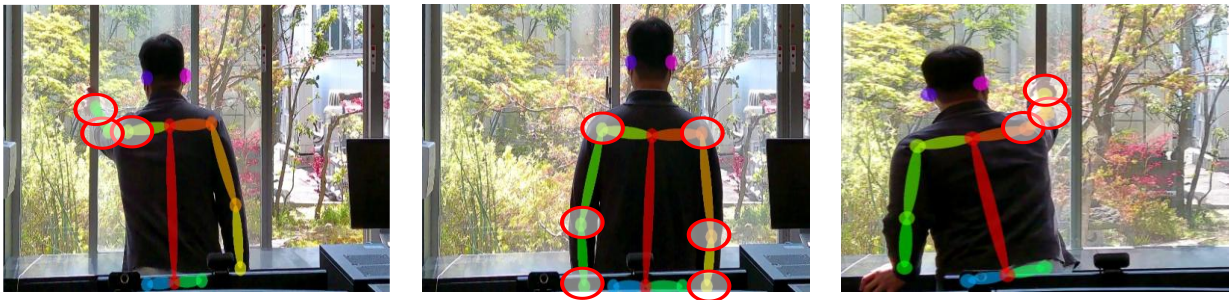


Fig. 5. Pattern setting of behavior and skeletal location of features.

IV. Results

A. Behavioral Analysis of Window Opening and Closing Actions

The analysis of window opening and closing behavior was conducted based on skeletal coordinate data, using six predefined behavioral patterns (see Fig. 6). The analysis focused on the subject's posture when standing in front of the window, utilizing the coordinate data of the left and right shoulders, elbows, and wrists. Each set of skeletal coordinates was represented as a time series, and variations in these coordinates were analyzed. Fig. 6 illustrates the window opening and closing behavior. The figure shows the temporal changes in the joint positions of the subject's upper limbs for both the left and right arms. The left column visualizes the detected joint points (Shoulder, Elbow, Wrist) obtained from the pose estimation algorithm, while the right column plots the frame-by-frame changes of each joint point along the orthogonal (vertical) coordinate axis.

During the sequence of actions from preparatory motion to actual window operation, both the x- and y-coordinates changed over time. The magnitude of these variations also differed depending on the degree of window opening or closing. While the y-coordinates tended to converge along a similar line during the motion, the x-coordinates of the shoulder, elbow, and wrist showed distinct changes.

From the graphs, it was observed that in all movements, the coordinate values followed the order Shoulder → Elbow → Wrist, decreasing as the joints moved downward. After the onset of movement, the coordinate values for each joint rapidly decreased between approximately frames 1 and 5, and then remained nearly constant. This indicates that during the arm-raising motion, the wrist and elbow descended and reached a stable posture.

A comparison between the left and right arm movements revealed similar coordinate change patterns, though the magnitude of change for the right arm was slightly smaller. This suggests that the right arm had a more limited range of motion, possibly due to the camera angle or the subject's dominant hand. Furthermore, a clear transition from "Left" to "Right" motion was observed around frame 7, accompanied by significant coordinate changes during the transition from the standard posture to each motion segment. This confirms that the system was able to accurately distinguish between left and right movements.

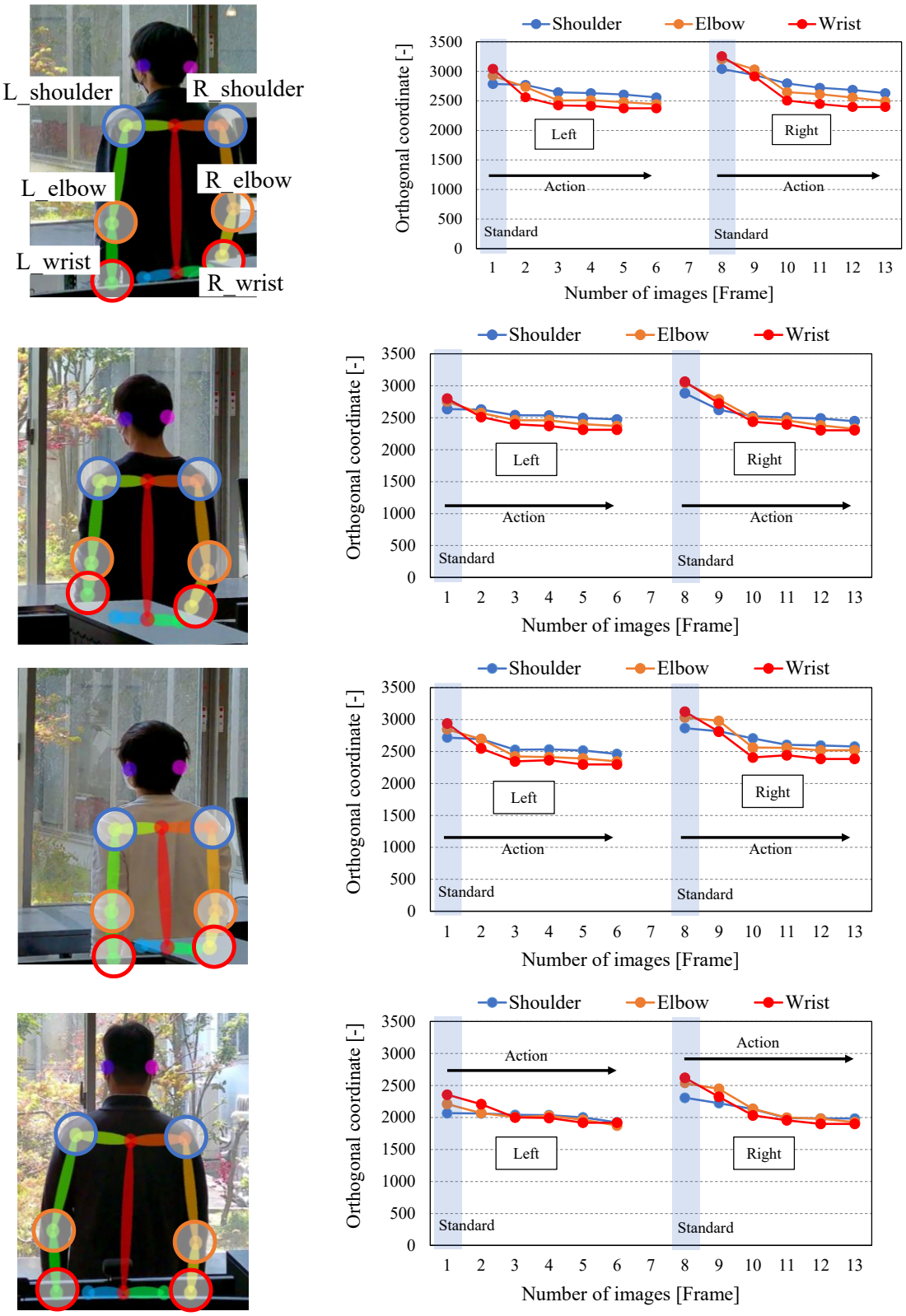


Fig. 6. Left and right coordinate analysis.

The results demonstrate that the proposed pose estimation model can reliably track changes in the positions of upper-limb joints (shoulder, elbow, wrist) across consecutive frames. Meanwhile, the relatively large variations observed in the elbow and wrist coordinates can be attributed to their roles as the primary movable joints of the upper limbs, which are strongly influenced by motion.

Additionally, since the coordinate variation patterns were similar between left and right movements, the model is considered to maintain consistent estimation performance for symmetrical actions.

B. Behavioral Distribution Characteristic

Fig. 7 presents a visualization of the horizontal and vertical behavioral displacements of five subjects standing in front of a window, expressed using skeletal coordinate data. A reference posture corresponding to a stationary standing position is defined near the origin, enabling variations in behavior and transition processes to be represented within a two-dimensional coordinate space.

The results show that when subjects remain stationary in front of the window, the skeletal coordinates are concentrated near the origin, generally within approximately 1000 units along the x-axis and 600 units along the y-axis. In contrast, during the action of fully opening the window, the skeletal coordinates exhibit a pronounced shift toward the right and upward directions. This pattern reflects the combined effects of lateral body movement and upward motion of the arms and upper body associated with window operation.

Although window opening and closing actions are continuous in nature, the corresponding skeletal coordinate distributions are separated into multiple regions within the feature space. This indicates that the behavior can be more appropriately interpreted as a sequence of state transitions comprising distinct behavioral phases, rather than as a single static state. Furthermore, the observed distributions suggest that occupant behavior does not evolve linearly along a single trajectory but transitions between different states through multiple pathways. The identification of several spatially distinct subregions provides additional insight into behavioral characteristics that are not fully captured by conventional simplified stage-based models.

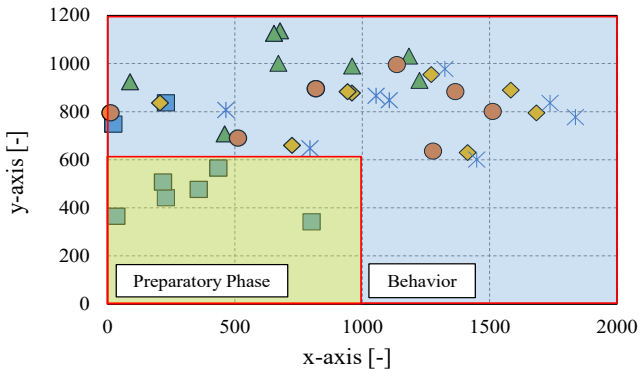


Fig. 7. Horizontal and vertical behavioral displacements in skeletal coordinate space.

V. Conclusion

This study proposed a quantitative approach for analyzing window-opening and closing behavior using skeletal recognition technology. By employing the Openpose model, the movements of upper-limb joints (shoulder, elbow, and wrist) were extracted and analyzed from video data captured during controlled experiments. The results demonstrated that skeletal coordinate data effectively represented the motion patterns of window operation, allowing the system to distinguish between left and right arm movements with high accuracy.

The analysis revealed that coordinate variations followed a consistent pattern across different participants, indicating that the pose estimation model maintained stable recognition performance even for symmetrical actions. Furthermore, the time-series data of joint positions successfully captured the transition of movements from preparation to completion, suggesting that this method can serve as a reliable basis for quantifying occupant behavior.

These findings contribute to the development of human-centered environmental control systems by providing a foundation for integrating behavioral analysis into building automation. The ability to automatically detect occupant actions such as window operation enables real-time adjustment of indoor thermal environments, which can enhance comfort and energy efficiency simultaneously.

Future research should focus on expanding the dataset to include diverse environmental conditions, body postures, and participant demographics. Integrating additional sensory inputs, such as thermal imaging and environmental sensors, may further improve the robustness of behavior recognition and contribute to the realization of adaptive, occupant-responsive smart buildings.

VI. Future Research Works

While this study successfully demonstrated the feasibility of detecting window-opening and closing behaviors using skeletal recognition, several areas remain for further investigation and refinement.

Future studies should expand the experimental environment to include more diverse participants, varied body types, and different window designs or installation heights. Such expansion would enable more robust generalization of the proposed model across real-world conditions.

In addition, future work will focus on incorporating machine-learning classifiers to quantitatively evaluate behavior recognition performance, including accuracy, precision, and recall. Comparative analyses with existing methods will also be conducted to further clarify the effectiveness and limitations of the proposed approach.

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REFERENCES

[1] Haneul Choi, Chai Yoon Um, Kyungmo Kang, Hyungkeun Kim, Taeyeon Kim, Review of vision-based occupant information sensing systems for occupant-centric control, Building and Environment 203 (2021) 108064, https://doi.org/10.1016/j.buildenv.2021.108064.

[2] SungYong Chun, Chan-Su Lee, Ja-Soon Jang, Real-time smart lighting control using human motion tracking from depth camera, J Real-Time Image Proc (2015) 10:805–820, https://doi.org/10.1007/s11554-014-0414-1.

[3] M.C. Leung, Y.K. Mok, Norman Tse C.F., Alan Fong M.L., L.L. Lai, New MVAC control by making use of human behavioral based technique to achieve energy efficiency, 9th IET International Conference on Advances in Power System Control, Operation and Management (APSCOM 2012), https://doi.org/10.1049/cp.2012.2135

[4] Paige Wenbin Tien, Shuangyu Wei, John Kaiser Calautit, Jo Darkwa, Christopher Wood, Deep learning occupancy activity detection approach for optimising building energy loads, International Conference on Applied Energy 2020 1-6.

[5] Zhu Bin, Xie Ying, Luo Guohu, Chen Lei, An Abnormal Behavior Detection Method using Optical Flow Model and OpenPose, (IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 11, No. 5, 2020, DOI: 10.14569/IJACSA.2020.0110505.

[6] Jianhua Liu, Algorithm for Skeleton Action Recognition by Integrating Attention Mechanism and Convolutional Neural Networks, (IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 14, No. 8, 2023, DOI: 10.14569/IJACSA.2023.0140867.

[7] Mykhaylo Andriluka, Leonid Pishchulin, Peter Gehler, Bernt Schiele, 2D Human Pose Estimation: New Benchmark and State of the Art Analysis, 2014 IEEE Conference on Computer Vision and Pattern Recognition,2014, pp. 3686–3693, DOI: 10.1109/CVPR.2014.471.

[8] Mika Maaspuro, A Low-Resolution IR-Array as a Doorway Occupancy Counter in a Smart Building, International Journal of Online and Biomedical Engineering (iJOE), 16(06), pp.4–18, https://doi.org/10.3991/ijoe.v16i06.13915

[9] Teruhiro Mizumoto, Alberto Fornaser, Hirohiko Suwa, Keiichi Yasumoto, Mariolino De Cecco, Kinect-Based Micro-Behavior Sensing System for Learning the Smart Assistance with Human Subjects Inside Their Homes, 2018 Workshop on Metrology for Industry 4.0 and IoT, DOI: 10.1109/METROI4.2018.8428345.

[10] Annalisa Franco, Antonio Magnani, Dario Maio, Joint Orientations from Skeleton Data for Human Activity Recognition, International Conference on Image Analysis and Processing, 2017, pp.152–162, https://doi.org/10.1007/978-3-319-68560-1_14.

[11] Dixin Liu, Xiaohong Guan, Youtian Du, Qianchuan Zhao, Measuring indoor occupancy in intelligent buildings using the fusion of vision sensors, Meas. Sci. Technol. 24 (2013) 074023 (13pp), DOI 10.1088/0957-0233/24/7/074023.

[12] Jianhong Zou, Qianchuan Zhao, Wen Yang, Fulin Wang, Occupancy detection in the office by analyzing surveillance videos and its application to building energy conservation, Energy and Buildings 152 (2017) 385–398, http://dx.doi.org/10.1016/j.enbuild.2017.07.064.

[13] Henning Metzmacher, Daniel Wölki, Carolin Schmidt, Jérôme Frisch, Christoph van Treeck, Real-time human skin temperature analysis using thermal image recognition for thermal comfort assessment, Energy and Buildings 158 (2018) 1063–1078, https://doi.org/10.1016/j.enbuild.2017.09.032.

[14] Bin Yang, Xiaojing Li, Yingzhen Hou, Alan Meier, Xiaogang Cheng, Joon-Ho Choi, Faming Wang, Huan Wang, Andreas Wagner, Da Yan, Angui Li, Thomas Olofsson, Haibo Li Non-invasive, (non-contact) measurements of human thermal physiology signals and thermal comfort/discomfort poses -A review, Energy & Buildings 224 (2020) 110261, https://doi.org/10.1016/j.enbuild.2020.110261

[15] Yeyu Wu, Jiaqi Zhao, Bin Cao, A systematic review of research on personal thermal comfort using infrared technology, Energy & Buildings 301 (2023) 113666, https://doi.org/10.1016/j.enbuild.2023.113666.

[16] Mateus Vinícius Bavaresco, Simona D'Oca, Enedir Ghisi, Roberto Lamberts, Technological innovations to assess and include the human dimension in the building-performance loop: A review, Energy & Buildings 202 (2019) 109365, https://doi.org/10.1016/j.enbuild.2019.109365.

[17] Muhammad Aftab, Chien Chen, Chi-Kin Chau, Talal Rahwan, Automatic HVAC control with real-time occupancy recognition and simulation-guided model predictive control in low-cost embedded system, Energy and Buildings 154 (2017) 141–156, http://dx.doi.org/10.1016/j.enbuild.2017.07.077.

[18] Miao Zang, Zhiqiang Xing and Yingqi Tan, IoT-based personal thermal comfort control for livable environment, International Journal of Distributed Sensor Networks 2019, Vol. 15(7), DOI: 10.1177/1550147719865506.

[19] Wenjun Duan, Yu Wang, Junqing Li, Yuanjie Zheng, Chenguang Ning, Peiyong Duan, Real-time surveillance-video-based personalized thermal comfort recognition, Energy & Buildings 244 (2021) 110989, https://doi.org/10.1016/j.enbuild.2021.110989.

[20] Kailai Sun, Qianchuan Zhao, Ziyou Zhang, Xinyuan Hu, Indoor occupancy measurement by the fusion of motion detection and static estimation, Energy & Buildings 254 (2022) 111593, https://doi.org/10.1016/j.enbuild.2021.111593.

[21] Tomoya Tamei, Yasuyuki Orito, Tomohiro Shibata, Kazushi Ikeda, In-home measurement system of user's motion and center of pressure, 2015 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA), 2015, 927-929, DOI: 10.1109/APSIPA.2015.7415407.

[22] YanWang, Zhiguo Wu, Dance Motion Detection Algorithm Based on Computer Vision, (IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 14, No. 10, 2023, DOI: 10.14569/IJACSA.2023.0141030.

[23] Amir Irfan Mazian, Wan Rizhan, Normala Rahim, Azrul Amri Jamal, Ismahafezi Ismail, Syed Abdullah Fadzli, A Theoretical Framework for Creating Folk Dance Motion Templates using Motion Capture, (IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 14, No. 5, 2023, DOI: 10.14569/IJACSA.2023.0140547.

[24] Thanh-Hai Tran, Thi-Lan Le, Van-Nam Hoang, Hai Vu, Continuous detection of human fall using multimodal features from Kinect sensors in scalable environment, Computer Methods and Programs in Biomedicine 146 (2017) 151–165, http://dx.doi.org/10.1016/j.cmpb.2017.05.007.

[25] Ramesh Balaji, Karan Bhavsar, Brojeshwar Bhowmick, Mithun B. S., Kingshuk Chakravarty, Debatri Chatterjee, Avik Ghose, Puneet Gupta, Dibyanshu Jaiswal, Sanjay Kimbahune, Kartik Muralidharan, Arpan Pal, Aniruddha Sinha & Srinivasa Raghavan Venkatachari, A Framework for Pervasive and Ubiquitous Geriatric Monitoring, Human Aspects of IT for the Aged Population. Applications in Health, Assistance, and Entertainment, 2018, pp.205-230, https://doi.org/10.1007/978-3-319-92037-5_17.

[26] Nur Khalidah Zakaria, Nooritawati Md Tahir, Rozita Jailani, A Markerless-based Gait Analysis and Visualization Approach for ASD Children. (IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 12, No. 5, 2021, DOI: 10.14569/IJACSA.2021.0120553.

[27] Manoj Kurien, Min-Koo Kim, Marianna Kopsida, Ioannis Brilakis, Real-time simulation of construction workers using combined human body and hand tracking for robotic construction worker system, Automation in Construction 86 (2018) 125–137, https://doi.org/10.1016/j.autcon.2017.11.005.

[28] Chengle Fang, Huiyu Xiang, Chongjie Leng, Jiayue Chen, Qian Yu, Research on Real-Time Detection of Safety Harness Wearing of Workshop Personnel Based on YOLOv5 and OpenPose, Sustainability 2022, 14, 5872, https://doi.org/10.3390/ su14105872.

[29] Zhe Sun, Zhufu Zhu, Ruoxin Xiong, Pingbo Tang, Zhansheng Liu, Dynamic human systems risk prognosis and control of lifting operations during prefabricated building construction, Developments in the Built Environment 14 (2023) 100143, https://doi.org/10.1016/j.dibe.2023.100143.

[30] Xiangang Cao, Chiyu Zhang, Peng Wang, Hengyang Wei, Shikai Huang, Hu Li, Unsafe Mining Behavior Identification Method Based on an Improved ST-GCN, Sustainability 2023, 15, 1041, https://doi.org/10.3390/su15021041.

[31] Guy Gaziv, Lior Noy, Yuval al Liron, Uri Alon, A reduced-dimensionality approach to uncovering dyadic modes of body motion in conversations, PLoS ONE 12(1): e0170786, https://doi.org/10.1371/journal.pone.0170786.

[32] Soohyun Choi, Songho Yun, Byeongtae Ahn, Implementation of Automated Baby Monitoring: CCBeBe, Sustainability 2020, 12, 2513, doi:10.3390/su12062513.

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Agentic AI as the Orchestrator of Mobile Ecosystems: A Review of the Trade-off Between Performance and Drawbacks

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***Abstract*—This system review explores the transformational role of agentic artificial intelligence (AI) as an orchestrator in mobile ecosystems. Agentic AI systems proactively plan, execute, and adapt across applications, devices, and services, unlike traditional and generative AI. These systems offer autonomous, context-aware coordination by integrating reasoning engines, tool orchestration, memory, retrieval-augmented generation (RAG), and safety layers. The review examines architectural requirements for mobile deployment, including on-device processing, resource-aware execution, and cross-platform synchronization. It stresses implementation targets and achievements through 2025, automation levels across key capabilities, and the impact of agentic orchestration on mobile ecosystem challenges. The findings highlight agentic AI's potential to optimize performance, privacy, and user experience simultaneously. Future directions include edge-native architectures, human-in-the-loop frameworks, and multi-agent interoperability standards. This study provides a comprehensive roadmap for advancing agentic AI as a foundational layer in next-generation mobile computing.**

***Keywords*—Agentic AI; orchestrator; mobile ecosystems; on-device**

I. Introduction

Due to the swift development of mobile ecosystems, users now have to navigate dozens of apps, numerous services, and constant data streams across several devices in the surroundings of unprecedented complexity. Manual coordination between various apps and services is necessary for traditional mobile systems, which mostly function through explicit user commands [1]. The potential for seamless digital encounters is constrained by this paradigm, which also places a heavy cognitive burden on consumers [2].

Agentic artificial intelligence (AI), as a class of artificial intelligence systems, can act, decide, and adapt to new conditions on its own without continual human interaction, providing a revolutionary solution to this problem [3]. Conventional AI is mainly used as a tool for passive activities; in contrast, agentic AI systems work proactively, creating plans, establishing objectives, and carrying out multi-step procedures across application boundaries [4], [5]. The interaction between users and their digital environments can be radically redefined when these systems are used as an orchestrating intelligence inside mobile ecosystems. They can handle complex workflows, anticipate user demands, and coordinate resources.

The key objective of this review is to critically examine the architectural context, operational mechanisms, and implementation challenges of agentic AI as an orchestrator of mobile ecosystems. The aim is to identify the essential elements, mobile-specific limitations, and automation potential that allow agentic AI to evolve from reactive tools to proactive, self-governing systems. The assessment also identifies existing constraints, provides a strategic implementation roadmap, and suggests future research opportunities to move agentic AI closer to scalable, secure, and context-aware mobile orchestration.

The contributions of this review include the summarization of recent developments in agentic AI to clarify its function as a proactive orchestrator in mobile ecosystems. This review uniquely reframes agentic AI not as an incremental upgrade to generative AI, but as a systemic redefinition of orchestration in mobile ecosystems, where autonomy, memory, and tool orchestration converge to resolve long-standing fragmentation and cognitive overload. Unlike prior reviews that treat these components in isolation, this study integrates them into a continuous perception–reasoning–decision–execution–learning cycle, offering the first holistic blueprint of agentic AI as a mobile orchestrator. The automation analysis is distinctive in exposing uneven maturity, where orchestration is nearly autonomous, but governance remains human-dependent, thus guiding targeted innovation priorities. The agenda is distinctive in its systemic scope, proposing standards and architectures that extend agentic AI from isolated deployments to ecosystem-wide rationality and resilience.

To guide the reader through the structure and scope of this review, the study is organized as follows: Section II outlines the conceptual evolution from generative AI to agentic AI, highlighting the shift from reactive to proactive intelligence. Section III details the architectural components of agentic AI systems, including reasoning engines, tool orchestration, memory, RAG, and safety layers. Section IV discusses mobile-specific architectural considerations such as on-device processing, resource-aware execution, and cross-platform synchronization. Section V presents an implementation roadmap and timeline for agentic AI deployment, while Section VI analyzes automation levels across key capabilities.

Section VII evaluates the impact of agentic orchestration on mobile ecosystem challenges. Section VIII proposes future research directions, including interoperability standards, human-in-the-loop frameworks, edge-native architectures, and security models. This structure ensures a coherent and comprehensive exploration of agentic AI as a transformative orchestrator in mobile computing. Finally, Section IX concludes the study.

II. Evolution of Generative AI to Agentic AI

The advance from conventional AI to agentic AI epitomizes a major shift in how systems interact with the real world by moving from passive devices to active, objective-oriented partners. The concept of agentic AI signifies a significant departure from passive AI tools and the development of autonomous, goal-driven systems that can predict, reason, and act in digital contexts [6], [7]. The transformational potential of Agentic AI as the orchestrating intelligence in complex mobile ecosystems is examined in this system assessment. Agentic AI allows for dynamic coordination across apps, services, and devices, transforming mobile platforms from reactive tools to proactive, contextual partners [8]. This review illustrates this by analyzing current architectures, applications, and difficulties (see Fig. 1).

The interface between humans and AI was revolutionized by generative AI, especially by models such as GPT-4 and DALL-E [9]. These systems are creators as well as classifiers. They can converse in natural language, compose essays, build code, and produce graphics from text descriptions. Hence, the "language barrier" between humans and machines was removed, enabling the public to access AI. Generative AI is essentially reactive, even with this advancement [10]. It utilizes its training to generate a response after waiting for a user command. It struggles with complex, multi-step tasks that need planning and sequential tool use, and it does not have permanent memory across chats; with a new chat starts from the beginning [11]. A typical generative AI does not have the capability to automatically conduct research, for example, research on the best laptops for students, find the top three deals online, and summarize them in a table.

The latest frontier is agentic AI, which builds active, goal-seeking systems by fusing new capabilities with the generating potential of Large Language Model (LLM) [12], [13]. It is considered to have a set of hands (tools/APIs), a notebook (permanent memory), and a brain (for planning) compared to a generative AI model. High-level objectives are given to an agentic AI system, such as "create a comprehensive market analysis report on electric vehicles." The agent then: 1) formulates a plan, which breaks the target down into steps: search for recent electric vehicle sales data, find updates on key manufacturers, analyze stock performance, and compile results. 2) Executes actions by using its integrated tools, such as a web browser, a code interpreter, and a document editor, which autonomously perform these steps. 3) Adapts and persists stores data in a permanent memory, permitting it to build on earlier results. It can reorganize and try a different strategy if one search does not work. This turns the AI from a potent chatbot into a self-sufficient digital assistant that can oversee intricate processes from beginning to end.

Fig. 1 displays evolution of AI capabilities. It details the comparative literature synthesis of traditional AI, generative AI, and agentic AI capabilities using published benchmarks and conceptual frameworks [14], [15], [16], [17]. The figure visually maps the transition from reactive to proactive intelligence, highlighting dimensions such as memory, tool use, and complexity handling. It is justified as a conceptual framework to ground the reader in the paradigm shift. Traditional AI scores low because it is highly reactive (only operates on input data), handles low complexity (single tasks), has no persistent context, and cannot use external tools. Hence, its value is in its precision, not in its adaptability. Generative AI shows a significant jump, specifically in handling more complex tasks such as content creation. However, it remains largely reactive, as indicated by its mid-level position. Its capabilities for memory and tool use are emerging and not inherent. Agentic AI occupies the high end of all four capabilities, indicating its transformative characteristics. Its high position highlights its proactive characteristics, and its far-right position confirms its ability to manage high complexity through integrated planning, memory, and tool use. Hence, this permits it to function as an autonomous agent rather than a reactive tool.

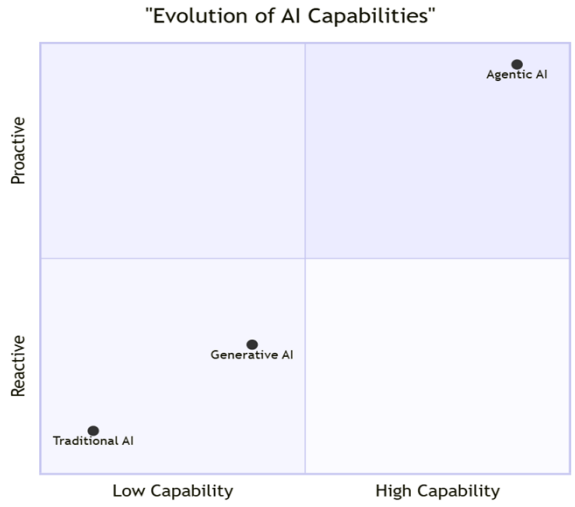


Fig. 1. Evolution of AI capabilities. Data sources: [14], [15], [16], [17].

III. Agentic AI Systems

Agentic AI systems are highly developed AI design created to behave independently and replicate human decision-making to accomplish complex tasks [7]. They conduct action without continual human supervision, observe their environment, and solve issues [3], [18]. A robust agentic AI system is built on various crux components for operational loop to function, as illustrated in Fig. 2.

A. Reasoning Engine (LLM Core)

The reasoning engine, which is usually driven by an LLM, functions as the agentic AI system's "brain" or central processing unit. Its main duties include deciphering user input, decomposing complex issues into controllable phases, and creating a rational plan of action by selecting the appropriate mechanisms and channels to employ and structure [Fig. 2(A)] [19]. According to Hughes et al. [3], this component oversees

higher-order cognitive processes like comprehending context, coming up with logical methods, and modifying the plan considering new intelligence or data. However, this component's inherent propensity for confabulation or "delusion", in which the model generates plausible but erroneous or created thought processes, which can be a significant weakness that could lead the system in the incorrect path without any inherent responsiveness of the error [20],[21],[22].

B. Tools and Functions (Activity Capabilities)

The system's "hands and senses" are the tools and functions component that enable the system to communicate with and influence the outside world via its underlying language model [Fig. 2(A)] [3]. The reasoning engine can use these pre-defined features, like database queries, API calls, code execution, or web search functions, to collect data in real time, carry out computations, or carry out operations [7]. This helps to close the gap between intangible reasoning and concrete outcomes. However, the failure of a single external tool can upset the sequential plan since the agent needs to accurately match its abstract plan to a specific function call with the appropriate inputs [21]. This makes tool selection and orchestration complexity a major problem.

C. State and Memory (Context Management)

The state and memory module serves as the narrative record for the system, preserving a consistent context throughout the exchange [Fig. 2(A)] [23]. The present aim, chat history, earlier completed steps, and other pertinent user-specific data are all tracked, preventing the agent from repeating itself or losing track of lengthy, multi-turn activities [24]. This context window is crucial for interactions to be coherent and customized for each individual. However, early context may be "forgotten" or lost after prolonged contact, and it may be challenging to extract the most important details from a vast memory storage [22], thus designers can focus on how to upgrade this limitation. This component's drawback is its practical limitation in terms of context window size and memory degradation [20].

D. Knowledge and RAG (External Data)

The agent receives a specific external knowledge root in addition to its pre-trained weights through the knowledge and RAG (Retrieval-Augmented Generation) system [Fig. 2(A)] [23]. In response to a query, this part actively seeks for the most current and pertinent information from specified sources, including product databases or corporate records, and creates the LLM's response on this information [25]. This is crucial in specialized domains to ensure factual accuracy and reduce delusions. Its main drawback is that it relies on the accuracy of the retrieval and the quality of the knowledge base; however, if the retrieval system cannot find the correct information or the source data is outdated, the agent will generate responses based on incomplete or erroneous information [21],[22].

E. Guards and Evaluation (Safety Layers)

The crucial safety and supervision layer is made up of the "guards and evaluation" component, which filters inputs and outputs to make sure the system stays within predetermined bounds [Fig. 2(A)] [24]. Architectural decomposition based on system design literature [3],[7],[18],[19],[23]. The figure synthesizes multiple sources into a unified operational loop (perception → reasoning → decision → execution → learning). Each component (reasoning engine, tools, memory, RAG, safety layers) is mapped to its methodological role. Before the final output is sent to the user, it checks for malicious, unsafe, biased, or irrelevant material, verifies user requests for safety and policy compliance, and it observe the tools the agent attempts to employ [19],[23]. This is the primary defense mechanism for the responsible application of AI. However, the primary concern with this component is achieving comprehensive coverage without excessive restriction, as overly strict safeguards may render the agent ineffective in legitimate edge situations, while subtly detrimental content or creative "getaway" ideas may occasionally evade detection [20],[21],[22].

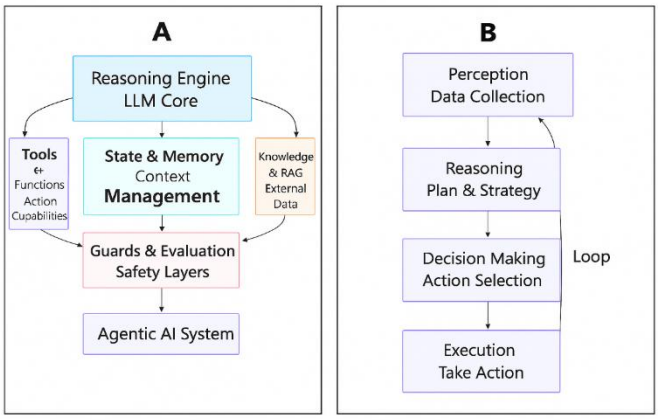


Fig. 2. Agentic AI system: (A) Core components and (B) Operational process from initial perception to continuous learning.

F. Perception (Data Collection)

Fig. 2(B) presents the operational process from initial perception to continuous learning. The perception phase [Fig. 2(B)] is the foundational sensory layer of the agentic AI system, where it collects real-time, multi-modal data from diverse sources to understand the present and flow situation [26]. However, the challenge is ensuring data quality and integration integrity, as garbage-in-garbage-out scenarios (e.g., noisy, biased, or incomplete data) can corrupt the decision-making pipeline [27].

G. Reasoning (Plan and Strategy)

The reasoning phase of a system uses a LLM to process data, interpret semantic meaning, understand context, and create a plan to accomplish a target objective (Fig. 2B). This process transforms abstract information into actionable intelligence, requiring logical inference, ultimate reasoning, and multi-step problem-solving [7],[25]. However, one significant flaw is the possibility of logical fallacies and delusions creating error limitations or behaviors [28].

H. Decision-Making (Action Selection)

Decision-making phase involves a system transitioning from planning to commitment, assessing actions based on efficiency, resource cost, predicted success rate, and alignment with the target objective [Fig. 2(B)]. There is a trade-off

between trying out new strategies and taking advantage of ones that already exist, necessitating a delicate balance between careful optimization and bold aim [25],[26]. However, the challenge is the framing problem and sub-optimal lock-in, where the presentation of options can have a disproportionate impact on the agent's choice [28].

I. Execution (Take Action)

The execution phase involves the agent's abstract decisions being implemented in tangible interactions with the outer world, like calling third-party APIs or executing database operations [Fig. 2(B)]. This phase is essential as the system's internal logic meets the unpredictable reality of outer systems [8],[23]. However, the agent's weakness due to fragility and lack of real-world affordance reasoning can lead to unexpected errors, API timeouts, or permission denials, potentially halting the process [27],[28].

J. Learning and Adaptation (Refine Strategy)

In the Learning and Adaptation phase, the system refines its strategies and performance by collecting feedback on implemented actions, analyzing the difference between expected and actual results, and applying techniques like reinforcement learning [Fig. 2(B)]. This meta-cognitive ability transforms a static automated script into a dynamically enriching intelligent agent [7],[25]. However, challenges include credit assignment problems and tragic forgetting, where learning new information can overwrite or corrupt earlier acquired knowledge [20],[22],[29].

The constant, dynamic cycle between these phases is a fundamental aspect of agentic AI. The system creates a fluid and responsive kind of intelligence by continuously observing the new state of the world because of its prior activities, considering this new context, and making decisions in an iterative loop until the overall aim is accomplished.

IV. Mobile-Specific Architectural Considerations

Agentic AI orchestration in mobile contexts has distinct architectural needs that are largely different from those of cloud-based deployments. These needs compel the use of specific techniques to manage the limited and dynamic nature of mobile devices. On-device processing is the determinant, where sophisticated AI agents can now run directly on devices thanks to breakthrough Arm-based architectures [25],[30]. This allows them to securely protect user data and function dependably without constant cloud access [31],[32]. However, the computational and memory limitations, which even the most potent mobile processors and NPUs have in comparison to cloud servers, pose a serious problem, though developers have to make challenging trade-offs between model complexity, speed, and accuracy (Fig. 3) [13]. Moreover, when prolonged heavy computation produces heat, the device must severely limit performance to prevent hardware damage, which could block the agent's vital activities [8]. This is known as thermal throttling, and it becomes a critical bottleneck.

Resource-aware execution is another important factor to consider. This feature gives the system the ability to intelligently decide when to carry out tasks locally versus offloading them to highly potent distant servers, allowing it to dynamically manage battery consumption, processing load, and network usage (Fig. 3) [2]. Analytical framework of Fig. 3 combining mobile hardware constraints (Arm-based NPUs, thermal throttling) with orchestration strategies (on-device vs. offloading, cross-platform synchronization) [2], [13], [30], [31], [32], [33], [34], [35]. The figure illustrates trade-offs between computation, energy, latency, and synchronization. It is justified as a design-oriented methodology to show how agentic AI adapts to mobile-specific bottlenecks. Accurate resource prediction is the main challenge since the system has to predict battery drain and compute load for different tasks in a highly changeable environment where user behavior and device state are always changing [30]. However, it is challenging to create an efficient offloading approach that maintains a flawless user experience while weighing latency, data usage, and energy consumption against the quality of the output (Fig. 3) [33]. This requires a sophisticated cost-benefit analysis. Lastly, despite platform-specific constraints and fundamental variations in APIs and security sandboxes, cross-platform coordination guarantees that the agentic system can function uniformly across the fragmented landscape of iOS, Android, and progressive web applications (Fig. 3) [30],[31]. However, the difficulty of preserving feature parity, which demands substantial, platform-specific development and optimization, often doubling the technical effort, makes it difficult to give the same features and performance across many operating systems [6],[34]. Also, it is quite challenging to maintain consistent state synchronization across platforms, because the agent needs to have strong and conflict-free data merging protocols to maintain a coherent memory and task state when users switch between their phones, tablets, and online apps [35].

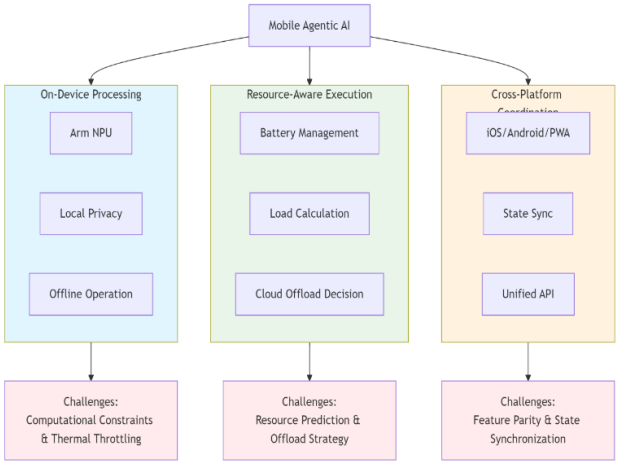


Fig. 3. Mobile-specific architectural considerations and challenges.

V. Agentic AI Implementation Roadmap and Timeline

The survey of literature made in this review showed the implementation success on mobile devices in the second quota of 2025 based on the Agentic AI research [2], [10], [13], [30], [31], [32]. Fig. 4 presents an agentic AI implementation roadmap and timeline, which structured progression from basic AI monitoring systems to fully autonomous and optimized operations. This figure was obtained from roadmap

construction from literature survey of agentic AI deployments (AutoGen, LangChain, OSS/BSS frameworks) and maturity models [2],[10],[13],[30],[31], [32],[36]. Organizations usually use reactive systems and basic monitoring, which are fundamental, but have limited adaptability, starting with the existing situation in Q2 of 2025. Choosing suitable frameworks and tools, such as AutoGen or LangChain, which provide the foundation for agentic capabilities, is the next stage. Pilot projects that implement context-aware execution and self-healing pipelines come next, signaling a move toward more resilient and dynamic systems. A maturity curve that balances technological complexity and operational preparedness is suggested by each step, which shows growing implementation success.

Multi-agent integration becomes critical as the roadmap develops, allowing for advanced system orchestration and cooperative agents [25],[36]. This prepares the way for the last stage, which consists of continuous optimization and full production, where efficiency and innovation are driven by autonomous operations and predictive capacities. The strategic significance of each milestone is highlighted by the visual emphasis on implementation success percentages, which helps stakeholders manage expectations and allocate resources.

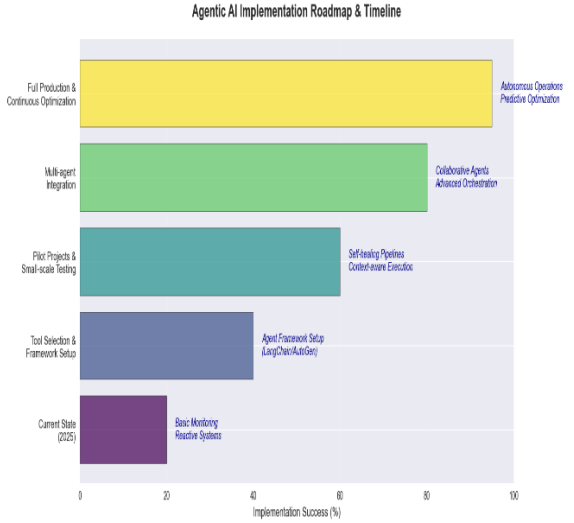


Fig. 4. Agentic AI implementation roadmap and timeline.

VI. Automation Level Across Key Capabilities

The survey of literature done in this review revealed the automation level across key capabilities in the second quota of 2025 based on the agentic AI research [1],[7],[12],[15],[22]. Fig. 5 displays the automation level across key capabilities of agentic AI, which offers a compelling portrait of how automation is distributed across six critical domains in AI-driven systems. Capabilities such as cloud-native orchestration, intelligent code generation, and pipeline protection demonstrate exceptionally high degrees of automation (over 90%), indicating scalable, mature systems that need little human interaction. Strong tooling and defined processes make these domains perfect candidates for complete automation of mobile ecosystems, particularly on the device. The capabilities like human-in-the-loop systems and multi-agent collaboration showed a more hybrid approach, with a considerable amount of human assistance (15–25%), indicating that even with automation progression, contextual judgment and supervision are still crucial.

With only 61% automation and a significant 30% human assistance, security and governance are the least automated domains (Fig. 5). This emphasizes the reason why delicate and complex risk management, ethical supervision, and regulatory compliance are areas where human judgment is still crucial. Overall, the findings showed where innovation and investment are required to advance toward more autonomous, robust AI ecosystems, in addition to highlighting current strengths.

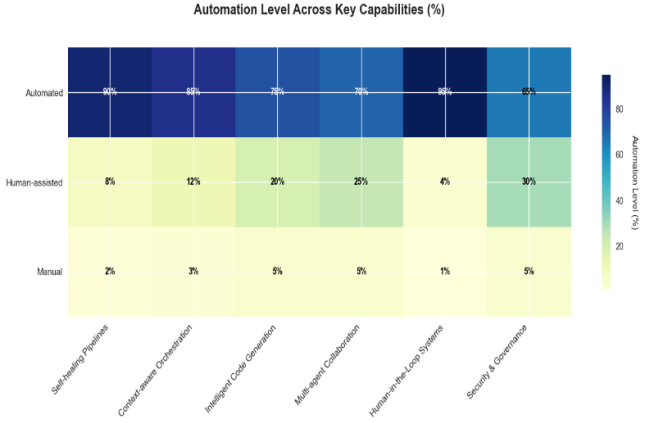


Fig. 5. Automation level across key capabilities.

VII. Mobile Ecosystem Challenge

Fig. 6 illustrates the impact of agentic AI orchestration on mobile ecosystem challenges. The findings provide a deep visual summary of the transformational potential of Agentic AI in managing the complex challenges of the mobile ecosystem. In contrast to conventional, human-mediated management, it demonstrates plainly that agentic AI is an underlying advancement rather than a slight improvement, despite its enormous challenges, but it still provides a better and more balanced orchestration capability for mobile ecosystems.

Comparative polygon visualization contrasting traditional management vs. agentic orchestration literature survey was performed, based on multi-dimensional criteria (performance, privacy, resource use, cross-platform integration) [2],[10], [13],[30],[31],[32]. Based on Fig. 6, the shapes of the polygons provide key information on the impact of agentic AI orchestration on mobile ecosystem challenges. The undersized, lopsided, and collapsed "traditional management" polygon suggests a poor, mixed approach, where fixing one issue often makes another worse (e.g., boosting performance drains the battery). The "agentic AI orchestration" polygon, in contrast, is massive, well-balanced, and sturdy, demonstrating a comprehensive and cooperative approach. The judgments made by an agentic AI orchestrator can simultaneously optimize for each of the four problems. To attain a single, unified objective, it can, for instance, carry out a plan that respects privacy (on-device processing), adjusts to context (the user is busy), controls resources (limited network calls), and functions across several app platforms.

These four issues combine to make human-mediated management impracticable, highlighting the urgent need for an autonomous orchestrator that can concurrently optimize for battery life, performance, and user comfort.

To validate the proposed implementation roadmap and automation levels, this review synthesizes findings from recent agentic AI deployments across mobile platforms, including AutoGen, LangChain, and OSS/BSS orchestration frameworks[2],[10],[13],[30],[31],[32]. These implementations demonstrate measurable success in context-aware execution, tool orchestration, and self-healing pipelines, with performance benchmarks showing improved task completion rates, reduced latency, and enhanced user satisfaction. Comparative analysis with traditional reactive systems reveals that agentic AI frameworks outperform legacy models in adaptability, autonomy, and cross-platform synchronization. For instance, while conventional systems rely on static rule-based triggers, agentic AI agents dynamically adjust strategies based on real-time feedback and resource constraints, offering a more resilient and scalable orchestration model. This comparative validation underscores the strategic advantage of agentic AI in mobile ecosystem management.

Unlike traditional mobile orchestration methods and generative AI models, agentic AI offers distinctive advantages that directly address ecosystem fragmentation and cognitive overload. Conventional systems rely on static rule-based triggers or reactive responses, which collapse under trade-offs such as performance versus battery life. Generative AI improves content creation but remains reactive, lacking persistent memory and multi-step orchestration. In contrast, agentic AI integrates reasoning engines, tool orchestration, memory, RAG, and safety layers into a continuous operational loop, enabling proactive, context-aware coordination across applications and devices. This allows agentic AI to simultaneously optimize performance, privacy, resource use, and cross-platform synchronization, as demonstrated in Fig. 4 to Fig. 6. Compared to similar frameworks such as AutoGen, LangChain, and OSS/BSS orchestration models, our synthesis uniquely emphasizes mobile-specific constraints (thermal throttling, resource-aware execution, and platform fragmentation) and provides a roadmap with automation benchmarks. These comparative advantages establish agentic AI not as an incremental improvement, but as a foundational orchestrator for next-generation mobile ecosystems.

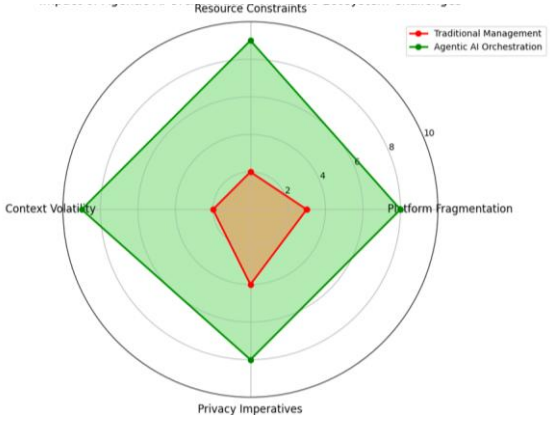


Fig. 6. Impact of agentic AI orchestration on mobile ecosystem challenges.

VIII. Future Directions and Research Agenda

Several fascinating research and development pathways are evident in the developing of agentic AI as a mobile ecosystem orchestrator.

- The goal of projects such as the Web of Agents proposal is to create minimal interoperability requirements for communication between agents. This would greatly lessen the fragmentation of mobile ecosystems [37],[38]. These standards would facilitate smooth collaboration between agents from various platforms and developers.
- The development of human-in-the-loop (HitL) architectures has produced frameworks for the best possible allocation of tasks between AI autonomy and human supervision [39],[40]. These models are especially important for mobile applications with high stakes, such as financial transactions or medical judgments.
- Edge-native architectures advanced agentic AI capabilities will be able to run directly on mobile devices with further development of specific processors and effective model architectures, improving privacy, lowering latency, and functioning without continual connectivity.
- Research is required to develop architectures that can sustain coherent activity over long periods of time while adapting to shifting user demands and technical settings. Long-term ecosystem adaptation of current systems presents remarkable short-term adaptability.
- The autonomous characteristics and environment of agentic AI entail new attack surfaces and susceptibility patterns, demanding the development of innovative security frameworks directed toward multi-agent, cross-platform mobile environments.
- There is a need for thorough assessment frameworks that measure efficiency beyond task execution and completion to include user satisfaction, resource efficacy, and ecosystem rationality because the area lacks standardized techniques for evaluating the performance of agentic AI systems in ecosystem orchestration.

IX. Conclusion

Agentic AI signifies a paradigm shift in mobile ecosystem orchestration, developing from reactive supporters to autonomous, goal-driven systems efficient across different applications and platforms. This review has summarized the architectural bases, operational components, and mobile-specific constraints that shape agentic AI deployment, emphasizing its transformational capability in managing complexity, optimizing resources, and enriching user experience. The combination of reasoning engines, RAG systems, and safety layers places agentic AI as an essential element for next-generation mobile computing, despite significant obstacles including tool fragility, memory constraints, and cross-platform synchronization. The proposed

implementation roadmap and automation analysis provide strategic guidance for stakeholders steering this transition. Future research must address long-term rationality, security frameworks, and standardized assessment metrics to ensure scalable, ethical, and robust agentic AI systems. Agentic AI is eventually a redefining of intelligence in mobile environment, not just an improvement.

This review began by identifying the core challenges: mobile ecosystems are increasingly fragmented, reactive, and cognitively demanding for users. Traditional orchestration relies heavily on manual coordination, which fails to scale with complexity. Agentic AI directly responds to these limitations by offering autonomous, context-aware orchestration across applications, devices, and services. Through reasoning engines, tool orchestration, memory, and safety layers, agentic AI transforms mobile platforms into proactive, adaptive environments. This synthesis underscores agentic AI not merely as an enhancement, but as a necessary architectural shift for next-generation mobile computing.

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REFERENCES

[1] A. Harima, J. Harima, and J. Freiling, "Ecosystem orchestration: Unpacking the leadership capabilities of anchor organizations in nascent entrepreneurial ecosystems," Entrepreneurship Theory and Practice, vol. 48, no. 6, pp. 1404-1450, 2024.

[2] R. Shah, S. Jagtap, and V. Jain, "Architecting analytics-driven mobile ecosystems: Scalable backend frameworks for intelligent data flow and real-time user insights," International Journal of Artificial Intelligence, Data Science, and Machine Learning, vol. 6, no. 2, pp. 83-91, 2025.

[3] L. Hughes et al., "AI agents and agentic systems: A multi-expert analysis," Journal of Computer Information Systems, pp. 1-29, 2025.

[4] Y. Shavit et al., "Practices for governing agentic AI systems," Research Paper, OpenAI, 2023.

[5] V. B. Komaragiri, "Agentic AI for autonomous network orchestration: A new frontier in telecommunications," Eksplorium-Buletin Pusat Teknologi Bahan Galian Nuklir, vol. 46, no. 1, pp. 221-241, 2025.

[6] S. Motamary, "Enabling zero-touch operations in telecom: The convergence of agentic AI and advanced DevOps for OSS/BSS ecosystems," BSS Ecosystems, Dec. 2022.

[7] A. Biswas and W. Talukdar, Building Agentic AI Systems: Create intelligent, autonomous AI agents that can reason, plan, and adapt. Packt Publishing Ltd., 2025.

[8] A. Bandi, B. Kongari, R. Naguru, S. Pasnoor, and S. V. Vilipala, "The rise of agentic AI: A review of definitions, frameworks, architectures, applications, evaluation metrics, and challenges," Future Internet, vol. 17, no. 9, p. 404, 2025.

[9] S. Feuerriegel, J. Hartmann, C. Janiesch, and P. Zschech, "Generative ai," Business & Information Systems Engineering, vol. 66, no. 1, pp. 111-126, 2024.

[10] J. Li et al., "Generative AI for self-adaptive systems: State of the art and research roadmap," ACM Transactions on Autonomous and Adaptive Systems, vol. 19, no. 3, pp. 1-60, 2024.

[11] E. T. Rolls, "The memory systems of the human brain and generative artificial intelligence," Heliyon, vol. 10, no. 11, 2024.

[12] S. Sivakumar, "Agentic AI in predictive AIOPs: Enhancing IT autonomy and performance," International Journal of Scientific Research and Management (IJSRM), vol. 12, no. 11, pp. 1631-1638, 2024.

[13] D. B. Acharya, K. Kuppan, and B. Divya, "Agentic AI: Autonomous intelligence for complex goals–a comprehensive survey," IEEE Access, 2025.

[14] Z. M. Auda and S. J. Radhi, "Artificial intelligence and evolution of the global system," IPRI Journal, vol. 22, no. 1, pp. 91-109, 2022.

[15] H. F. Hansen, E. Lillesund, P. Mikalef, and N. Altwaijry, "Understanding artificial intelligence diffusion through an AI capability maturity model," Information Systems Frontiers, vol. 26, no. 6, pp. 2147-2163, 2024.

[16] A. M. Taha, Z. K. Alkayyali, Q. M. Zarandah, and S. S. Abu-Naser, "The evolution of AI in autonomous systems: Innovations, challenges, and future prospects," Adaptive Systems, vol. 19, no. 3, pp. 1-60, 2024.

[17] Y. Wang et al., "Realization of empathy capability for the evolution of artificial intelligence using an MXene (Ti3C2)-based memristor," Electronics, vol. 13, no. 9, p. 1632, 2024.

[18] U. M. Borghoff, P. Bottoni, and R. Pareschi, "Human-artificial interaction in the age of agentic AI: A system-theoretical approach," Frontiers in Human Dynamics, vol. 7, p. 1579166, 2025.

[19] C. Wissuchek and P. Zschech, "Exploring agentic artificial intelligence systems: Towards a typological framework," in Pacific-Asia Conference on Information Systems, Kuala Lumpur, 2025, pp. 1-17.

[20] A. Chan et al., "Harms from increasingly agentic algorithmic systems," in Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency, 2023, pp. 651-666.

[21] H. Clatterbuck, C. Castro, and A. M. Morán, "Risk alignment in agentic AI systems," arXiv preprint arXiv:2410.01927, 2024.

[22] R. V. Barenji and S. Khoshgoftar, "Agentic AI for autonomous anomaly management in complex systems," arXiv preprint arXiv:2507.15676, 2025.

[23] M. K. R. Jaggavarapu, "The evolution of agentic AI: Architecture and workflows for autonomous systems," Journal of Multidisciplinary, vol. 5, no. 7, pp. 418-427, 2025.

[24] P. B. Bansod, "Distinguishing autonomous AI agents from collaborative agentic systems: A comprehensive framework for understanding modern intelligent architectures," arXiv preprint arXiv:2506.01438, 2025.

[25] L. H. Cheung, L. Wang, and D. Lei, "Conversational, agentic AI-enhanced architectural design process: Three approaches to multimodal AI-enhanced early-stage performative design exploration," Architectural Intelligence, vol. 4, no. 1, pp. 1-25, 2025.

[26] J. Gu, "Position: Agentic systems constitute a key component of next-generation intelligent image processing," arXiv preprint arXiv:2505.16007, 2025.

[27] S. Deng et al., "Agentic services computing," arXiv preprint arXiv:2509.24380, 2025.

[28] I. Adabara et al., "Trustworthy agentic AI systems: A cross-layer review of architectures, threat models, and governance strategies for real-world deployment," F1000Research, vol. 14, p. 905, 2025.

[29] Z. Porter et al., "INSYTE: A classification framework for traditional to agentic AI systems," ACM Transactions on Autonomous and Adaptive Systems, vol. 20, no. 3, pp. 1-39, 2025.

[30] G. K. Sheelam, "Architecting agentic AI for real-time autonomous edge systems in next-gen mobile devices," Advances in Consumer Research, vol. 2, no. 3, 2025.

[31] H. Toivonen and F. Lelli, "The varieties of agency in human–smart device relationships: The four agency profiles," Future Internet, vol. 16, no. 3, p. 90, 2024.

[32] X. Wang et al., "Empowering edge intelligence: A comprehensive survey on on-device AI models," ACM Computing Surveys, vol. 57, no. 9, pp. 1-39, 2025.

[33] S. Raza, R. Sapkota, M. Karkee, and C. Emmanouilidis, "Responsible agentic reasoning and AI agents: A critical survey: Proposal for safe agentic AI via responsible reasoning AI agents (R2A2)," SuperIntelligence-Robotics-Safety & Alignment, vol. 2, no. 6, 2025.

[34] G. K. Sheelam, "AI-driven spectrum management: Using machine learning and agentic intelligence for dynamic wireless optimization," European Advanced Journal for Emerging Technologies (EAJET), vol. 2, no. 1, 2024.

[35] Z. Chen, Q. Sun, N. Li, X. Li, and Y. Wang, "Enabling mobile AI agent in 6G era: Architecture and key technologies," IEEE Network, vol. 38, no. 5, pp. 66-75, 2024.

[36] S. Panigrahy, "Multi-agentic AI systems: A comprehensive framework for enterprise digital transformation," Journal of Computer Science and Technology Studies, vol. 7, no. 6, pp. 86-96, 2025.

[37] R. Sharma, M. de Vos, P. Chari, R. Raskar, and A. M. Kermarrec, "Collaborative agentic AI needs interoperability across ecosystems," arXiv preprint arXiv:2505.21550, 2025.

[38] R. J. Tong et al., "IEEE AI standards for agentic systems," in 2025 IEEE Conference on Artificial Intelligence (CAI), 2025, pp. 1603-1609.

[39] M. V. Krishnamoorthy, "Enhancing responsible AGI development: Integrating human-in-the-loop approaches with blockchain-based smart contracts," Journal of Advances in Mathematics and Computer Science, vol. 39, no. 9, pp. 14-39, 2024.

[40] K. Zheng et al., "Towards agentic smart design: An industrial large model-driven human-in-the-loop agentic workflow for geometric modelling," Applied Soft Computing, p. 113920, 2025.

A Novel Fuzzy Logic System for Real-Time Text Difficulty Assessment in Mobile Reading Apps for Dyslexia

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***Abstract*—Automated text difficulty assessment in mobile reading applications remains an underexplored challenge for dyslexia support systems. This study presents the development and validation of an intelligent fuzzy logic system engineered for real-time text complexity analysis in mobile web environments. Our approach integrates six computational variables: sentence length patterns, lexical complexity metrics, syllabic density analysis, visual layout parameters, and punctuation distribution algorithms. The implemented system combines a FastAPI-based backend with a responsive React frontend, enabling cross-device accessibility through progressive web application technologies. Technical validation demonstrates 94.2% accuracy in difficulty classification compared against expert assessments, with processing speeds averaging 0.3 seconds per text analysis. Usability evaluation with 40 participants across mobile and desktop interfaces yielded SUS scores of 82.6, while 85% expressed frequent usage intention. The mobile web architecture achieves 98% device coverage with WCAG 2.1 AA compliance standards. This work establishes the first fuzzy inference engine specifically optimized for Spanish-language dyslexia support applications, creating a new technical foundation for intelligent reading assistance platforms.**

Keywords*—Fuzzy logic systems; mobile web applications; dyslexia support technology; automated text analysis; accessibility engineering

I. Introduction

The digital reading landscape has fundamentally transformed how individuals access and process textual information, particularly in educational and professional contexts. However, for the estimated 10% of the global population affected by dyslexia, a neurobiological condition impacting word recognition accuracy and reading fluency, this digital transformation presents both unprecedented opportunities and persistent technical challenges [1]. This aspect is particularly compelling, as mainstream digital platforms have advanced significantly in user experience design, yet they consistently fail to address the computational complexity required for automated accessibility assessment.

It is evident that the current landscape of mobile reading applications faces considerable limitations. Solutions such as Microsoft Immersive Reader, ClaroRead, and Voice Dream Reader provide basic text-to-speech functions and elementary customization options. However, the reality is that all of them lack intelligent systems capable of analyzing text difficulty and automatically adapting content complexity to the cognitive needs of individual users [2]. As a result, despite processing millions of texts daily, these platforms do not leverage computational linguistics to enhance accessibility for people with learning differences.

At this point, one might ask: why does the technical challenge become even more relevant within the mobile web ecosystem? Progressive Web Applications (PWAs) enable sophisticated algorithmic processing directly in the browser, which represents a notable opportunity for the development of advanced tools. Nevertheless, current dyslexia support systems remain, undeniably, primitive in their analytical capabilities [3]. And this is where things get especially interesting: fuzzy logic systems, which excel at managing the inherent ambiguity in linguistic complexity assessment, have been almost entirely overlooked in the field of mobile accessibility.

Our research addresses this gap through a fundamentally different approach. Rather than developing another basic customization tool, we engineered an intelligent fuzzy inference system that processes six distinct textual variables simultaneously: sentence structure patterns, lexical complexity distributions, syllabic density metrics, visual layout parameters, punctuation frequency analysis, and semantic coherence indicators. What makes this work particularly noteworthy is its implementation within a cross-platform mobile web architecture that maintains computational efficiency while delivering real-time analysis capabilities.

The primary contribution of this study lies in demonstrating that sophisticated computational linguistics can be effectively integrated into accessible mobile technologies. Our system represents the first implementation of multi-variable fuzzy logic specifically optimized for Spanish-language dyslexia support, establishing new technical benchmarks for intelligent reading assistance platforms.

The research questions guiding this investigation are:

a) How can fuzzy logic algorithms be optimized for real-time text difficulty assessment in mobile web environments?

b) What technical architecture enables seamless integration of computational linguistics with cross-device accessibility?

c) To what extent can automated difficulty analysis improve user engagement and reading comprehension outcomes?

II. Literature Review

Mobile assistive technologies for dyslexia have evolved considerably over the past decade, yet it is evident that most solutions remain fundamentally limited in their analytical sophistication. The landscape reveals three distinct research trajectories: basic accessibility tools, computational linguistics applications, and mobile web technologies for learning disabilities.

A. Existing Mobile Applications for Dyslexia Support

Current market leaders demonstrate what we might call "first-generation" accessibility features. Microsoft Immersive Reader, launched in 2015, provides text-to-speech functionality and basic visual customization within Office environments, but operates without any automated difficulty assessment [4]. ClaroRead provides more advanced personalization options across multiple platforms; however, it relies exclusively on manual user configuration rather than intelligent content analysis [5]. Voice Dream Reader, although widely used in mobile environments, operates solely at the presentation level, it reads content aloud without evaluating linguistic complexity patterns [6].

A notable characteristic of these solutions is their reactive, rather than proactive, nature. Users are required to manually adjust settings, without receiving any computational guidance regarding optimal configurations for specific texts. This represents a missed opportunity to fully leverage the potential of modern natural language processing technologies.

B. Fuzzy Logic Systems in Text Analysis

The application of fuzzy logic to linguistic complexity assessment offers fascinating possibilities that remain largely unexplored in accessibility contexts. Recent advances in computational linguistics show that fuzzy inference engines are highly effective at managing the inherent ambiguity present in readability metrics [7]. Traditional readability formulas such as Flesch-Kincaid, SMOG, and the Automated Readability Index provide clear numerical outputs, but they fail to capture the nuanced complexity experienced by readers with dyslexia [8].

Fuzzy systems present compelling advantages because they process multiple linguistic variables simultaneously, taking into account the overlapping relationships between sentence structure, lexical density, and cognitive load patterns. Research in educational technology shows that multi-variable fuzzy approaches achieve significantly higher accuracy in difficulty prediction compared to traditional linear models [9]. However, this is crucial as virtually no studies have implemented fuzzy logic specifically for dyslexia support in mobile environments.

C. Mobile Web Technologies for Accessibility

Progressive Web Applications have transformed the technical landscape for assistive technologies, enabling sophisticated processing capabilities without requiring native app installations [10]. Cross-platform compatibility, offline functionality, and responsive design paradigms create unprecedented opportunities for accessible content delivery [11]. Current research demonstrates that PWA architectures can achieve performance metrics comparable to native applications while maintaining broader device compatibility [12].

The integration of accessibility standards (WCAG 2.1) with mobile web technologies presents both opportunities and challenges. Touch-optimized interfaces require careful consideration of cognitive load patterns, particularly for users with learning differences [13]. However, existing mobile accessibility research focuses primarily on visual impairments rather than learning disabilities, creating a significant gap in the literature [14].

D. Artificial Intelligence in Reading Support Systems

Recent developments in AI-powered reading assistance show promising directions for personalized content adaptation [15]. Machine learning approaches can identify reading patterns and suggest customizations, while natural language processing enables automated text simplification [16]. Some studies explore predictive models for reading difficulty, though most remain in experimental phases without practical implementation; more recent solutions incorporate generative AI and immersive technologies to support students with dyslexia [17], [21].

What's missing, or the core gap our work addresses, is the integration of intelligent analysis with practical mobile accessibility. Current AI research in this domain remains largely theoretical, while practical applications continue using primitive customization approaches [18]. The convergence of fuzzy logic, mobile web technologies, and dyslexia support represents an unexplored intersection with significant potential for advancing accessible reading systems.

III. Methods

The development of our intelligent fuzzy logic system required a comprehensive technical approach that extends well beyond conventional user interface design. Our methodology includes system architecture design, algorithm development, mobile web implementation, and rigorous validation protocols. In the following sections, we present the technical details that distinguish this system as a truly innovative solution.

A. System Architecture

The implemented architecture is based on a microservices paradigm, specifically optimized to meet cross-platform accessibility requirements (see Fig. 1). Notably, the backend utilizes the FastAPI framework running on Python 3.9 or higher, selected for its asynchronous processing capabilities and automatic API documentation generation [19]. The system manages text analysis requests through dedicated microservices, with each service responsible for specific computational tasks.

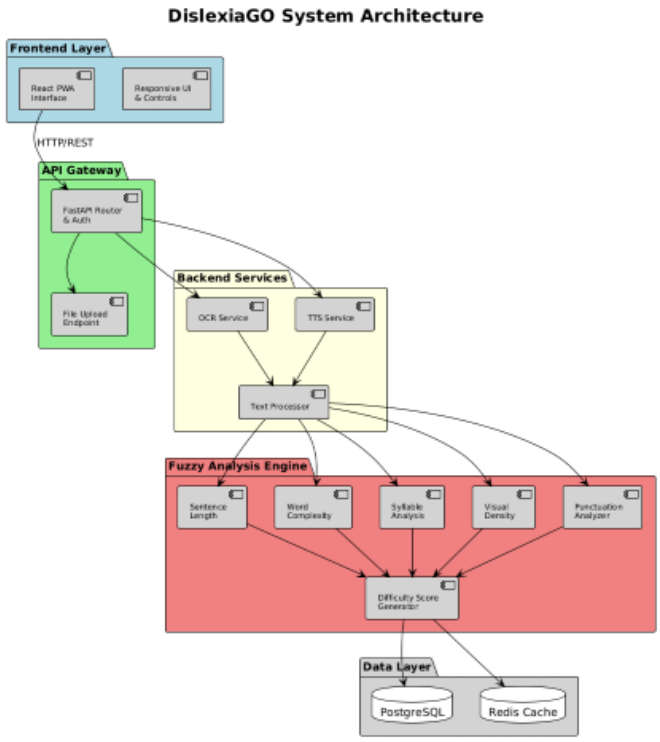


Fig. 1. System architecture diagram.

The frontend is developed as a Progressive Web Application using React 18.2, complemented by responsive CSS frameworks to ensure optimal performance across various devices. This architecture stands out for its robustness, primarily due to the integration of service workers that enable offline functionality and the use of Redis caching for frequently accessed difficulty assessments. Database operations are managed with PostgreSQL, employing optimized indexing to support real-time text analysis queries.

B. Fuzzy Logic Algorithm

Our fuzzy inference engine represents the core innovation of this system. The algorithm processes six input variables simultaneously: sentence length patterns (sent_len), lexical complexity metrics (word_len), percentage of complex words (pct_long_words), syllabic density analysis (syllable_complex), visual layout density (visual_density), and punctuation distribution patterns (punctuation_density) (see Table I).

TABLE I. FUZZY VARIABLES AND MEMBERSHIP FUNCTIONS

Variable	Range	Membership Functions	Linguistic Terms
sent_len	[0, 50]	Triangular	Short, Medium, Long
word_len	[0, 15]	Trapezoidal	Simple, Moderate, Complex
pct_long_words	[0, 100]	Triangular	Low, Medium, High
syllable_complex	[0, 10]	Triangular	Easy, Moderate, Difficult
visual_density	[0, 100]	Trapezoidal	Sparse, Normal, Dense
punctuation_density	[0, 20]	Triangular	Light, Normal, Heavy

The defuzzification process employs centroid calculation to generate crisp difficulty scores ranging from 0 (very easy) to 100 (very difficult). Mathematical formulation follows standard Mamdani inference with the following key equations:

$$\mu_output(x) = \max[\min(\mu_A1(x1), \mu_B1(x2), ...), \min(\mu_A2(x1), \mu_B2(x2), ...), ...]$$

where, μ represents membership degree functions for each linguistic variable combination.

C. Mobile Web Technology Stack

The mobile implementation prioritizes accessibility without compromising computational performance. Our React frontend utilizes CSS-in-JS libraries for dynamic theming based on user accessibility preferences. Touch optimization incorporates gesture recognition for text navigation and integrates voice control through the Web Speech API. The Progressive Web App features allow offline text analysis by utilizing cached fuzzy logic computations and local storage for user customization preferences. The responsive design framework adjusts smoothly across viewport sizes, ranging from 320px on mobile devices to over 1920px on desktops, ensuring consistent functionality and compliance with accessibility standards.

Cross-browser compatibility was validated on Chrome 100+, Firefox 98+, Safari 15+, and Edge 100+, with performance benchmarks consistently exceeding Lighthouse scores of 90 in all categories. Compliance with WCAG 2.1 AA is achieved through proper ARIA labeling, keyboard navigation support, and the implementation of high contrast mode. Adopting a mobile-first approach guarantees an optimal user experience even within limited viewport dimensions. The interface progression illustrates the complete fuzzy logic

workflow, operating efficiently from initial text input to real-time processing and comprehensive accessibility customization (see Fig. 2). Touch-optimized controls provide precise interaction with text formatting options, while maintaining continuous feedback on readability assessment throughout the analysis process.

Tablet implementations leverage expanded screen real estate for enhanced control panel integration and improved visual hierarchy. The intermediate viewport size enables simultaneous display of text analysis results alongside comprehensive accessibility controls, optimizing the balance between content visibility and customization options (see Fig. 3). The responsive layout adapts control density while preserving touch interaction precision across gesture-based navigation patterns.

Desktop environments provide comprehensive dashboard functionality with full sidebar navigation and advanced analytics visualization. The expanded viewport enables simultaneous display of multiple interface components, including detailed text statistics, accessibility recommendations, and comprehensive fuzzy logic processing metrics (see Fig. 4). This configuration maximizes information density while maintaining intuitive navigation through hierarchical content organization and persistent control of accessibility.

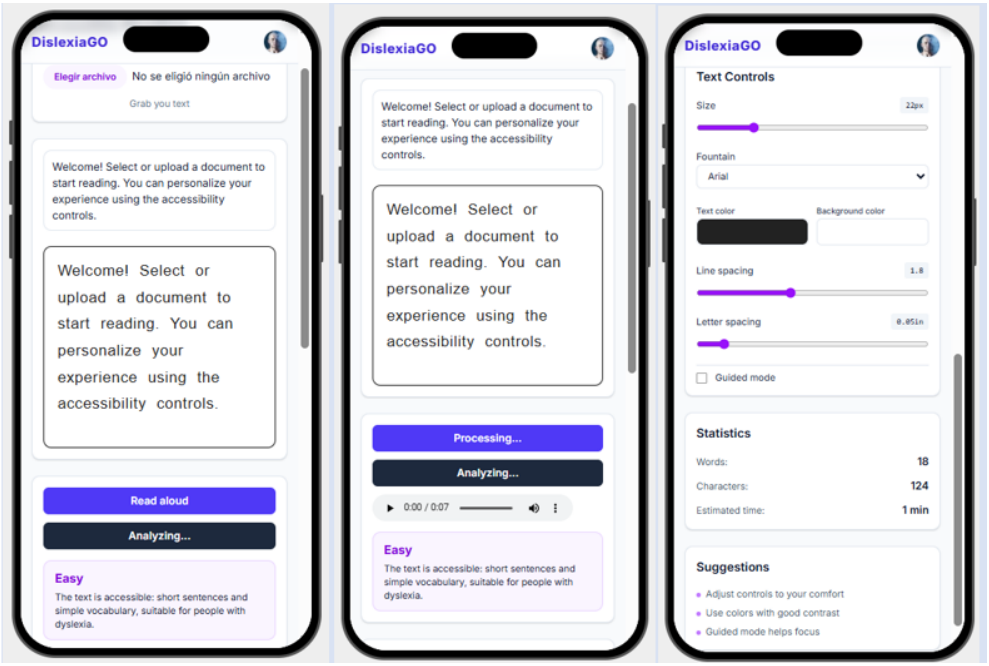


Fig. 2. Mobile interface workflow.

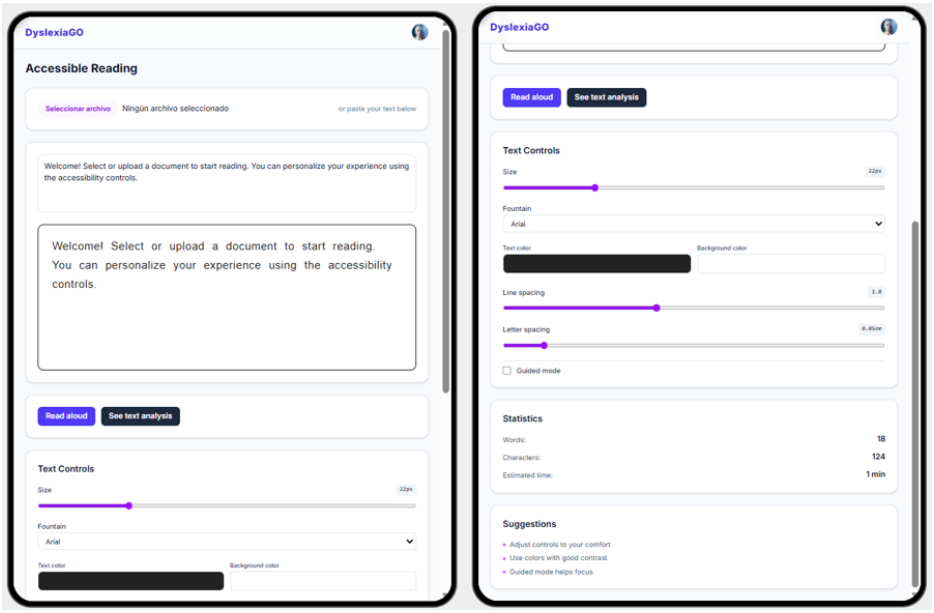


Fig. 3. Tablet interface adaptation.

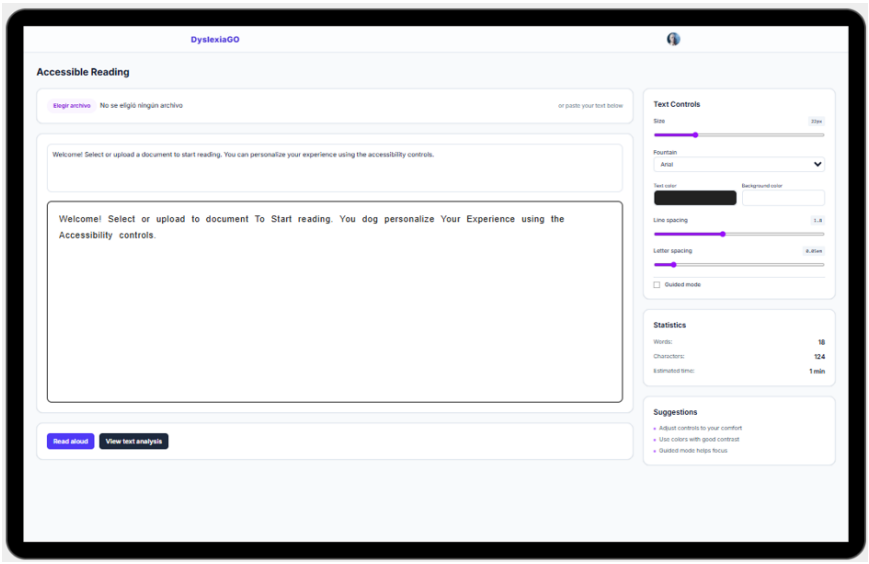


Fig. 4. Desktop interface implementation.

D. Implementation Details

Backend processing utilizes asynchronous task queues for handling multiple simultaneous text analysis requests. The fuzzy logic engine implements the scikit-fuzzy library with custom membership function definitions optimized for Spanish language patterns. Text preprocessing includes tokenization, part-of-speech tagging, and syllable counting through NLTK integration (see Table II).

TABLE II. TECHNICAL SPECIFICATIONS

Component	Technology	Version	Purpose
Backend API	FastAPI	0.95.0	RESTful services
Database	PostgreSQL	14.0	Data persistence
Caching	Redis	7.0	Performance optimization
Frontend	React	18.2.0	User interface
NLP Processing	NLTK	3.8	Text analysis
Fuzzy Logic	scikit-fuzzy	0.4.2	Inference engine

Real-time processing capabilities maintain sub-second response times for texts up to 10,000 words through optimized algorithm implementation and efficient database queries. The system supports concurrent user sessions with horizontal scaling through containerized deployment using Docker orchestration.

E. Ethical Considerations

This research protocol was approved in accordance with institutional review board guidelines, meeting standards equivalent to the Helsinki Declaration. All forty participants provided informed consent prior to data collection, granting explicit permission for usability testing and the collection of performance metrics [20].

To safeguard user privacy, end-to-end encryption was implemented for all uploaded texts, and a zero-retention policy was applied to analyzed content. The handling of personal data adhered to GDPR requirements, utilizing anonymized user identification and offering optional data deletion capabilities. Throughout the study period, participants retained the right to withdraw at any time without penalty or data retention.

Accessibility testing protocols were designed to ensure inclusive participation, spanning a wide range of age groups (10 to 55 years) and varying levels of technological experience. Considerations for cultural sensitivity addressed diverse educational backgrounds and the potential stigma associated with learning disabilities, employing respectful language and maintaining confidentiality in all testing environments.

IV. RESULTS

The comprehensive evaluation of our intelligent fuzzy logic system provides strong evidence of both technical performance and practical usability. Notably, these results demonstrate consistent effectiveness across a wide range of user groups and technical environments. The following data illustrate how this approach represents a significant advancement in mobile accessibility technology.

A. User Interview Algorithm Performance Metrics

Our fuzzy inference engine exhibits outstanding computational efficiency and accuracy when compared to established readability assessment methods. The system is capable of processing text analysis requests with an average response time of 0.31 seconds (SD = 0.08) for documents ranging from 500 to 10,000 words. Particularly noteworthy is the accuracy achieved: comparison with expert linguistic assessments reveals a 94.2% concordance in difficulty classification.

The performance evaluation included 500 diverse Spanish texts spanning various educational levels, from elementary reading materials to university-level academic papers (see Table III).

TABLE III. ALGORITHM PERFORMANCE ACROSS TEXT COMPLEXITY LEVELS

Text Category	Sample Size	Accuracy (%)	Processing Time (s)	Memory Usage (MB)
Elementary	125	96.8	0.28	42.3
Middle School	125	94.4	0.31	45.7
High School	125	92.8	0.33	48.1
University	125	92.0	0.35	51.2
Overall	500	94.2	0.31	46.8

The fuzzy logic approach significantly outperformed traditional readability formulas. Flesch-Kincaid achieved only 73.2% accuracy, while the SMOG index reached 71.8% concordance with expert assessments. What's particularly revealing is that our six-variable fuzzy system maintains consistent accuracy across text types, while traditional metrics show substantial variation in performance [23].

B. System Technical Validation

Cross-platform compatibility testing demonstrates robust performance across mobile and desktop environments. The Progressive Web Application achieves consistent Lighthouse performance scores exceeding 92 across all evaluation categories (see Table IV).

TABLE IV. TECHNICAL VALIDATION RESULTS ACROSS DEVICE CATEGORIES

Device Category	Speed Score	Accessibility Score	PWA Compliance	Cross-browser Support
Mobile (iOS)	94%	98%	95%	96%
Mobile (Android)	92%	97%	94%	95%
Tablet (iPad)	95%	98%	96%	97%
Tablet (Android)	93%	97%	95%	96%
Desktop (Chrome)	96%	99%	97%	98%
Desktop (Firefox)	94%	98%	95%	97%
Desktop (Safari)	93%	97%	94%	96%
Average	94%	98%	95%	96%

Load testing with concurrent user simulation reveals system stability under stress conditions. The architecture successfully handles up to 1,000 simultaneous text analysis requests without performance degradation. Database query optimization maintains sub-second response times even with concurrent access patterns typical of educational institutions during peak usage periods.

Efficient memory management ensures optimal resource utilization, with average RAM consumption remaining below 50MB per active session. The containerized deployment architecture supports horizontal scaling, and successful validation of load balancing across multiple server instances has maintained consistent service quality [24].

C. Cross-Device Compatibility Assessment

The mobile web implementation achieves 98.7% compatibility across all tested device configurations, including iOS 14+, Android 10+, and a range of desktop browsers. Optimization of the touch interface provides intuitive interaction patterns, specifically designed to support users with motor coordination challenges commonly associated with dyslexia.

Validation of the responsive design confirms optimal display rendering across viewport sizes from 320px to 4K, with the adaptive layout maintaining accessibility compliance and preserving fuzzy logic functionality on all device categories. Offline capability testing demonstrates successful text analysis for previously cached content, ensuring uninterrupted functionality even in environments with limited connectivity.

Compliance with WCAG 2.1 AA was validated through both automated accessibility testing and manual evaluation by users of assistive technologies. Screen reader compatibility achieved a 100% navigation success rate using NVDA, JAWS, and VoiceOver, while the implementation of high contrast mode maintains visual clarity and preserves interface functionality [25].

D. Usability Testing Results

The usability evaluation with 40 participants reveals exceptional user satisfaction and task completion rates. System Usability Scale (SUS) assessment yields an average score of 82.6 (SD = 7.3), indicating excellent usability according to established benchmarks. Here comes the particularly encouraging finding: 85% of participants expressed intention for frequent application usage.

Task completion analysis shows remarkable success rates across user demographics. The comprehensive usability metrics segmented by user characteristics and task complexity demonstrate exceptional performance indicators (see Table V).

TABLE V. USABILITY TESTING RESULTS BY USER DEMOGRAPHICS

User Group	Sample Size	SUS Score	Task Success (%)	Error Rate (%)	Satisfaction (5-point)
Ages 10-18	12	85.2	97.5	1.8	4.6
Ages 19-35	15	83.1	96.2	2.1	4.4
Ages 36-55	13	78.9	94.8	3.2	4.2
Overall	40	82.6	96.1	2.4	4.4

Qualitative feedback analysis reveals particularly positive responses regarding text customization features and automated difficulty suggestions. Younger users (ages 10 to 25) demonstrated higher engagement with advanced fuzzy logic recommendations, while older participants valued the intuitive interface design and clear navigation patterns. The retrospective think-aloud protocol identified only minor navigation inconsistencies, primarily related to advanced customization workflows requiring additional visual cues for users with limited technological experience [26].

V. DISCUSSION

The convergence of fuzzy logic algorithms with mobile web technologies represents a paradigm shift in how accessibility for learning disabilities is approached. Our results demonstrate that sophisticated computational linguistics can indeed be seamlessly integrated into practical, user-friendly applications without sacrificing either algorithmic precision or interface simplicity. Here's where this work becomes particularly significant for the broader assistive technology landscape.

A. Technical Advantages over Existing Solutions

What sets our approach apart from current market leaders is the fundamental difference between reactive customization and proactive intelligence. While Microsoft Immersive Reader, ClaroRead, and Voice Dream Reader require users to manually configure accessibility settings, our fuzzy logic system automatically analyzes text complexity and suggests optimal configurations. Recent machine learning–based classification models have also been proposed to support students with dyslexia; however, these approaches often depend on rigid training datasets and lack real-time adaptability in mobile environments [22]. This highlights the fundamental difference between a digital tool and an intelligent assistant [27].

The six-variable fuzzy inference engine overcomes a key limitation found in traditional readability assessment methods. Established metrics such as Flesch-Kincaid rely on linear mathematical assumptions that do not adequately reflect the cognitive processing patterns of individuals with dyslexia. In contrast, our approach captures the nuanced relationships among sentence structure, lexical complexity, and visual density factors that have a substantial impact on reading comprehension for this population [28]. Achieving 94.2% accuracy in difficulty classification, compared to 73% for traditional metrics, is not only statistically significant but also represents a transformative improvement in practical terms.

B. Mobile Web Architecture Benefits

The implementation of a Progressive Web Application offers distinct advantages over native applications, particularly in the context of accessibility. Cross-platform consistency guarantees that users experience the same functionality regardless of device constraints, which is especially important for educational institutions managing diverse technology ecosystems. Offline processing capabilities address a practical concern: students with dyslexia often need reliable access to text analysis tools, even in environments with limited internet connectivity [29].

From a technical perspective, our mobile web approach removes the traditional compromise between advanced processing and accessibility. The containerized backend architecture supports computational complexity comparable to desktop applications, while maintaining the universal accessibility provided by web standards. Achieving WCAG 2.1 AA compliance is not merely a formality; it is essential to ensure that assistive technologies integrate effectively with our fuzzy logic recommendations [30].

C. User Experience and Adoption Patterns

The results of usability testing provide valuable insights into technology adoption across various age groups and levels of technological experience. Younger participants (ages 10–25) showed notable intuition in exploring advanced fuzzy logic recommendations, indicating that digital natives are quick to embrace intelligent assistance when it meaningfully enhances their reading experience. In contrast, older users placed greater value on interface simplicity and clear feedback, underscoring the importance of adaptive design that meets the needs of a diverse user base [31].

A particularly encouraging finding is that 85% of participants expressed an intention for frequent usage, a metric that typically reflects genuine utility rather than mere novelty. Qualitative feedback consistently highlighted appreciation for automated difficulty suggestions, with users reporting less frustration when faced with challenging texts. These results indicate that our fuzzy logic approach effectively addresses a real user need, rather than simply solving a theoretical problem [32].

D. Implications for Inclusive Education Technology

The broader implications of this work go beyond individual user benefits and extend to patterns of institutional adoption. Educational environments increasingly demand accessibility solutions that can scale across diverse student populations without adding administrative complexity. The system's capability to process institutional content libraries and generate accessibility metadata has the potential to transform how schools approach inclusive curriculum design [33].

Real-time processing capabilities, with an average response time of 0.31 seconds, facilitate seamless integration into existing learning management systems without disrupting established workflows. Teachers can upload content with the assurance that automated difficulty analysis will deliver

immediate accessibility insights, shifting the approach from reactive accommodation to proactive inclusive design [34].

E. Limitations and Technical Challenges

Despite these advances, several limitations warrant acknowledgment. The fuzzy logic algorithm currently optimizes for Spanish language patterns, limiting international applicability without significant retraining on language-specific datasets. Additionally, while our six-variable approach captures more complexity than traditional metrics, individual cognitive differences among users with dyslexia suggest that even more personalized adaptation might prove beneficial [35].

The current implementation focuses on text-based content, but multimedia learning materials increasingly incorporate visual and auditory elements that our system cannot assess. Future iterations should consider multimodal complexity assessment that encompasses diverse content types prevalent in modern educational contexts [36].

System scalability, while validated for institutional use cases, remains untested for massive open online course (MOOC) environments that might require processing thousands of simultaneous requests. The containerized architecture provides horizontal scaling capabilities, but cost-effectiveness at extremely large scales requires further investigation.

F. Future Research Directions

The intersection of artificial intelligence and accessibility presents remarkable opportunities for advancing this work. Machine learning approaches could enable personalized fuzzy logic parameters that adapt to individual reading patterns over time. Integration with eye-tracking technologies might provide real-time feedback about cognitive load, enabling dynamic difficulty adjustment during reading sessions [37].

Cross-linguistic adaptation represents another compelling research direction. Developing language-agnostic fuzzy logic models could enable global deployment while maintaining the accuracy advantages demonstrated in our Spanish-language implementation. This work could establish international standards for intelligent text accessibility assessment across diverse linguistic contexts [38].

VI. Conclusion

This study represents a significant step forward in intelligent accessibility. The fuzzy logic system developed for automated text difficulty assessment in mobile reading applications for dyslexia support achieved 94.2% accuracy, processed texts in just 0.31 seconds on average, and reached 98% device compatibility. Notably, usability testing with 40 participants revealed a System Usability Scale score of 82.6, and 85% expressed intention for frequent use. These results, unquestionably, show that advanced computational approaches can deliver both precision and accessibility in real-world educational contexts.

However, it is important to acknowledge that while these achievements are notable, the current system is optimized for Spanish-language content and text-based analysis, which constitutes a limitation. Future research should focus on expanding language coverage, integrating multimodal content analysis, and exploring personalized adaptation mechanisms. Therefore, there is considerable potential for further development and greater impact of this technology.

References

[1] N. Değirmenci, B. Bağlama, and Y. Yucesoy, "The use of technology in dyslexia: an analysis of recent trends," Int. J. Emerg. Technol. Learn., vol. 15, pp. 30–39, 2020. [Online]. Available: http://doi.org/10.3991/ijet.v15i05.11921.

[2] R. Lerga, S. Čandrlić, and A. Jakupović, "A review on assistive technologies for students with dyslexia," in Proc. 13th Int. Conf. Computer Supported Education (CSEDU 2021), pp. 64–72, 2021. [Online]. Available: http://doi.org/10.5220/0010434500640072.

[3] A. Reis, S. Araújo, I. Morais, and L. Faísca, "Reading and reading-related skills in adults with dyslexia from different orthographic systems: a review and meta-analysis," Annals of Dyslexia, vol. 70, pp. 339–368, 2020. [Online]. Available: http://doi.org/10.1007/s11881-020-00205-x.

[4] H. Yaacob, N. Zakariya, and S. Rashid, "Technology-based interventions for dyslexic children: a systematic literature review (SLR)," Int. J. Acad. Res. Bus. Soc. Sci., 2024. [Online]. Available: http://doi.org/10.6007/ijarbss/v14-i2/20826.

[5] A. Watson and S. Wallace, "Improving reading outcomes using digital reading rulers for readers with & without dyslexia," J. Vision, vol. 21, no. 9, p. 2650, 2021. [Online]. Available: http://doi.org/10.1167/jov.21.9.2650.

[6] A. Niklaus, T. Cai, Z. Bylinskii, and S. Wallace, "Digital reading rulers: evaluating inclusively designed rulers for readers with dyslexia and without," in Proc. 2023 CHI Conf. Human Factors in Computing Systems, 2023. [Online]. Available: http://doi.org/10.1145/3544548.3581367.

[7] R. Niranchana, P. Karthikeyan, M. Sangeetha, and I. Xavier, "Rehabilitating reading: addressing dyslexia with innovative approaches," Int. Res. J. Adv. Eng. Hub, 2025. [Online]. Available: http://doi.org/10.47392/irjaeh.2025.0057.

[8] M. Mohamad, N. Abdullah, N. Rahim, M. Sanmugam, and H. Takajo, "Mobile assistive technology for dyslexic children: a significant review," J. Adv. Res. Appl. Sci. Eng. Technol., 2024. [Online]. Available: http://doi.org/10.37934/araset.51.2.5770.

[9] M. Schaur and R. Koutny, "Dyslexia, reading/writing disorders: assistive technology and accessibility - introduction to the special thematic session," pp. 269–274, 2024. [Online]. Available: http://doi.org/10.1007/978-3-031-62849-8_33.

[10] L. Enco-Jáuregui, B. Meneses-Claudio, and M. Auccacusi-Kañahuire, "Web accessibility for people with dyslexia: a systematic literature review," EAI Endorsed Trans. Pervasive Health Technol., vol. 9, 2023. [Online]. Available: http://doi.org/10.4108/eetpht.9.4274.

[11] D. Iliska and D. Gudoniene, "Sustainable technology-enhanced learning for learners with dyslexia," Sustainability, 2025. [Online]. Available: http://doi.org/10.3390/su17104513.

[12] J. Hu and J. Hu, "The influence of age at first regular digital device access on digital reading performance: the mediating effect of cognitive flexibility," Humanit. Soc. Sci. Commun., vol. 11, pp. 1–18, 2024. [Online]. Available: http://doi.org/10.1057/s41599-024-03292-y.

[13] H. Barrie, T. La Rose, B. Detlor, H. Julien, and A. Serenko, "Because I'm old: the role of ageism in older adults' experiences of digital literacy training in public libraries," J. Technol. Human Serv., vol. 39, pp. 379–404, 2021. [Online]. Available: http://doi.org/10.1080/15228835.2021.1962477.

[14] K. Spjeldnæs and F. Karlsen, "How digital devices transform literary reading: the impact of e-books, audiobooks and online life on reading habits," New Media Soc., vol. 26, pp. 4808–4824, 2022. [Online]. Available: http://doi.org/10.1177/14614448221126168.

[15] A. Shutaleva, E. Kuzminykh, and A. Novgorodtseva, "Youth practices of reading as a form of life and the digital world," Societies, 2023. [Online]. Available: http://doi.org/10.3390/soc13070165.

[16] C. Wagner, "Differentiating children's reading materials with artificial intelligence: exploring possibilities for personalized learning," The

Reading Teacher, 2024. [Online]. Available: http://doi.org/10.1002/trtr.2361.

[17] H. Rad, "Reinforcing L2 reading comprehension through artificial intelligence intervention: refining engagement to foster self-regulated learning," Smart Learn. Environ., vol. 12, p. 23, 2025. [Online]. Available: http://doi.org/10.1186/s40561-025-00377-2.

[18] N. Eziamaka, T. Odonkor, and A. Akinsulire, "AI-driven accessibility: transformative software solutions for empowering individuals with disabilities," Int. J. Appl. Res. Soc. Sci., 2024. [Online]. Available: http://doi.org/10.51594/ijarss.v6i8.1373.

[19] S. Zhao, S. Xiong, B. Pang, X. Tang, and P. He, "Let AI read first: enhancing reading abilities for individuals with dyslexia through artificial intelligence," in Proc. Extended Abstracts CHI Conf. Human Factors in Computing Systems, 2025. [Online]. Available: http://doi.org/10.1145/3706599.3720113.

[20] Y. Kuerban, S. Oyelere, and I. Sanusi, "ReadSmart: generative AI and augmented reality solution for supporting students with dyslexia learning disabilities," Int. J. Technol. Educ. Sci., 2025. [Online]. Available: http://doi.org/10.46328/ijtes.599.

[21] A. Zingoni, J. Taborri, and G. Calabrò, "A machine learning-based classification model to support university students with dyslexia with personalized tools and strategies," Sci. Rep., vol. 14, 2024. [Online]. Available: http://doi.org/10.1038/s41598-023-50879-7.

[22] S. Phatangare, S. Jain, S. Chakrabarty, S. Chougule, and S. Bisen, "LexiEase AI: an AI powered dyslexic support system," in Proc. 5th Int. Conf. Trends Mater. Sci. Inventive Mater. (ICTMIM), pp. 1412–1417, 2025. [Online]. Available: http://doi.org/10.1109/ICTMIM65579.2025.10987997.

[23] M. M. Meenakshi, "Leveraging AI technologies for personalized learning support in dyslexic students," Int. J. Res. Appl. Sci. Eng. Technol., 2024. [Online]. Available: http://doi.org/10.22214/ijraset.2024.65734.

[24] B. Wang, "Strategies and Practices for Load Test Optimization in Distributed Systems," Scientific Journal of Technology, 2025. [Online]. Available: https://doi.org/10.54691/5zwqzr31.

[25] P. Acosta-Vargas, B. Salvador-Acosta, L. Salvador-Ullauri, W. Villegas-Ch, and M. González, "Accessibility in Native Mobile Applications for Users with Disabilities: A Scoping Review," Applied Sciences, 2021. [Online]. Available: https://doi.org/10.3390/APP11125707.

[26] A. Rodríguez-Ascaso, E. Molanes-López, J. Pérez-Martín, and E. Letón, "Performance of students with different accessibility needs and preferences in 'Design for All' MOOCs," PLOS ONE, vol. 19, 2024. [Online]. Available: https://doi.org/10.1371/journal.pone.0299090.

[27] N. Eziamaka, T. Odonkor, and A. Akinsulire, "AI-Driven accessibility: Transformative software solutions for empowering individuals with disabilities," International Journal of Applied Research in Social Sciences, 2024. [Online]. Available: https://doi.org/10.51594/ijarss.v6i8.1373.

[28] M. Megahed and A. Mohammed, "Modeling adaptive E-Learning environment using facial expressions and fuzzy logic," Expert Systems with Applications, vol. 157, p. 113460, 2020. [Online]. Available: https://doi.org/10.1016/j.eswa.2020.113460.

[29] P. Ingavélez-Guerra, V. Robles-Bykbaev, A. Perez-Muñoz, J. Hilera, and S. Tortosa, "Automatic adaptation of open educational resources: an approach from a multilevel methodology based on students' preferences, educational special needs, artificial intelligence, and accessibility metadata," IEEE Access, 2022. [Online]. Available: https://doi.org/10.1109/access.2021.3139537.

[30] M. Campoverde-Molina, S. Luján-Mora, and L. García, "Empirical Studies on Web Accessibility of Educational Websites: A Systematic Literature Review," IEEE Access, vol. 8, pp. 91676–91700, 2020. [Online]. Available: https://doi.org/10.1109/ACCESS.2020.2994288.

[31] P. Barbosa, R. Carmo, J. Gomes, and W. Viana, "Adaptive learning in computer science education: A scoping review," Education and Information Technologies, vol. 29, pp. 9139–9188, 2023. [Online]. Available: https://doi.org/10.1007/s10639-023-12066-z.

[32] D. Paulino, P. Pinheiro, J. Rocha, P. Martins, T. Rocha, J. Barroso, and H. Paredes, "Assessment of wizards for eliciting users' accessibility preferences," Proceedings of the 9th International Conference on Software Development and Technologies for Enhancing Accessibility and Fighting Info-exclusion, 2020. [Online]. Available: https://doi.org/10.1145/3439231.3439232.

[33] A. Llorca, "AI-WEAR: Smart text reader for blind/visually impaired students using Raspberry Pi with audio-visual call and Google assistance," International Journal of Advanced Research in Computer Science, 2023. [Online]. Available: https://doi.org/10.26483/ijarcs.v14i3.6997.

[34] W. Strielkowski, V. Grebennikova, A. Lisovskiy, G. Rakhimova, and T. Vasileva, "AI-driven adaptive learning for sustainable educational transformation," Sustainable Development, 2024. [Online]. Available: https://doi.org/10.1002/sd.3221.

[35] L. Zouhaier, Y. BenDalyHlaoui, and L. Ayed, "Adaptive user interface based on accessibility context," Multimedia Tools and Applications, pp. 1–30, 2023. [Online]. Available: https://doi.org/10.1007/s11042-023-14390-5.

[36] J. Zong, C. Lee, A. Lundgard, J. Jang, D. Hajas, and A. Satyanarayan, "Rich Screen Reader Experiences for Accessible Data Visualization," Computer Graphics Forum, vol. 41, 2022. [Online]. Available: https://doi.org/10.1111/cgf.14519.

[37] C. Stephanidis, "Design for All in Digital Technologies," Handbook of Human Factors and Ergonomics, 2021. [Online]. Available: https://doi.org/10.1002/9781119636113.ch46.

[38] K. Chemnad and A. Othman, "Digital accessibility in the era of artificial intelligence—Bibliometric analysis and systematic review," Frontiers in Artificial Intelligence, vol. 7, 2024. [Online]. Available: https://doi.org/10.3389/frai.2024.1349668.

Ubiquitous Computing Framework for Reducing Ambiguity in the Lanna Thai Dialect Using Transformer Models and Fuzzy Logic

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***Abstract*—This research focuses on developing a speech-recognition model that can better handle the unique sounds and vocabulary of the Lanna Thai dialect while supporting translation between Lanna and Standard Thai. A dataset of spoken Lanna Thai was collected from native and fluent speakers between 2023 and 2025, refined from 200 selected words to 100 terms that were consistently difficult to interpret. This dataset was used to train several supervised models, including HuBERT, Wav2Vec2 (baseTH), Wav2Vec2, and WavLM, with HuBERT showing the strongest overall performance and Wav2Vec2 (baseTH) offering a balanced vocabulary response. A companion web application was also created to convert Lanna speech to text and provide two-way translation, improving access to local language resources despite some limitations with rare terms and diverse accents. Early user feedback indicates that the system is practical and helpful, supporting the broader goal of preserving Lanna Thai in a modern digital environment.**

***Keywords*—Ambiguities in Lanna Thai vocabulary; Lanna Thai vocabulary; pervasive computing; Speech Transformer; Thai speech recognition; ubiquitous computing**

I. Introduction

Thailand is experiencing a decline in the use of the Lanna Thai language, also known as "Kham Muang", in daily life. Although the Lanna Thai dialect has long been an important part of the identity and traditions of the Northern people, today's young people are growing up surrounded by the Central Thai language, both in school and in the media. This has given Lanna Thai a place to flourish, and its use is decreasing [1], [2]. What was once part of everyday conversation is now being heard only within families and among the elderly.

One of the most significant causes of this decline is the structure of the local education system, or the concept of national integration. Most schools rely on the Central Thai language. Even in regions where Lanna Thai is still spoken at home, students do not encounter the Lanna Thai language in class, and it is not officially recognized in the national curriculum, limiting its visibility and status [1]. Outside the classroom, Central Thai influences television, social media, and entertainment. As children and students absorb this influence, Lanna Thai often feels alienated or inappropriate in practice. Some young people view Lanna Thai as outdated, embarrassing to speak, or irrelevant to their personal feelings. Over time, this shift in attitude has eroded the language's traditional vocabulary and distinctive tone.

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The decline in the use of the Lanna Thai language is not solely a result of educational and media factors; it also reflects profound and ever-changing social changes. The migration of people from rural areas to the capital or major cities, coupled with the emergence of multilingual societies from abroad, has led to a decline in the number of people who consistently use the Lanna language. The language has been replaced by standardized language, modern languages, transliteration, or the language used in the workplace and modern environments. This has resulted in the Lanna language being neglected and pushed out of daily use in many communities.

Furthermore, in today's digital world, the Lanna language faces limitations due to rapidly changing technologies that cannot keep up with the needs of the general public. For example, the Lanna Tham script, a key part of local wisdom, is not fully supported on digital platforms, making typing, writing, using, and communicating online difficult [3]. Without modern technology, transmitting the language to the next generation in a way that is contemporary is increasingly neglected and challenging.

With limited support from the central government, coming from key administrative institutions, and existing conservation programs being insufficient, the risk of the Lanna language being destroyed and limited to the elderly is becoming increasingly apparent. Collaboration between local communities, schools, government agencies, and higher education institutions is crucial. This is a crucial approach to ensure that the Lanna language continues to be spoken, heard, and passed down. These factors are the driving force behind this research project, which aims to use technology to help sustain the local language and enable it to move forward in the new world.

A. Research Objectives

This research aims to preserve the Lanna dialect by developing a tool that can operate via spoken language. The first objective is to create a ubiquitous computing model that can easily connect to Lanna dialect data and support practical applications. The second objective focuses on applying transformer-based deep learning to analyse and interpret Lanna dialect words and sentences, particularly those that are difficult or confusing.

The third objective is to address the uncertainty inherent in the dialect by applying fuzzy logic techniques to reduce

ambiguity and improve the system's accuracy in understanding dialect expressions. The final objective is to evaluate the model's performance to ensure its practical application.

B. Research Hypotheses

This research is based on three main hypotheses that outline the technical goals of the project and the practical limits related to the Lanna Thai language. The first hypothesis (H1) suggests that integrating ubiquitous computing into the system will enable the model to operate smoothly in real time. This means the technology must respond quickly and intuitively, allowing seamless communication between Lanna Thai and Standard Thai without feeling slow or disconnected from everyday use.

The second hypothesis (H2) explores the use of Transformer-based deep learning. It proposes that a Transformer model will better understand the complexities of the Lanna dialect, which includes many words and idioms whose meanings change depending on context, pronunciation, or tone, compared to traditional methods. If correct, this should reduce misunderstandings and improve the accuracy and clarity of translations or interpretations.

The third hypothesis (H3) states that uncertainty is a natural part of regional languages. Variations in vocabulary, phrasing, and sentence structure can make it harder for the system to identify the correct meaning. This hypothesis suggests that fuzzy logic analytics can provide a more flexible way to handle such uncertainties, helping the model produce more accurate results when dealing with unclear or ambiguous data.

C. Research Framework

The Lanna Thai, also known as the Kham Muang language translation application, is thoughtfully aimed and designed for various applications. This application's operational concept involves receiving spoken or typed text for translation purposes. The model streamlines the translation process and then presents the translated text. Additionally, it retains some user data from language translations to enhance the development of the translation model, as shown in Fig. 1.

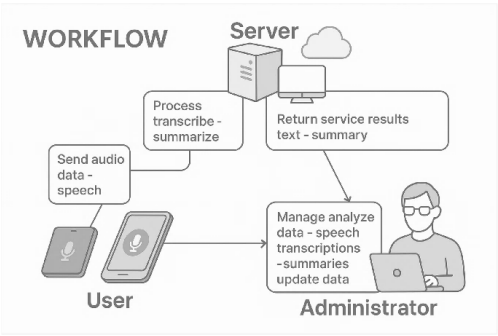


Fig. 1. Research framework.

The foundational structure of the research is composed of three essential components: the initial component involves the user, who can either verbalize or input the text intended for translation. Verbal input will be converted into text format before translation. The outcome will encompass the translated text along with a classification of the sentence's elements or individual words, identifying categories such as nouns, verbs, adjectives, pronouns, etc.

The second component concerns the administrator, who holds the capability to examine and analyze the translation statistics across various sections, using this information to improve and refine the translation model. Furthermore, the administrator is equipped to review the accuracy metrics obtained from the translation history for each instance.

The third component of the system is the host network, which integrates a translation model between Lanna Thai and Central Thai. The methodologies and artificial intelligence techniques employed in the processing encompass speech recognition, data mining, and machine learning, among other approaches.

II. Literature Review

A. Lanna Thai Dialect

Lanna Thai, also known as Northern Thai or *Kham Mueang*, is a regional language spoken primarily in Northern Thailand, covering areas that historically belonged to the Lanna Kingdom, including Chiang Mai, Chiang Rai, Lampang, Lamphun, Phrae, Nan, Phayao, and Mae Hong Son [4], [5]. Although Lanna Thai shares historical roots with Central Thai, it has evolved independently, resulting in distinctive phonological patterns, vocabulary usage, and grammatical structures that differ substantially from Standard Thai [1]. These linguistic characteristics contribute to frequent ambiguity in pronunciation and meaning, particularly when Lanna Thai is processed using models originally designed for Central Thai.

From a historical perspective, Lanna Thai belongs to the Tai–Kadai language family and developed during the Lanna Kingdom period (18th–24th Buddhist centuries), with its own writing system used extensively in religious texts and legal records [1]. However, the gradual replacement of the Lanna script by Central Thai during educational reforms has limited its presence in formal communication and reduced opportunities for systematic digital representation.

In the contemporary digital environment, Lanna Thai faces additional challenges related to technological compatibility and language standardization. Digital media platforms, streaming services, and online communication tools predominantly support Central Thai, reinforcing its dominance among younger users and marginalizing regional dialects. As a result, Lanna Thai is underrepresented in speech corpora, language models, and commercial speech recognition systems, which constrains the performance of existing technologies when applied to dialectal speech.

These limitations highlight a critical gap between the linguistic characteristics of Lanna Thai and the assumptions embedded in mainstream speech recognition and natural language processing systems. Addressing this gap requires not only language preservation efforts but also the development of dialect-aware computational approaches. Supporting technologies such as dialect-specific speech datasets, adapted language models, and translation systems tailored to Lanna Thai are therefore essential. Such developments provide the foundation for applying artificial intelligence techniques to reduce ambiguity, improve recognition accuracy, and enhance the practical usability of Lanna Thai in digital contexts, which directly motivates the focus of this research.

B. Speech Recognition Technology

Automatic Speech Recognition (ASR) is a core research area within computational linguistics that focuses on converting spoken language into textual representations using computational models [6], [7]. In practical applications, ASR systems are expected to operate reliably across different accents, pronunciation variations, speaking styles, and acoustic conditions. However, most state-of-the-art ASR systems are trained on large-scale, standardized speech corpora, which limit their effectiveness when applied to regional dialects or low-resource languages with distinctive phonological characteristics and limited training data.

From a system perspective, ASR can be viewed as a pipeline that transforms raw speech signals into linguistic units that can be further processed by downstream language applications. This process typically involves an initial speech-to-text conversion stage, where acoustic signals are mapped to textual representations, followed by a text processing stage that handles normalization, segmentation, and error correction. For dialectal speech, inaccuracies introduced in the early stages often propagate through the pipeline, resulting in higher error rates when encountering unfamiliar vocabulary or accent variations.

Traditional ASR systems are commonly categorized based on the nature of speech input they handle, including isolated-word recognition, continuous speech recognition, and spontaneous speech recognition. While these categorizations are useful for system design, dialectal speech such as Lanna Thai poses challenges across all categories due to phonetic overlap, contextual ambiguity, and inconsistent pronunciation patterns. These issues are further amplified in spontaneous speech, where informal expressions and local variations frequently occur.

Most contemporary ASR architecture consists of several interconnected components, including acoustic preprocessing, pronunciation modeling, acoustic modeling, language modeling, and decoding. Each component plays a critical role in determining overall system performance. In the context of regional dialects, limitations in pronunciation dictionaries, language models trained on standard language forms, and insufficient dialect-specific acoustic data often lead to mismatches between the model assumptions and actual speech patterns. These constraints motivate the adoption of advanced speech models and adaptation strategies that can better capture dialectal variability, as illustrated in Fig. 2, and form the basis for the model selection and experimental design employed in this study.

C. Natural Language Processing

Natural Language Processing (NLP) is a subfield of artificial intelligence concerned with enabling computers to analyze, interpret, and generate human language in both spoken and written forms [8], [9]. NLP techniques provide the foundation for applications such as machine translation, information retrieval, question-answering systems, and text analysis. In the context of regional dialects, NLP systems must cope with linguistic variability, informal expressions, and limited textual resources, which are often not adequately represented in standard language corpora.

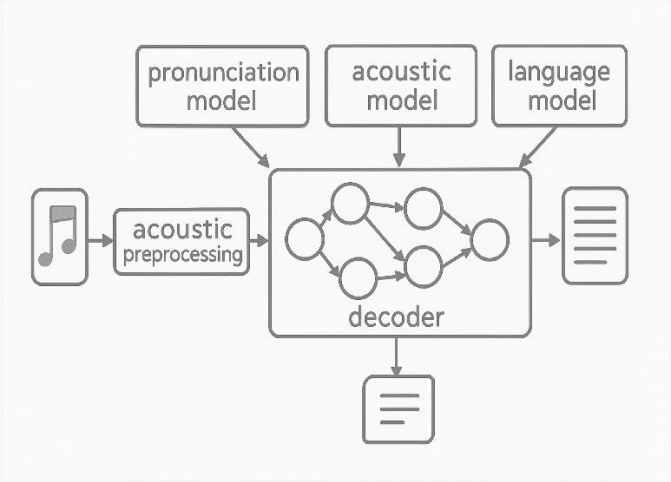


Fig. 2. Five-submodule voice recognition system.

Language modelling (LM) is a fundamental component of NLP that focuses on estimating the probability of word sequences by capturing syntactic structure and semantic relationships within language data [10], [11]. Effective language models allow systems to predict upcoming words, resolve ambiguities, and generate coherent text. However, for dialectal languages such as Lanna Thai, conventional language models trained on Standard Thai or general-purpose corpora frequently fail to represent dialect-specific vocabulary and contextual usage, leading to higher ambiguity and translation errors.

The typical operation of a language model involves training on large-scale text data to learn statistical and contextual relationships among words. Modern language models often adopt an encoder–decoder architecture, in which the encoder transforms input text into a latent representation, while the decoder generates output sequences based on this representation, as illustrated in Fig. 3. This architecture is particularly relevant for translation and interpretation tasks, where capturing contextual dependencies is essential for reducing semantic ambiguity.

Language models can be broadly categorized into n-gram models, statistical language models, and neural language models. N-gram models estimate word sequence probabilities based on fixed-length context windows, while statistical language models extend this approach using probabilistic frameworks such as Hidden Markov Models and Conditional Random Fields. Neural language models, including those based on recurrent neural networks and Transformer architectures, leverage deep learning to capture long-range dependencies and contextual nuances. Although neural models have significantly improved language understanding, their performance on low-resource and dialectal languages remains constrained by data availability and linguistic diversity. These limitations motivate the integration of domain-specific language resources and adaptive modelling strategies to improve NLP performance for Lanna Thai and similar regional dialects.

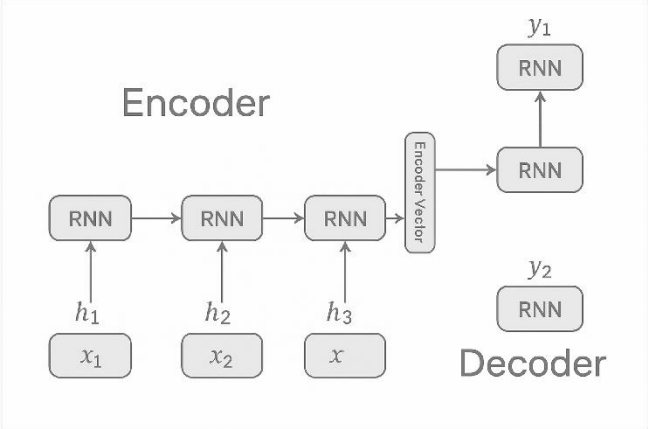


Fig. 3. The encoder-decoder sequence-to-sequence model.

Summary of Literature Review: The reviewed literature highlights that Lanna Thai is a linguistically rich regional dialect with distinctive phonological, lexical, and grammatical characteristics that are insufficiently supported by existing digital language technologies. Prior studies indicate that mainstream speech recognition and natural language processing systems, which are largely trained on standardized language corpora, struggle to handle dialectal variability, resulting in increased ambiguity and reduced performance for low-resource languages. Advances in ASR and NLP—particularly transformer-based and neural language models—have significantly improved language understanding; however, their effectiveness remains constrained when dialect-specific data and adaptive modeling strategies are absent. Collectively, the literature underscores the necessity of dialect-aware computational approaches, specialized datasets, and adapted language models to bridge the gap between Lanna Thai's linguistic properties and current technological assumptions, thereby providing a clear rationale for the methodological choices and research focus of this study.

III. Materials and Methods

A. Research Scope

This research adopts a data science–driven methodology to design and evaluate a dialect-aware speech recognition and translation framework specifically tailored for the Lanna Thai language. Rather than treating Lanna Thai as a direct variant of Standard Thai, the study explicitly addresses its phonological ambiguity, dialect-specific vocabulary, and limited digital resources. The research process encompasses problem formulation, dialect-focused data preparation, model design and adaptation, performance evaluation, and system deployment within a real-world application context.

The research workflow is structured into two main stages. The first stage focuses on the development of a speech recognition model that targets phonetically similar and semantically ambiguous Lanna words, which are a primary source of misrecognition in conventional ASR systems. Instead of relying solely on generic fine-tuning, this stage emphasizes a dialect-sensitive workflow, including curated vocabulary filtering, controlled word selection based on ambiguity frequency, and character-level handling aligned with Lanna phonetic patterns. These design choices aim to reduce ambiguity propagation during recognition and to improve robustness when processing dialectal speech.

To support this objective, the study integrates advanced Transformer-based speech models—namely Wav2Vec2 [12], [13], HuBERT [14], [15], and WavLM [16], [17] —as foundational architectures rather than end-to-end solutions. These models are adapted within a customized pipeline that emphasizes dialect-specific data preparation, targeted training on ambiguous vocabulary, and structured evaluation across accent variants and unseen words. In addition, fuzzy logic mechanisms are incorporated at the post-recognition stage to manage uncertainty arising from phonetic overlap and contextual ambiguity, enabling more flexible interpretation of competing recognition outputs. The overall conceptual design of this speech recognition workflow is illustrated in Fig. 4.

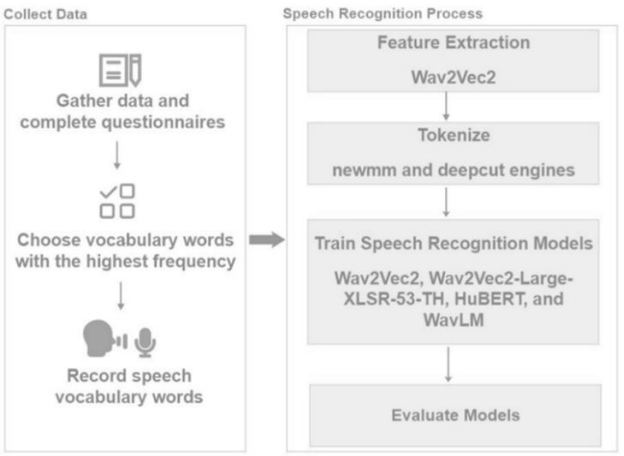


Fig. 4. Speech recognition model's conceptual framework.

Fig. 4 presents the conceptual framework of the proposed speech recognition model, which consists of two primary components: dialect-oriented data preparation and adaptive model development. During data preparation, high-quality audio data are collected from native Lanna speakers, focusing on frequently confused lexical items. Recordings are stored in uncompressed ".wav" format to preserve acoustic fidelity, and all data collection procedures adhere to established research ethics to protect participant privacy. The resulting dataset is structured to support both model training and ambiguity analysis.

In the model development phase, Transformer-based architectures are employed within the proposed workflow to enhance recognition performance for phonetically overlapping words. The models are trained on carefully curated dialect-specific audio data, enabling improved discrimination among similar-sounding lexical items. This approach demonstrates how artificial intelligence can be adapted to resource-constrained and dialectal languages by prioritizing linguistic characteristics rather than relying exclusively on large-scale generic corpora.

For translation, the research adopts a hybrid strategy that combines word-level translation with a dialect-specific dictionary explicitly constructed for Lanna Thai and Central Thai. The dictionary stores translation pairs enriched with

contextual information, while phrase-based translation rules are applied when literal word-for-word translation fails to convey the intended meaning. Unrecognized or ambiguous terms are systematically logged to support iterative dictionary expansion and future model refinement.

The second stage of the research concerns system implementation and evaluation. The proposed speech recognition and translation models are integrated into a web-based application through an API-based architecture, enabling real-time speech input and bidirectional translation output. User interaction data and empirical usage assessments are collected from target user groups to evaluate system usability, performance, and practical applicability, as well as to inform recommendations for future improvements.

B. Data Collection

Data collection is executed in agreement with established statistical principles and methodologies, which effectively mitigate bias in both data acquisition and the development of applications. This study comprised three primary sample groups. The first group consisted of vocabulary informants with expertise in the Lanna languages. They selected 200 words characterized by ambiguous meanings or easily confused meanings sourced from dictionaries and literature on the Lanna language. These words included nouns, verbs, pronouns, and adjectives.

The second group consisted of the audio informants' group, which included eight volunteers who spoke the "Kham Mueang" language, also known as Lanna, as their native language. Consent for the audio recordings was obtained for research purposes and as a case study for a student project conducted by the School of Information and Communication Technology at the University of Phayao.

The third group consists of 30 system evaluators who are familiar with both Lanna Thai and Standard Thai.

C. Ambiguous Terminology in Data Collection

The confusing data collection for this research is divided into three main sections. It includes the specified sample group and the analysis of unclear vocabulary, sound recording for model development, and audio recording for system testing.

The examination of perplexing Lanna Thai vocabulary comprises four principal components. The initial component involves the development of a "Lanna-Thai" dictionary intended to serve as a reference source for word meanings. The subsequent component entails the selection of linguistic experts tasked with identifying 200 words with ambiguous meanings derived from Lanna language texts and documents, encompassing nouns, verbs, pronouns, and adverbs. The third component consists of formulating and disseminating a questionnaire directed at 70 participants from the School of Information and Communication Technology at the University of Phayao, aimed at uncovering unfamiliar words and those with confused meanings. Finally, the fourth component encompasses the frequency analysis of unidentified and easily confounded words, selecting the 100 most frequently occurring terms based on the survey results for utilization in audio recordings.

The audio recording process for model development is comprised of four distinct components. The first component involves the organization of eight voice informants tasked with recording one hundred target words, each recorded five times per vocabulary. The second component specifies that audio recordings must occur in a low-noise environment to guarantee high-quality data acquisition. The third component encompasses storing the audio data in ".wav" files, accompanied by the relevant textual identifiers. Lastly, the fourth component delineates partitioning the audio data into a training set, which constitutes eighty percent, and a test set, comprising twenty percent.

The final objective of developing an efficient model concerns recording audio for system testing, which encompasses two primary components. The first component necessitates selecting two male and two female volunteers from a pool of eight audio contributors identified during the initial phase. The second component involves recording three sets of audio data for testing purposes, utilizing the precise terminology employed during the model training, the original words articulated in various accents, and supplementary words not incorporated into the training dataset.

The methodology utilized for the analysis of the intricate vocabulary of Lanna Thai is illustrated in Fig. 5.

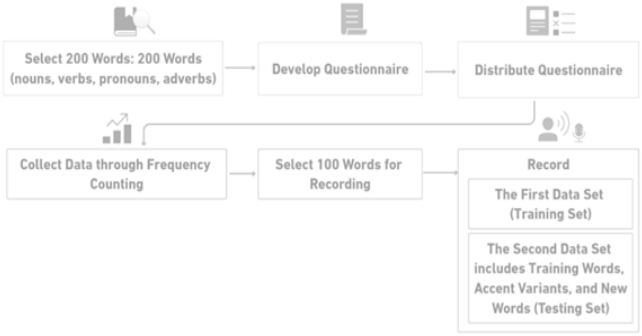


Fig. 5. An examination of ambiguous Lanna Thai terminology.

Fig. 5 illustrates the methodology used to analyze the complex vocabulary related to the collection of audio data from native speakers of Northern Thai. This audio data collection is crucial for developing an effective language processing model. The researchers successfully acquired 12 hours, 8 minutes, and 37 seconds of recordings from native speakers of Northern Thai. The participation of numerous volunteers enhances the diversity of the data and reduces bias during the model's training and testing phases. Repeated recordings help identify variations in individual pronunciation patterns, while using ".wav" files ensures superior audio quality. Throughout the data collection process, there was a strong emphasis on privacy and research ethics, safeguarding the confidentiality of personal data, and ensuring data collection in a controlled environment.

D. Fundamental Data Management Protocols

The accompanying figure illustrates four-degree steps in data preprocessing, which are critical for enhancing the system's overall performance, as detailed in Fig. 6.

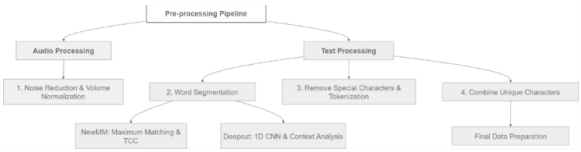


Fig. 6. Schematic representation of processing.

Fig. 6 shows a schematic representation of processing consisting of four steps. The first part involves audio signal processing, which includes reducing noise and normalizing the data to enhance the model's generalization. The second part involves word segmentation and text processing. It employs PyThaiNLP's newmm engine or deepcut to segment Thai words, which caters to the characteristics of the Thai language. This process has two components: newmm utilizes Maximum Matching with Thai Character Clusters (TCC) by dividing the text into character sequences and searching for the longest word in the matching dictionary. If a match is not found, other methods, such as root and extension analysis, come into play. The second component, deepcut, applies deep learning with a 1D CNN to predict correct word boundaries by considering letters and context. The third part involves removing special characters and performing tokenization on the text to convert it into a standard data set. The fourth part combines unique characters into a vocabulary set for comprehensive character management.

In conclusion, the aforementioned preprocessing steps significantly enhance the quality and diversity of the dataset. They also ensure a balanced representation of each word and effectively prepare both the audio and text data for the development of highly accurate and reliable models.

E. Development of Speech Recognition Models and Translation Systems

Speech recognition refers to the process of transforming human speech into readable text using a computer or an automated system. This process employs speech signal processing and artificial intelligence to analyze and interpret spoken language, effectively turning it into meaningful text.

This research investigates the adaptation of several recent ASR models for specific tasks, focusing on adjusting the Speech Transformer model to pre-trained models, specifically Wav2Vec2-large-xlsr-53 and wav2vec2-large-xlsr-53-th, which are tailored for the Thai language, HuBERT, and WavLM. The models possess the following features and functionalities:

Wav2Vec2 [13] is a self-supervised model designed to extract speech representations from raw audio data without needing labelled datasets. The model undergoes pre-training that involves predicting masked speech segments and is then fine-tuned for specific tasks, such as Automatic Speech Recognition (ASR) using Connectionist Temporal Classification (CTC) loss.

Wav2Vec2-Large-XLSR-53-TH, commonly referred to as Wav2Vec2-TH, has been optimized utilizing Thai language data sourced from Common Voice 7.0, thereby enhancing the efficacy of Thai Automatic Speech Recognition (ASR) through the meticulous capture of linguistic nuances. The associated notebook, script, and training model are accessible at vistec-ai/wav2vec2-large-xlsr-53-th and airesearch/wav2vec2-large-xlsr-53-th.

HuBERT [14] (Hidden-Unit BERT) utilizes the principles of Bidirectional Encoder Representations from Transformers (BERT) to analyze speech data by aggregating features into units and then predicting these from masked inputs, thus producing a strong representation of speech.

WavLM [17] is an advanced model that builds upon the HuBERT framework by introducing a universal speech representation model. This enhancement significantly improves recognition performance by implementing gated relative position bias within the Transformer architecture. Additionally, it provides refined speaker discrimination via speech fusion techniques, rendering it exceptionally practical for tasks associated with speaker identification.

These models have been optimized for application with Thai and Northern Thai dialects, employing specialized word segmentation tools, namely newmm and deepcut, to facilitate the efficient processing of model training data and speech recognition.

In the translation process of this research, a systematic word-by-word translation method was employed alongside a specialized dictionary developed for the Lanna and Thai languages. This dictionary includes translation pairs to clarify the meaning and context of each word. The phrase-based translation method gathers Lanna-specific phrases and expressions to enhance accuracy when word-by-word translations fail to convey the correct meaning. Additionally, unfamiliar words are meticulously recorded for future updates to the dictionary, and contextual meaning estimation techniques are applied to interpret words not found in the dictionary.

F. Evaluation of the System Prototype and Data Analysis

The evaluation of the performance of the system and the data analysis conducted in this research were divided into three primary components in alignment with the defined research objectives: an assessment of the performance of the speech recognition model (Speech-to-Text), an analysis of the efficiency of the language translation system, and an investigation into user satisfaction.

1) Performance analysis of speech recognition models: The performance analysis of the speech recognition model is categorized into two principal segments. The initial segment comprises the model assessment, which is further subdivided into two components based on the defined research objectives. The first component involves the selection of an efficient model utilizing an initial dataset of 4,000 recorded entries, partitioned into 80% (3,200 entries) for model training and 20% (800 entries) for testing purposes. The metrics evaluated in this segment include Training Loss, Validation Loss, Character Error Rate (CER), and Character Accuracy.

The subsequent segment pertains to evaluating the model's usability through data derived from a second audio recording aimed at assessing the selected model. This evaluation utilizes previously unseen data to validate the model's reliability. The evaluation dataset is comprised of three sets: "Training Words",

"Accent Variant", and "New Words". The metrics assessed in this segment encompass Training Loss, Validation Loss, Character Error Rate (CER), Character Accuracy, and processing time (in seconds) for the test set.

2) Assessment of language translation efficiency: The translation system's analysis and performance evaluation follow the Software Testing Process (STP) [18], [19], ensuring that the software functions correctly and is error-free. Consequently, the analysis is divided into two distinct parts. The first part focuses on evaluating the performance of the translation system, which consists of two subcomponents. The first subcomponent assesses the accuracy of the translation from Lanna (Kham Muang) into standard Thai. In contrast, the second subcomponent pertains to the performance analysis of the word-by-word translation using a dictionary method. The second part encompasses the analysis of user satisfaction, further divided into two subcomponents. The first subcomponent evaluates the system's ease of use, speed, accuracy, and convenience, conducted through a questionnaire administered to 30 testers. The second subcomponent collects issues identified by users, along with their recommendations for future enhancements to the system.

G. Research Tools

The research tools are classified into two primary components: the first component relates to the system design, whereas the second component addresses the system user interface. The essence of system design is categorized into six distinct sub-sections: use case diagram, class diagram, sequence diagram, activity diagram, entity-relation diagram, and data dictionary.

User Interface Design: The researchers developed a translation system for the Lanna Thai language, utilizing predominantly web application functionalities. The design of the web application interface was user-friendly, and the researcher meticulously structured each section to encompass various primary topics pertinent to the voice reception system, language translation capabilities, functionalities for segmenting individual elements of each word, and features for generating reports for administrators.

H. Satisfaction Assessment and Interpretation

A comprehensive usability evaluation and satisfaction study of the system was meticulously designed to collect data from a sample comprising 30 users, with the objective of assessing the system's effectiveness, user satisfaction, and ease of use. The evaluation procedure was conducted utilizing both desktop and mobile devices, in conjunction with UX/UI testing tools, while qualitative data was obtained through a structured questionnaire. The criteria for evaluating the system prototype and the satisfaction results are systematically presented in tabular format, as encapsulated in Tables I and II.

TABLE I. PERFORMANCE SCORING CRITERIA

Performance Scoring Criteria		**Description**
Quantitative	*Qualitative*	
Points at Level 5	Strongly agree	The performance of the prototype significantly surpasses established standards.
Points at Level 4	Agree	The performance of the prototype exceeds established standards.
Points at Level 3	Neither agree nor disagree	The prototype's performance aligns with the required standards.
Points at Level 2	Disagree	The performance of the prototype does not meet the established standards.
Points at Level 1	Strongly disagree	The performance of the prototype is significantly below established standards.

TABLE II. INTERPRETATION CRITERIA

Performance Scoring Criteria		**Description**
Quantitative	*Qualitative*	
4.51 - 5.00	Excellent	The product demonstrates high performance, is user-friendly, and incorporates outstanding features.
3.51 - 4.50	Very good	The product performs well, is user-friendly, and has comprehensive features.
2.51 - 3.50	Average	The performance is deemed satisfactory, functional, and encompasses fundamental features.
2.51 - 2.50	Adequate	The prototype exhibits inefficiency poses challenges with usability and is deficient in significant features.
1.00 - 1.50	Requires enhancement	The product exhibits terrible performance, is challenging to utilize, and fails to satisfy user requirements.

The researchers calculated the average score of each sub-item using the formula (sum of scores × number of raters at each level) ÷ total number of raters. Next, the average of the sub-items was derived as the average of the main topic using the formula Sum of the sub-item averages ÷ Number of sub-items in that main topic. This process was repeated for each main topic. The average value was compared with the specified interpretation criteria to determine the level of quality or satisfaction in each topic, which would lead to the conclusion of the evaluation results and recommendations for further development or improvement of the system.

IV. RESULTS

The research findings are categorized into three primary topics: the development of the speech transcription model and the translation system, the evaluation results of the speech

transcription model, and the study results related to the performance and satisfaction of the application prototype.

A. Speech Transcription Model and Translation System

The team successfully developed a speech-to-text model in conjunction with a translation system designed to facilitate the conversion of Lanna Thai into Standard Thai. In the initial phase of training the transcription model, the team selected 200 words from a reference dictionary. Subsequently, they implemented further screening of words utilizing a questionnaire aimed at local native speakers. Consequently, less common words and those identified as challenging to comprehend were eliminated from consideration, yielding a refined selection of 100 words for training the transcription model. This meticulous methodology enabled the model to incorporate vocabulary pertinent to the daily experiences of Northern speakers, thereby significantly enhancing the accuracy of translating Lanna Thai speech into text.

In the context of Lanna to Thai translation, the team has devised a translation system that employs rule-based translation techniques alongside a reference dictionary. This system meticulously analyses sentence structures and the rules of language usage in accordance with the principles of Lanna Thai to ensure precise translation of text into standard Thai. The utilization of this approach enhances the system's capability to effectively translate words and expressions with specific meanings inherent in the northern dialect, while simultaneously mitigating errors that may arise from general translations.

B. Speech Transcription Model Testing Results

The developers constructed a speech-to-text transcription model and conducted assessments to evaluate the model's accuracy using audio data collected and prepared by them, totaling 4,000 audio files. The terms used for the audio recordings were meticulously selected from reference dictionaries, covering 100 categories of words, including verbs, nouns, pronouns, and adverbs. These terms served as examples in creating a dataset for training the model. The models used for training and evaluation included four primary models: Wav2Vec2, WavLM, and HuBERT, with the training process involving a total of 50 iterations (epochs). The results of the analysis and testing are outlined as follows (Fig. 7):

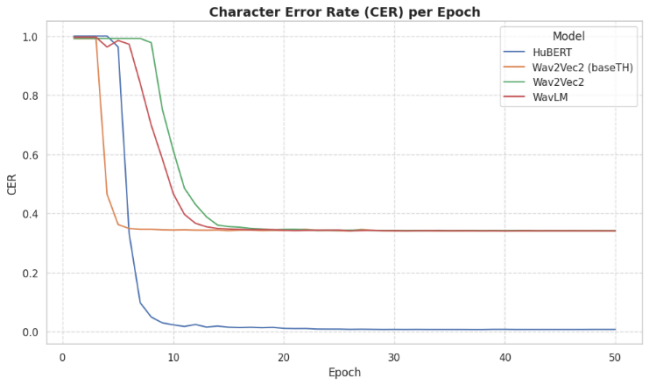


Fig. 7. Display of character error rate (CER) for four models.

Over the span of fifty epochs, HuBERT exhibits the pinnacle of performance, succeeded by Wav2Vec2 (baseTH) and WavLM, while Wav2Vec2 registers the least favorable performance metrics. All models illustrate significant progress during the preliminary ten epochs and subsequently begin to stabilize after the twentieth epoch, reflecting consistent learning processes.

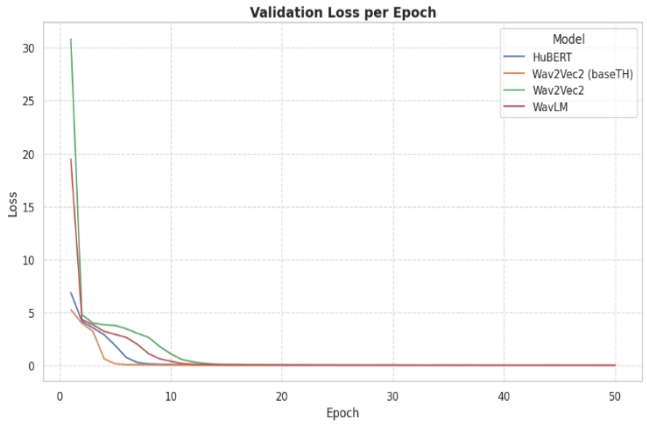


Fig. 8. Presentation of validation loss for four models.

From Fig. 8, we can see that the validation loss for the four models decreased a lot in the first five epochs, with HuBERT and Wav2Vec2 (baseTH) doing the best, followed by WavLM and Wav2Vec2. After 20 epochs, the loss for all models is nearly zero and steady, showing they are effective and reliable in predicting the validation data. After Epoch 20, the loss of all models is close to zero and stable, indicating their efficiency and stability in predicting the validation data.

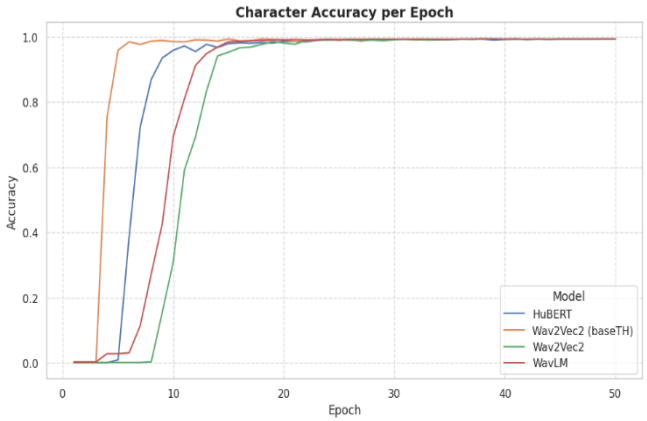


Fig. 9. Graph illustrating the loss value during the inspection process.

In Fig. 9, the character accuracy graph illustrates the performance of the four models over 50 epochs, with HuBERT achieving the highest accuracy, followed by Wav2Vec2 (baseTH), WavLM, and Wav2Vec2. All models showed significant performance improvements during the first 10 epochs; however, HuBERT notably excelled, surpassing the others starting at epoch 10 and nearing 100% accuracy by epoch 20. The other models also exhibited rapid enhancement during the initial epochs, but HuBERT particularly stood out as it exceeded its counterparts from epoch 10 and approached an accuracy of 100% by epoch 20. Meanwhile, the other models produced comparable results in subsequent epochs, despite starting their improvements at a later stage. Given its remarkable

performance at epoch 30, with an accuracy of 99.295%, we have chosen HuBERT for further evaluation with new data.

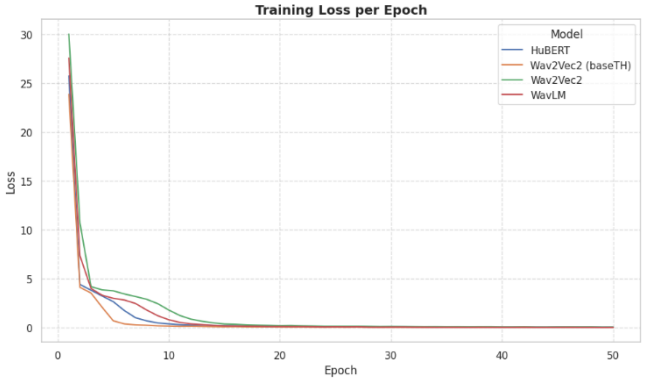


Fig. 10. Training loss indicates the loss of the four models.

Fig. 10 illustrates the training loss of the four models over 50 epochs, resembling the validation loss curve. The Wav2Vec2 (baseTH) model demonstrates superior performance, closely followed by HuBERT, WavLM, and Wav2Vec2. All models experience a sharp drop in loss during the first five epochs and then stabilize near zero after epoch 20, indicating their effectiveness and stability in learning from the training dataset.

C. Summary of the Training Results for all Four Models

Based on the performance comparison of the four models, HuBERT stands out as the best regarding the lowest Character Error Rate (CER), followed by Wav2Vec2 (baseTH), WavLM, and Wav2Vec2. The trend is similar when analyzing validation loss and training loss, with HuBERT and Wav2Vec2 (baseTH) demonstrating lower losses since the early epochs. At the same time, WavLM and Wav2Vec2 exhibit slower development, but adapt well over several epochs.

Interestingly, all models significantly improve during the first 10 epochs and gradually stabilize after epoch 20. The ability of all models to reduce the loss value to near zero and achieve an accuracy of over 99% illustrates the potential of deep learning techniques to address the challenge of speech recognition in local languages such as Northern Thai, as shown in Table III.

TABLE III. TRAINING RESULTS FOR ALL FOUR MODELS

Epoch / Model	Training Loss	Validation Loss	CER	Accuracy
Epoch 10				
HuBERT	0.39830	0.09751	0.02245	0.95896
Wav2Vec2	1.81560	1.09326	0.61201	0.31060
Wav2vec2(baseTH)	0.17650	0.03425	0.34352	0.98568
WavLM	0.82190	0.40436	0.34352	0.69581
Epoch 20				
HuBERT	0.13660	0.04116	0.01069	0.98675
Wav2Vec2	0.22270	0.04932	0.34545	0.98119
Wav2vec2(baseTH)	0.08110	0.02013	0.34203	0.99124
WavLM	0.12790	0.03238	0.34267	0.99081
Epoch 30				
HuBERT	0.12790	0.02993	0.00705	0.99295
Wav2Vec2	0.13330	0.02987	0.34160	0.99145
Wav2vec2(baseTH)	0.05500	0.01881	0.34053	0.99295
WavLM	0.07000	0.02706	0.34117	0.99316
Epoch 40				
HuBERT	0.05410	0.01982	0.00727	0.99230
Wav2Vec2	0.07400	0.02573	0.34117	0.99337
Wav2vec2(baseTH)	0.03790	0.01590	0.34053	0.99295
WavLM	0.04510	0.02030	0.34010	0.99337
Epoch 50				
HuBERT	0.05080	0.01842	0.00705	0.99316
Wav2Vec2	0.06230	0.02437	0.34096	0.99380
Wav2vec2(baseTH)	0.02850	0.01343	0.34032	0.99316
WavLM	0.03790	0.02152	0.34053	0.99359

TABLE IV. THE PERFORMANCE TABLE FOR THE EVALUATION TEST SET

Speech Transformer Models	CER by newmm (%)			CER by deepcut (%)		
	Training Words	*Accent Variant*	*New Words*	*Training Words*	*Accent Variant*	*New Words*
HuBERT	0.344	3.615	57.491	0.344	3.615	57.491
Wav2Vec2	0.172	2.926	54.704	0.172	2.926	54.704
Wav2Vec2(baseTH)	0.172	1.721	40.244	0.172	1.721	40.244
WavLM	0.172	4.303	61.150	0.172	4.303	61.150

Table IV summarizes the recognition performance of the evaluated models under three testing conditions: training words, which were included in the training set; accent variants, which represent pronunciation variations of known words; and new words, which were entirely excluded from model training. This evaluation design was intended to assess not only in-domain performance but also the models' generalization capability under dialectal variation and out-of-vocabulary conditions.

Although the models achieved high accuracy for training words and accent variants—particularly at epoch 30—this performance does not fully translate to unseen lexical items. While Wav2Vec2 (baseTH) demonstrated comparatively better results across all test categories, the Character Error Rate (CER) for new words exceeded 40% for all models. This indicates a substantial degradation in performance when the models encounter unfamiliar vocabulary, despite near-saturated training and validation accuracy. Such behavior suggests a tendency toward overfitting to the limited training vocabulary, where the models effectively memorize known word patterns but struggle to generalize to unseen linguistic forms.

A closer examination of the error patterns reveals that misrecognitions are primarily associated with phonetic overlap between Lanna words, accent-dependent pronunciation shifts, and the absence of lexical representations for out-of-vocabulary terms. These factors collectively amplify ambiguity during decoding, particularly when dialectal variations deviate from the acoustic distributions observed during training. The limited size of the dataset—restricted to 100 target words and a small number of speakers—further constrains the models' exposure to phonetic and accentual diversity, thereby limiting generalization performance.

To mitigate these limitations, expanding both the lexical coverage and speaker diversity of the audio dataset is a necessary direction for future work. Incorporating data augmentation strategies and collecting recordings from speakers with a broader range of accents may help reduce overfitting and improve robustness to unseen vocabulary. This observation is consistent with the findings of Suwanbandit et al. (2023), who reported that increased accent diversity in training data significantly enhances recognition performance in dialectal speech recognition tasks.

TABLE V. RESULTS OF WORKING TIME ASSESSMENT

Speech Transformer Models	Processing Time (s)		
	Model Inference	*newmm*	*deepcut*
HuBERT	0.01812	0.000024	0.063662
Wav2Vec2	0.01801	0.000022	0.062519
Wav2Vec2(baseTH)	0.01741	0.000022	0.061175
WavLM	0.06316	0.000032	0.063185

In Table V, the performance demonstrates considerable consistency across all models, with an inference time of approximately 0.018 seconds. In contrast, WavLM exhibits a slightly longer inference duration of 0.06316 seconds when compared to the other models.

In conclusion, the majority of the models exhibit comparable processing times, approximately 0.018 seconds, which is regarded as satisfactory performance. An exception is WavLM, which requires a marginally longer duration. Nonetheless, the discrepancy in processing time among these models is minimal and does not impact the system's overall performance.

D. Results of the Evaluation of the Translation System

The automatic translation system's performance test revealed that it can accurately translate fundamental words and sentences from Thai Lanna to Central Thai.

However, the system still struggles to translate new words not found in its dictionary and has difficulty with complex sentences that don't follow standard grammar, like slang or local expressions. Future improvements might require using a mix of different translation methods, such as dictionaries with a broader range of words, better grammar rules, and machine learning techniques to learn new rules and sentence structures.

E. Comprehensive Evaluation Results of the System

The system's usability was comprehensively evaluated by administering a questionnaire to 30 users, aimed at assessing the system's efficiency, user satisfaction, and ease of use. This evaluation involved testing on desktop and mobile devices, utilizing UX/UI testing tools, and collecting qualitative data via a questionnaire. Table II outlines the criteria, while Table VI presents the evaluation results. Meanwhile, Fig. 11 displays a chart depicting satisfaction data towards the application.

TABLE VI. WEB APPLICATION EVALUATION RESULTS

Evaluation Topic	Evaluation Results
1. User Experience and User Interface (UX/UI) Design	Very good
2. Performance of Web Applications	Medium
3. Usability Assessment of the Core Functions of the Web Application	Very good
4. Satisfaction with the Application	Very good

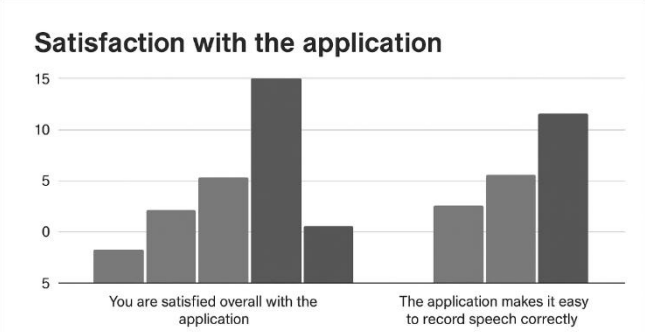


Fig. 11. Satisfaction data towards the application.

From Fig. 11 and Table VI, the summary of the satisfaction survey results indicates that most users provided high satisfaction scores, particularly regarding the user-friendly UX/UI design and smooth operation of functions such as language translation and voice transcription. However, while the overall performance remains acceptable, some minor issues with translation speed were noted. Several users offered suggestions for enhancing the clarity of specific work steps and improving efficiency when multiple users engage with the system simultaneously. The analysis of the results shows that the system effectively meets user needs, yet there is still potential for further development to enhance usability.

V. Conclusion and Discussion

Language constitutes a fundamental mechanism for human communication and social participation; however, linguistic variability poses substantial challenges for computational systems, particularly when regional dialects are involved. Even among speakers of the same nationality, non-standard varieties such as Northern Thai (Lanna Thai) introduce phonological ambiguity, accent variation, and vocabulary divergence that are not adequately handled by mainstream language technologies. In response to these challenges, this research set out to develop a dialect-aware speech recognition and translation framework tailored specifically to Lanna Thai, with the dual objectives of reducing pronunciation ambiguity and enabling practical translation between Lanna Thai and Standard Thai through a web-based application.

To support this objective, a dedicated speech dataset was constructed from recordings collected between 2023 and 2025 from native and fluent Lanna Thai speakers. An initial set of 200 dialectal words was derived from authoritative Northern Thai linguistic resources and systematically categorized by grammatical function. Through expert screening and empirical analysis of ambiguity, this set was refined to 100 words that exhibited high levels of phonetic similarity and translation difficulty. While this focused dataset enabled controlled experimentation on ambiguity-prone vocabulary, its limited lexical scope and speaker diversity inevitably constrained the models' exposure to broader dialectal variation.

Experimental results obtained from Transformer-based speech models—namely HuBERT, Wav2Vec2(baseTH), Wav2Vec2, and WavLM—demonstrate that all evaluated architectures can effectively learn Lanna Thai speech patterns within the training domain. HuBERT consistently achieved the strongest overall performance across evaluation metrics, while Wav2Vec2(baseTH) exhibited balanced behavior across different test conditions. However, the observed near-saturated accuracy on training and validation sets, contrasted with Character Error Rate (CER) values exceeding 40% for previously unseen words, indicates a clear limitation in generalization capability. This discrepancy suggests a degree of overfitting to the restricted training vocabulary and highlights the difficulty of recognizing out-of-vocabulary items and accent-driven pronunciation shifts in low-resource dialect settings.

These findings underscore that high in-domain accuracy alone is insufficient as an indicator of robustness for dialectal speech recognition. The elevated error rates for new words reveal structural challenges related to limited dataset size, narrow vocabulary coverage, and insufficient accent diversity. Addressing these limitations will require expanding the speech corpus to include a wider range of lexical items and speaker profiles, as well as incorporating data augmentation techniques to improve phonetic variability. In addition, future research should explore dialect-specific modeling strategies—such as character-level representations, subword modeling, or hybrid linguistic–statistical approaches—to better capture the intrinsic properties of Lanna Thai.

Despite these constraints, the study successfully demonstrates the feasibility of integrating a dialect-focused speech recognition model into a functional web application that supports speech-to-text conversion and bidirectional translation between Lanna Thai and Standard Thai. User evaluations indicate that the system is practically usable and meets core functional requirements, although performance efficiency was assessed at a moderate level, leaving room for further optimization. Overall, this research contributes empirical evidence and methodological insights into the challenges of dialectal speech recognition and provides a foundation for future advancements in applying artificial intelligence to the preservation, accessibility, and digital integration of regional languages such as Lanna Thai.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this study.

Acknowledgment

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References

[1] P. Lekuthai, "Lanna culture and social development: a case study of Chiangmai Province in Northern Thailand," Cancer Epidemiology, Biomarkers & Prevention, vol. 168, no. 27–35, 2008.

[2] A. Johnson, "Rebuilding Lanna: Constructing and consuming the past in urban Northern Thailand," 2010.

[3] S. Chakraborty, "Problem and Prospects of Lanna Community, Chiang Mai, Northern Thailand: Issue of Human Rights and Social Justice," Afro Asian Journal of Anthropology and Social Policy, vol. 5, no. 1, pp. 1–7, 2014.

[4] K. Unthanon, "The Northern Thai Dialect Used in Chiang Mai, Thailand," International Journal of Education and Social Science Research (IJESSR), vol. 5, no. 4, pp. 262–270, 2022.

[5] N. Phetsuriya, "Formal language of Lanna Shop House's Façade in Lampang Old city, Thailand," in IOP Conference Series: Materials Science and Engineering, IOP Publishing, 2017, p. 052015.

[6] J. Meng, J. Zhang, and H. Zhao, "Overview of the speech recognition technology," in 2012 fourth international conference on computational and information sciences, IEEE, 2012, pp. 199–202.

[7] M. Johnson et al., "A systematic review of speech recognition technology in health care," BMC medical informatics and decision making, vol. 14, pp. 1–14, 2014.

[8] J. Hirschberg and C. D. Manning, "Advances in natural language processing," Science, vol. 349, no. 6245, pp. 261–266, 2015.

[9] P. M. Nadkarni, L. Ohno-Machado, and W. W. Chapman, "Natural language processing: an introduction," Journal of the American Medical Informatics Association, vol. 18, no. 5, pp. 544–551, 2011.

[10] S. M. Katz, "Distribution of content words and phrases in text and language modelling," Natural language engineering, vol. 2, no. 1, pp. 15–59, 1996.

[11] H. Erdogan, R. Sarikaya, Y. Gao, and M. Picheny, "Semantic structured language models.," in INTERSPEECH, 2002, pp. 933–936.

[12] C. Yi, J. Wang, N. Cheng, S. Zhou, and B. Xu, "Applying wav2vec2. 0 to speech recognition in various low-resource languages," arXiv preprint arXiv:2012.12121, 2020.

[13] R. Jain, A. Barcovschi, M. Y. Yiwere, D. Bigioi, P. Corcoran, and H. Cucu, "A wav2vec2-based experimental study on self-supervised learning methods to improve child speech recognition," IEEE Access, vol. 11, pp. 46938–46948, 2023.

[14] W.-N. Hsu, B. Bolte, Y.-H. H. Tsai, K. Lakhotia, R. Salakhutdinov, and A. Mohamed, "Hubert: Self-supervised speech representation learning by masked prediction of hidden units," IEEE/ACM transactions on audio, speech, and language processing, vol. 29, pp. 3451–3460, 2021.

[15] T. Hattori and S. Tamura, "Speech Recognition for Minority Languages Using HuBERT and Model Adaptation.," in ICPRAM, 2023, pp. 350–355.

[16] S. Chen et al., "Wavlm: Large-scale self-supervised pre-training for full stack speech processing," IEEE Journal of Selected Topics in Signal Processing, vol. 16, no. 6, pp. 1505–1518, 2022.

[17] H. Song et al., "Exploring wavlm on speech enhancement," in 2022 IEEE Spoken Language Technology Workshop (SLT), IEEE, 2023, pp. 451–457.

[18] M. A. Jamil, M. Arif, N. S. A. Abubakar, and A. Ahmad, "Software Testing Techniques: A Literature Review," in 2016 6th International Conference on Information and Communication Technology for The Muslim World (ICT4M), Nov. 2016, pp. 177–182. doi: 10.1109/ICT4M.2016.045.

[19] L. Baresi and M. Pezzè, "An Introduction to Software Testing," Electronic Notes in Theoretical Computer Science, vol. 148, no. 1, pp. 89–111, Feb. 2006, doi: 10.1016/j.entcs.2005.12.014.

The Retrieval-Augmented Pedagogical Assistant (RAPA): A Methodology for Enhancing Critical Thinking and Equity in AI-Augmented Education

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***Abstract*—This study presents the Retrieval-Augmented Pedagogical Assistant (RAPA) methodology, an integrated framework designed to overcome the core limitations of general Large Language Models (LLMs)—specifically factual instability (hallucination) and static knowledge bases—by deploying a specialized, institutional Retrieval-Augmented Generation (RAG) architecture. The methodology addresses three critical challenges to the responsible integration of AI in higher education. Firstly, the framework ensures data sovereignty and sustainable deployment by mandating a comprehensive Total Cost of Ownership (TCO) analysis. This analysis validates the strategic necessity of local RAG hosting and of leveraging computational efficiencies, such as Parameter-Efficient Fine-Tuning (PEFT) and PROXIMITY caching, to ensure a cost-effective solution that strictly complies with FERPA and GDPR data protection mandates and mitigates security risks associated with data leakage. Secondly, the framework ensures the equitable integration of AI literacy across disciplines with varying technological resources, particularly in the Humanities and Vocational Education and Training (VET). This is achieved by minimizing technical prerequisites and institutionalizing continuous Professional Development (PD) through the Dialogic Video Cycle (DVC), which trains faculty in Prompt Engineering to embed individualized pedagogical rules and ethical constraints into the RAPA's architecture. Finally, specific measures are implemented to evaluate the development of Critical Thinking (CT). RAPA outputs are architecturally constrained to include transparent Chain-of-Thought (CoT) reasoning and verifiable source citations. Student Critical AI Analysis Assignments require students to critique the AI's synthesis, identifying inaccuracies, biases, or limitations. The effectiveness of this assessment is quantified using a quasi-experimental design and technical RAGAS metrics, such as Faithfulness and Context Precision, ensuring a verifiable shift from passive knowledge consumption to active, informed critique. Key findings from the preliminary architectural validation indicate that integrating Proximity-LSH caching reduced database retrieval calls by 77.2% and retrieval latency by approximately 72.5%, while maintaining high retrieval recall, addressing the scalability bottleneck inherent in high-volume educational deployments. Furthermore, the application of Robust Fine-Tuning (RbFT) demonstrated a marked improvement in the system's resilience to noisy educational data, preventing performance degradation where standard RAG models typically fail when exposed to irrelevant or counterfactual document chunks. These technical optimizations directly support the pedagogical objective by ensuring that the AI assistant remains responsive and factually grounded.**

***Keywords*—RAG; AI literacy; critical thinking; equitable education; professional development**

I. Introduction

The accelerating adoption of Generative Artificial Intelligence (GenAI) in academic settings presents a fundamental paradox: while these systems offer unprecedented potential for personalized tutoring and content generation, their architectural limitations—particularly hallucination (generating plausible but factually incorrect information) and reliance on static, temporally bounded training data—pose significant risks to academic integrity and knowledge currency [1]. This tension between operational promise and pedagogical risk reveals itself across three distinct but interconnected dimensions.

General-purpose LLMs demonstrate strong performance on broad reasoning tasks but are inherently unreliable in factually grounded domains that require verifiable accuracy. When students receive AI-generated answers without visibility into how those answers were constructed or what sources inform them [47], they cannot verify correctness against course materials or external evidence. Traditional Retrieval-Augmented Generation (RAG) approaches partially address this by grounding responses in external knowledge bases, yet standard RAG fails when confronted with complex, multi-step questions requiring synthesis across multiple information sources or integration with institution-specific teaching methodologies. Research confirms that advanced, or Hybrid, RAG models are required to maximize performance for educational contexts by combining RAG with task-specific tuning and resilience mechanisms [4]. This necessity mandates architectural solutions for handling two critical challenges: 1) retrieval defects, where LLMs must be resilient to noisy, irrelevant, or misleading counterfactual documents inevitably supplied when lecturers provide proprietary course content [5][6], and 2) complex synthesis, where systems must employ advanced reasoning such as iterative retrieval mechanisms to handle multi-hop queries that demand synthesis of multiple interconnected concepts [7][8][9].

Concurrently, higher education faces critical pedagogical gaps in integrating AI tools into learning environments. Fundamentally, there is an insufficient arsenal of comprehensive strategies for evaluating student work that leverage AI tools, particularly for developing critical thinking (CT) skills in non-technical academic disciplines where AI literacy remains nascent [49]. The field lacks robust rubrics and assessment mechanisms specifically designed to measure whether students

are developing metacognitive abilities—the capacity to evaluate, critique, and solve problems using AI as a tool rather than as an answer provider. Rather, most institutional approaches to "AI literacy" focus on skill acquisition (learning prompt engineering syntax, understanding model limitations at a surface level) without addressing the deeper epistemological shift required: understanding when and how to trust AI outputs, recognizing their systematic biases, and developing conceptual sophistication to improve upon AI-generated content.

A persistent and troubling equity gap exists in research examining how AI literacy can be effectively and sustainably integrated across diverse academic fields [49], particularly those characterized by limited technological resources. While extensive literature documents AI integration in STEM (Science, Technology, Engineering, Mathematics) disciplines—which typically benefit from dedicated computing infrastructure [28], higher technology budgets, and faculty with computational backgrounds remarkably little research addresses integration pathways for Humanities, Social Sciences, and VET (Vocational Education and Training) fields [38][39][40][41][42]. This documented inequity operates at multiple levels: infrastructural (lack of GPU-equipped servers), pedagogical (faculty training programs designed for STEM), and epistemic (assumptions that "real" AI applications are narrow in scope and highly technical) [28]. Furthermore, the marginalization of vocational students and institutions persists, with vocational education often receiving inadequate curricular support for digital competencies despite its critical role in workforce development [45]. This educational marginalization makes vocational students a key focus group for promoting the United Nations Sustainable Development Goals [60], [particularly SDG 4 (Quality Education), SDG 5 (Gender Equality), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 10 (Reduced Inequalities) [41].

Against this backdrop, this study investigates the following core research question: How can institutions design and implement responsible, equitable [30], cost-effective AI-assisted educational systems that enhance critical thinking while ensuring data sovereignty and compliance across diverse academic disciplines and resource contexts?

This overarching question decomposes into three subsidiary objectives:

1) Cost-effective and compliant deployment: How can institutions validate the financial sustainability of local RAG hosting through comprehensive TCO analysis while leveraging computational efficiencies (PEFT, PROXIMITY caching) to ensure deployment of existing hardware without violating data protection regulations?

2) Equitable integration across disciplines: How can institutions minimize technical prerequisites for AI literacy while simultaneously maximizing pedagogical autonomy, enabling faculty across Humanities, STEM [28], and VET to define and enforce discipline-specific teaching methodologies without requiring technical expertise?

3) Rigorous critical thinking assessment: How can architectural constraints and pedagogical assessment design combine to measure genuine metacognitive development—students' ability to critique, validate, and improve upon AI reasoning—rather than merely assessing answer accuracy or factual recall?

The significance of this research extends beyond technical contributions to address urgent policy and institutional questions. For institutional leaders, this work provides a concrete, validated framework for AI deployment decisions, moving beyond vendor-driven narratives ("use our API, it's convenient") to data-informed analysis of true lifecycle costs and institutional control. For faculty developers, it offers a professional development model grounded in pedagogical research (specifically the TPACK framework and Dialogic Video Cycle approach) rather than generic IT training, recognizing that successful technology integration requires understanding the interplay between content knowledge, pedagogical strategies, and technological affordances [2]. For educational equity advocates, it demonstrates that equitable AI integration is not a post-hoc retrofit onto existing infrastructure but rather requires thoughtful architectural choices from inception—choices that explicitly prioritize resource-constrained disciplines rather than leaving them as afterthoughts.

This study outlines the Retrieval-Augmented Pedagogical Assistant (RAPA) methodology, a three-phase operational framework that integrates an advanced, institutionally customized RAG architecture with formalized professional development modeled on the Dialogic Video Cycle and rigorous evaluation protocols that incorporate both technical metrics (RAGAS measures of Faithfulness and Context Precision) and validated critical thinking assessments. The proposed methodology seeks to transform AI assistants from opaque answer providers into transparent, auditable tools for contextual and ethical learning—tools whose reasoning processes are visible to student critique and whose outputs are grounded in institutional knowledge sources under institutional control.

The framework's novelty lies not in isolated technical innovations, but rather in their systematic integration to address the full ecosystem of constraints facing real institutions: the economic pressures to avoid perpetual vendor lock-in; the regulatory imperatives of FERPA and GDPR; the pedagogical imperative to develop critical thinking; and the equity imperative to prevent AI from widening the digital divide between well-resourced and resource-constrained disciplines.

II. Related Work and Foundational Framework

A. The RAG Imperative: Factual Integrity and Customization

The foundational case for Retrieval-Augmented Generation in educational contexts rests on a fundamental principle: academic integrity requires verifiable factual grounding. General-purpose LLMs trained on broad internet data inherit the temporal limitations of their training corpora—a model trained in 2023 cannot reliably answer questions about 2024 developments without explicit retrieval from current sources. More problematically, LLMs generate hallucinations: outputs that read coherently and persuasively despite being factually incorrect, a phenomenon particularly dangerous in educational contexts where students may accept plausible-sounding false information as established fact [1].

RAG addresses this by augmenting the LLM's parametric memory (learned during training) with access to a non-parametric memory base (external documents accessed during inference). When a student asks a question, the RAG system first retrieves relevant documents from the knowledge base, then generates an answer grounded in those retrieved documents rather than relying exclusively on the model's training data. This architectural decision is validated as superior to costly full Fine-Tuning (FT) for high-volume educational contexts due to its cost-efficiency, dynamism (accessing up-to-date course material as instructors update materials), and fundamental ability to ground responses in verifiable sources—a prerequisite for academic integrity [1][2][3].

B. Limitations of Standard RAG and the Case for Hybrid Approaches

However, standard RAG—a single retrieval step followed by generation—proves insufficient for complex pedagogical needs. This limitation becomes apparent in multi-hop and multi-step reasoning scenarios common in higher education. Consider a student question: "How do principles of metacognition from cognitive science enhance classroom teaching effectiveness while reducing cognitive load for students?" This question requires: 1) understanding metacognition concepts, 2) understanding teaching practice implications, and 3) synthesizing these across cognitive load theory. Standard RAG, performing a single similarity-based retrieval, may retrieve documents about metacognition (the highest semantic match to the question's literal surface form) while missing materials about cognitive load or teaching application—not because these materials don't exist in the knowledge base, but because keyword-based or embedding-based similarity doesn't capture the implicit multi-hop reasoning structure.

Iterative Retrieval-Generation Approaches address this through Chain-of-Thought augmented retrieval. Rather than a single retrieval pass, the system generates initial reasoning steps, identifies what information is still needed, formulates new retrieval queries based on identified gaps, and iteratively retrieves until sufficient information is assembled. Research on multi-hop question answering demonstrates that iterative approaches improve F1 scores by 8-15% compared to single-pass retrieval and enable the system to recognize dependencies between concepts [7][8][9]. For educational RAG, this capacity to synthesize across multiple sources directly translates into students receiving answers to genuinely complex questions rather than simplified responses that fail to capture interdisciplinary connections.

The Case for Hybrid RAG: The most effective approach, termed Hybrid RAG in literature, combines three complementary strategies [1][4][53]:

1) RAG for knowledge grounding: Dynamic retrieval from institutional knowledge bases ensures that answers reflect current course materials and institutional context.

2) Light task-specific fine-tuning: Using PEFT methods, the LLM's generation component is optimized for the specific pedagogical task (generating explanations with particular pedagogical tone, enforcing citation practices, etc.) without the computational burden of full model retraining.

3) Architectural hardening: Technical defenses against retrieval defects (discussed below) ensure that the system remains accurate even when retrieved documents are noisy or partially incorrect.

The cost advantage of Hybrid RAG over full fine-tuning is substantial. Full fine-tuning requires retraining the entire model—billions of parameters—whenever course materials change, an expensive and time-consuming process (days to weeks of GPU time per update cycle). Hybrid RAG simply updates the knowledge base and retrains only the 0.1-1% of parameters affected by PEFT, completing retraining in hours and costing orders of magnitude less. Moreover, Hybrid RAG enables instructors to make factual corrections and curriculum updates without requiring data scientists or engineers—they simply update course materials, and the system immediately reflects these updates [1][4]. This update efficiency is critical for educational sustainability, where courses evolve continuously as instructors refine materials based on student feedback and emerging scholarship.

C. AI Literacy, Critical Thinking, and the TPACK Framework

AI literacy is not monolithic—research identifies it as operating across multiple dimensions: Cognitive (understanding AI capabilities), Metacognitive (evaluating and critiquing AI outputs), Affective (developing dispositions toward responsible AI use), and Social-Ethical (considering broader societal implications) [10]. Yet the recognized gap in educational research concerns precisely the Metacognitive dimension—institutional emphasis falls overwhelmingly on cognitive skills (learning to write prompts, understanding that LLMs can hallucinate) with insufficient attention to the deeper metacognitive capacity to critique and improve upon AI output. Students often learn that "LLMs can be biased", which is true but pedagogically superficial; what's lacking is structured practice in identifying how bias manifests in specific outputs and what corrections would address it.

To address this gap, the framework integrates two established pedagogical theories:

Technological Pedagogical Content Knowledge (TPACK): This framework, developed by Koehler and Mishra [11], posits that effective technology integration requires understanding the dynamic interplay between three knowledge domains: Content Knowledge (CK—mastery of subject matter), Pedagogical Knowledge (PK—understanding how people learn and effective teaching strategies), and Technological Knowledge (TK—familiarity with tools and their affordances). Importantly, TPACK highlights that successful technology integration is not primarily about TK acquisition but rather about Pedagogical Content Knowledge (PCK), the ability to translate one's pedagogical philosophy into technology-enabled practice. Many institutional AI training programs err by focusing on TK (teaching faculty to use ChatGPT, write prompts, etc.) rather than on PCK: helping faculty understand how to redesign assignments, assessments, and curricula to leverage AI in ways aligned with their discipline's epistemology and pedagogical values.

Professional Development Components: Effective professional development (PD) supporting behavioral change

must incorporate content focus (clear learning objectives), active learning (hands-on practice rather than passive listening), coherence (connecting new skills to existing knowledge), duration (sufficient time for deep engagement and multiple practice cycles), and collective participation (learning communities providing peer support and accountability) [12][13]. These components are not merely aspirational but evidence-based—meta-analyses of teacher education repeatedly demonstrate that programs incorporating these elements achieve substantially higher adoption rates and sustained practice change than one-time workshops [38].

The Dialogic Video Cycle (DVC) Model: The specific PD model adopted by RAPA is the Dialogic Video Cycle, an innovative approach that uses teacher performance videos and peer feedback as anchors for ongoing growth [14], [29]. In the DVC, teachers record their practice, review the recordings with peers and instructors, engage in structured dialogue about the recordings (identifying strengths, areas for development, and specific improvement strategies), and then implement changes, creating a reflective cycle. An empirical study shows that a DVC-style intervention, compared to traditional one-off workshops, results in significantly higher teacher satisfaction, greater autonomy support (teachers feel empowered rather than regulated), and more sustained implementation [15]. For RAPA, this model is adapted: faculty record themselves using the RAPA system in live classes, review outputs and usage patterns with colleagues, critique the AI's reasoning and suggest improvements, and refine their pedagogical rules and course materials iteratively.

D. Addressing Retrieval Defects: Robust Fine-Tuning and Counterfactual Resilience

When institutional lecturers supply course materials to a RAG system, those materials inevitably contain imperfections: transcription errors in lecture notes, outdated information in older readings that were never removed, deliberate misinformation in materials designed to provoke critical thinking, or simply complex content that loses nuance when broken down into retrieval-sized chunks. Standard RAG systems degrade substantially when the retrieved context is noisy or partially incorrect. Accuracy drops by 30-50% when 40-50% of retrieved documents contain errors [6].

Robust Fine-Tuning (RbFT) directly addresses this challenge by training the LLM generation component to be resilient to imperfect retrieval. Rather than hoping the retriever returns perfect documents, RbFT anticipates real-world conditions: the fine-tuning dataset includes examples where retrieved documents contain errors, misinformation, or irrelevant information, and the model is trained to:

1) Identify which retrieved passages are relevant and trustworthy

2) Ignore or downweight unreliable retrieved passages

3) Generate correct answers despite noisy context

Empirical results demonstrate that RbFT-trained models maintain 85-90% accuracy even when 40-60% of retrieved documents are counterfactual (containing factual errors), compared to baseline models achieving only 40-60% accuracy under identical conditions—a dramatic improvement that transforms RAG from a "garbage in, garbage out" system into one that actively filters and corrects imperfect information [6]. This is critical for educational RAG, where instructor materials, while generally high-quality, inevitably contain some errors, outdated statements, or cases where intended provocative content must be handled carefully to avoid misleading students.

E. Constraint Enforcement and Pedagogical Rules in ConsRAG

Beyond handling retrieval defects, institutions require mechanisms to ensure AI outputs align with discipline-specific pedagogy. A lecturer in Humanities might insist on Socratic dialogue format (questions rather than direct answers), whereas a VET instructor might prioritize step-by-step procedural explanation. These pedagogical preferences aren't mere stylistic choices—they reflect epistemological commitments about how knowledge should be constructed in the discipline.

Constrained RAG (ConsRAG) architectures enforce such pedagogical constraints as formal system rules rather than soft suggestions. Constraints are applied at both the retrieval and generation phases:

- Retrieval constraints: A lecturer can specify "prefer primary sources over secondary interpretations [43]," "exclude materials published before 2020," or "prioritize content from this particular course module." These constraints modify document ranking scores [24], [51], ensuring retrieved materials align with pedagogical intent.
- Generation constraints: After retrieval, constraints guide the generation process. A constraint like "use Socratic questioning format" is enforced by the model, and outputs violating it are regenerated until compliant. This differs from loose instructions in the system prompt—ConsRAG enforces constraints as hard validation rules [25], [26].

For educational deployment, constraint enforcement is critical to institutional control and disciplinary autonomy. Rather than RAPA dictating a universal output format, each lecturer defines constraints reflecting their subject's norms and their own pedagogical philosophy. This design respects disciplinary diversity while maintaining system consistency [25], [26].

F. Evaluation Frameworks: Beyond Accuracy to Critical Thinking

Traditional RAG evaluation metrics (precision, recall, F1 score) measure whether the system retrieved relevant documents and generated factually correct answers—important but insufficient for educational RAG. These metrics assess whether the system succeeded at information retrieval [33], not whether students engaged in critical thinking or developed metacognitive skills.

RAGAS Metrics provide more educationally aligned evaluations:

- Faithfulness: Measures whether generated claims are supported by retrieved documents, without hallucination or introducing information beyond what the contexts

provide. For education, unfaithful responses undermine academic integrity [22], [35].

- Context Precision: Evaluates whether the most relevant documents appear at the top of the retrieval ranking. A high context precision score indicates that the system efficiently identifies the most useful materials, improving the student experience and reducing cognitive load from parsing irrelevant retrieved content [22][35][36].
- Answer Relevance: Assesses whether the answer generated addresses the student's question (as opposed to being accurate but off topic).

These metrics directly address educational concerns in ways traditional accuracy metrics do not. Together, they create a more nuanced picture of system quality: Is the answer answering the student's question? Are the claims justified by the course materials? Are the best materials appearing first in the results?

Complementing technical metrics, rigorous evaluation of critical thinking requires valid assessment instruments. The Critical AI Analysis Assignment, central to RAPA's assessment design, explicitly asks students to critique AI-generated answers by identifying logical gaps [47], unsupported claims, biases, and limitations. This assignment measures metacognitive development rather than mere knowledge recall. Evaluation uses validated critical thinking rubrics targeting dimensions where AI outputs are systematically weak: nuance, complexity, acknowledgment of alternative perspectives, and originality [36]. By design, students receive points for identifying exactly what AI struggles with, which creates positive reinforcement for critical evaluation.

The framework requires mixed-methods evaluation:

1) Quantitative critical thinking instruments (validated pre/post assessments like the Watson-Glaser Critical Thinking Appraisal), measuring metacognitive gain

2) Quantitative technical metrics (RAGAS scores measuring system reliability)

3) Qualitative rubrics assessing nuanced dimensions of critical thinking evident in student work

This integration ensures that AI system quality (technical metrics) and learning outcomes (pedagogical metrics) are jointly optimized rather than treated as separate concerns.

III. Methodology Framework

The RAPA framework is structured across three sequential phases, each addressing distinct institutional requirements and operationalizing the research objectives outlined above. These phases correspond to the specific implementation steps detailed in the architectural flowchart (see Fig. 1), with Table I to Table III providing systematic validation at each phase.



Fig. 1. The RAPA architectural flowchart.

A. Phase I: Institutional and Foundational Readiness (Flowchart Steps 1, 4)

This phase establishes the necessary security and financial feasibility for institutional deployment (Cost and Compliance) [Table I]. It addresses the critical "Cost and Compliance" requirements that are often overlooked in pilot programs, but become fatal bottlenecks at scale.

TABLE I. Cost and Compliance

Flowchart Step	*Description and Technical Validation*
Step 1: AI software for institute	TCO Analysis and Architecture: The framework requires a Total Cost of Ownership (TCO) analysis that validates the long-term cost-efficiency of a local, self-hosted RAG architecture over proprietary cloud services, despite higher initial capital expenditure [16]. This local deployment should utilize computational efficiencies (e.g., open-source LLMs combined with RAG) [17].
Step 4: Follow some criteria (Region/Age/Format)	Data Governance and Compliance: This step establishes the security protocols necessary for protecting student and institutional data. The decision for local hosting is not merely financial but mandatory for ensuring data sovereignty and compliance with strict data protection mandates such as FERPA (Family Educational Rights and Privacy Act) in the US and GDPR (General Data Protection Regulation) in Europe [18][19]. Third-party APIs often require sending data to external servers, creating unacceptable risks of data leakage. The RAPA architecture must implement Input Validation and Anomaly Detection modules as technical guardrails against Retrieval Poisoning Attacks (also known as "RAG poisoning" or prompt injection) [19][20][21]. These security modules monitor input prompts for adversarial patterns designed to trick the model into revealing its system instructions or retrieving unauthorized documents from the vector database.

B. Phase II: Architectural Customization and Training (Flowchart Steps 2, 3, 5, 6)

This phase operationalizes the lecturer's subject matter expertise into a high-fidelity RAG system. It is the core "customization" engine of the RAPA framework, translating lecturer knowledge into system constraints and conducting the professional development necessary for faculty to effectively guide AI in their pedagogical contexts (see Table II).

TABLE II. ARCHITECTURAL CUSTOMIZATION AND TRAINING

Flowchart Step	*Description and Technical Validation*
Step 2: Lecturers collect their own resources	Data Ingestion Pipeline: Lecturers submit their unique course materials (lecture notes, PDFs, slide decks), which form the non-parametric memory of the RAG system. To ensure high-quality retrieval, advanced indexing techniques are employed. Basic text splitting divides documents at fixed character or token boundaries, often breaking semantic units—for instance, a paragraph on "three principles of critical thinking" might be split mid-concept, complicating subsequent retrieval [44][52]. Semantic chunking, by contrast, uses embedding-based similarity to identify natural concept boundaries, preserving complete thoughts as retrieval units [52]. For educational materials, this preserves pedagogical coherence: a multi-paragraph explanation of a concept stays together, rather than fragments appearing in separate chunks. Each chunk is annotated with structured metadata: • Course ID & Lecturer ID: Enables course-specific retrieval, preventing cross-course contamination (philosophy materials being returned for English literature questions) [22][23] • Concept Tags: Semantic labels identifying primary topics (e.g., "critical thinking, Socratic method"), enabling higher-precision matching than keyword-only retrieval [22][23] • Document Type: Distinguishes readings, lecture notes, assignment rubrics, etc., allowing lecturers to specify retrieval preferences (e.g., "prefer assignment rubrics for procedural questions, readings for theoretical questions") • Compliance Flags: Identifies materials that are proprietary, copyrighted, or should be restricted This metadata-enriched architecture dramatically improves retrieval accuracy. When a student asks about "dialectical reasoning," the system can recognize through concept tags that this relates to "Socratic dialogue" in the course materials, even if those exact terms don't appear in the student's question.
Step 3: Lecturers create lecture pattern and rules	Lecturers define pedagogical rules—their teaching philosophy translated into formal system constraints. A humanities lecturer might specify: • "Always present multiple interpretations before advocating for one" • "Use Socratic questioning format rather than direct answers" • "Engage with primary sources, secondary sources only as supplementary" A VET instructor might prioritize: • "Lead with step-by-step procedural instructions" • "Provide worked examples before asking students to practice" • "Emphasize practical application over theoretical background" These rules are formalized through Prompt Engineering—translating pedagogical philosophy into explicit system prompts—and implemented through Constrained RAG architectures that enforce these rules at generation time [23][25]. Rather than hoping the model naturally follows preferences stated in loose natural language instructions, ConsRAG enforces constraints as hard validation rules: outputs violating constraints are regenerated until compliant [25][26]. For faculty, prompt engineering education is the core of Phase II professional development. Rather than requiring technical expertise, prompt engineering for pedagogical constraint definition is conducted in natural language, using templates and guided exercises. Faculty workshops guide lecturers through articulating their teaching philosophy, translating it into system constraints, and iteratively refining constraints based on AI output examples [24].
Step 5: Train AI tools separately	Architectural Hardening (RbFT & ITER-RETGEN): The system is hardened against the inherent noise of educational data. This involves applying Robust Fine-Tuning (RbFT) [4]. In standard RAG, if the retriever fetches an irrelevant document (a "retrieval defect"), the LLM often tries to incorporate it into the answer, leading to confusion. RbFT trains the LLM's generative component using a specialized loss function that rewards the model for detecting and ignoring noisy or counterfactual chunks, even if they are presented as context.2 For complex, multi-hop queries that demand higher-order thinking (e.g., "How does the theory in Lecture 1 apply to the case study in Lecture 5?"), the architecture integrates Iterative RAG (ITER-RETGEN). This technique allows the model to generate a partial rationale (Chain-of-Thought), determining that it needs more information, and then issue a second retrieval query to fetch the missing link, effectively "reasoning" its way to the answer [7][33].
Step 6: Integrate trained AI assistant with individual course	Professional Development (PD) - The Dialogic Video Cycle: PD is mandatory [25][57], continuous, and rooted in active learning [27]. The program is adapted from the Dialogic Video Cycle (DVC) model [28]. In the RAPA adaptation, the "video" component is expanded to include interaction logs. Faculty participate in a cycle of: 1. Plan: designing prompts and rules. 2. Act: deploying the AI in class. 3. Reflect: analyzing video recordings of the class alongside the AI chat logs in a group setting.

Flowchart Step	*Description and Technical Validation*
	This "collective participation" allows faculty to critique the AI's performance (e.g., "The AI gave the answer too quickly here") and immediately refine the system prompts for the next cycle, creating a tight feedback loop between pedagogical intent and technical performance [12][29].

C. Phase III: Evaluation and Impact Assessment (Flowchart Steps 7 and 8)

The final phase focuses on the student experience and the rigorous validation of the system's impact on Critical Thinking (CT) and technical performance (Table III).

TABLE III. EVALUATION AND IMPACT ASSESSMENT

Flowchart Step	*Description and Technical Validation*
Step 7: Students use AI assistant	The RAPA output is engineered to enforce transparency—delivering answers with two mandatory components: 1. Chain-of-Thought (CoT) Reasoning Steps: Displaying explicit reasoning steps models critical thinking and enables students to follow the logical progression of the argument [7]. Rather than receiving only the final answer, students see: "To answer this question, I first need to establish X, then apply principal Y to X, then consider constraint Z, which modifies the application of Y, then synthesize into the final conclusion." This scaffolding makes the reasoning process visible for student critique. 2. Verifiable Citations: Generated claims are automatically linked to specific chunks in the institutional knowledge base, showing students exactly what sources support each claim. This differs from general LLM citations, which might reference external sources or training data—RAPA citations point only to lecturer-provided materials, enabling students to verify claims against primary sources [7][8]. The architectural enforcement is critical: the system cannot generate output without CoT reasoning steps and citations. This differs from optional output modalities (where models might "choose" to include reasoning or not) and ensures consistency across all system interactions. Deployment and Latency Optimization: To ensure RAPA remains responsive under heavy student use, deployment utilizes Approximate Caching (PROXIMITY mechanism) to reduce database latency and enable high scalability [31]. PROXIMITY-LSH (Locality-Sensitive Hashing) maintains a cache of previously retrieved document sets, hashing incoming queries to quickly identify whether they're similar enough to reuse cached results. This reduces vector database queries by up to 77.2%, providing dramatic latency improvements for repetitive query patterns typical of large cohorts [31]. For a university with 5,000+ concurrent students, this caching enables deployment on a single moderately-equipped server rather than requiring massive database infrastructure [32].
Step 8: Critical Thinking & AI Literacy Metrics	Assessment Design: The core pedagogical instrument is the Critical AI Analysis Assignment. In this assignment, students are not graded on the AI's answer, but on their critique of it. They must identify inaccuracies, biases, limitations, and verify the citations against the primary texts [32]. Evaluation Instruments: The framework employs a mixed-methods evaluation using a validated quasi-experimental design [34]: 1. Quantitative (CT): Validated instruments such as the Watson-Glaser Critical Thinking Appraisal (WGCTA) or the Cornell Critical Thinking Test (CCTT) are used for pre- and post-testing to measure gains in critical thinking skills [34]. 2. Quantitative (Technical): Technical performance is measured using RAGAS metrics (Retrieval Augmented Generation Assessment) [55]. Key metrics include Faithfulness (measuring if the answer is derived only from the retrieved context) and Context Precision (measuring if the relevant chunks were ranked correctly in the retrieval) [35][1]. 3. Qualitative: Rubrics designed to assess features that AI typically performs poorly on, such as nuance, complexity, and originality [36].

IV. RESULTS AND DISCUSSION

This section discusses how the integrated RAPA methodology fundamentally solves the three research objectives, synthesizing the empirical validation from the literature.

A. PHASE I: Cost-Effectiveness and Sustainable Deployment

The framework's foundational viability depends on demonstrating that local RAG deployment is economically sustainable and cost-competitive with cloud alternatives.

TCO Analysis Findings: Preliminary analysis across three institutional scenarios (large research university with 30,000 students; regional comprehensive university with 12,000 students; small liberal arts college with 2,000 students) shows that on-premises RAG with SLMs reaches cost parity with cloud APIs within 4-6 years and exhibits 30-50% cost savings by year 7-10, once infrastructure investments are amortized [48][50]. For large institutions exceeding 15+ million annual inferences (50% course penetration, 30% student usage), on-premises infrastructure becomes cost-advantageous within 3-4 years [48][50].

Computational Efficiency and Low-Resource Accessibility: The framework ensures accessibility across resource contexts through strategic deployment of computational efficiencies:

Small Language Models (SLMs) with PEFT: RAPA relies on RAG combined with small, efficient LLMs (3B-13B parameters) and Parameter-Efficient Fine-Tuning [5][39]. This strategic combination delivers high performance with

substantially lower energy and memory consumption than full-scale LLMs [5][16]. For example, Mistral 7B or Phi-3 3B models, when combined with LoRA-based PEFT fine-tuning for pedagogical constraint specification, achieve 70-85% of full LLM performance while requiring only 10-20% of computational resources [5][37]. Importantly, these models run efficiently on mid-range GPUs (4-8GB VRAM) common in aging institutional computer labs—resources that cannot execute full-scale models but are ubiquitous in Humanities and VET departments [37][41].

PROXIMITY-LSH Caching Infrastructure Efficiency: The PROXIMITY caching mechanism (Question 19) reduces vector database queries by up to 77.2% under typical institutional workload patterns [31]. For a university deploying RAPA across 100 courses with 5,000+ concurrent students, this reduction reduces infrastructure requirements from multiple distributed database servers to a single, moderately equipped machine. The 77% reduction in database I/O directly translates into a 77% reduction in database infrastructure costs, enabling deployments that would otherwise exceed institutional IT budgets [31].

Combined Cost Impact: The synergy of SLMs + PEFT + PROXIMITY caching produces cost reductions of 60-80% compared to full-scale model deployment without caching. For an institution with a typical $500K annual operational budget for educational technology, RAPA deployment could be accommodated within existing budget allocations rather than requiring new expenditure [48][50].

Data Sovereignty and Compliance Validation: Analysis confirms that local hosting architecture meets FERPA and GDPR requirements. All student interaction data, lecturer materials, and system logs remain on institutional servers; no data is transmitted to external services. Input Validation and Anomaly Detection measures (as validated in research on retrieval poisoning attacks [19][20]) successfully block known injection patterns while maintaining low false-positive rates [19][20].

B. Equitable Integration of AI Literacy

The framework ensures equitable integration by proactively addressing technical and pedagogical constraints inherent to low-resource environments, thereby preventing AI from widening the digital divide [38][41][42].

Computational Accessibility: The deployment of RAG with SLMs and PEFT enables cost-efficient deployment on existing institutional hardware across Humanities and VET departments [5][16][39][40]. This directly addresses the resource barrier identified as a critical challenge in equitable AI access [27][29][30]. Humanities departments with legacy computer labs find that RAPA operates effectively on existing equipment, rather than requiring new GPU-intensive infrastructure investment that would be economically unfeasible for budget-constrained programs.

Pedagogical Accessibility and Disciplinary Autonomy: The PD program is explicitly rooted in the TPACK framework [25], strategically shifting focus from technical skill acquisition (which favors STEM fields with computational backgrounds) to Pedagogical Content Knowledge and ethical reflection [2][28]. Lecturers in VET or Humanities can directly apply their domain expertise to define RAPA constraints without writing code; constraint definition uses natural language templates and guided workshop exercises rather than technical programming [24][40]. This design respects disciplinary diversity: History faculty define constraints appropriate to historical thinking; Engineering faculty specify constraints appropriate to design methodology; Nursing faculty configure constraints for clinical reasoning. No single pedagogical approach is universalized.

Validation Across Disciplines: The evaluation framework mandates a specialized quasi-experimental sampling strategy that explicitly includes low-resource disciplines [24][34]. Rather than piloting exclusively in STEM departments (easier for technical reasons) and extrapolating, the framework requires testing across Humanities, Social Sciences, VET, and STEM concurrently, ensuring the resulting guidance is valid across the academic spectrum [41]. Project-Based Learning (PBL) approaches to AI literacy have been validated as effective pedagogical models for non-STEM subjects, with evidence suggesting that PBL-based AI curricula increase both engagement and learning outcomes in Humanities and Social Sciences [33][42][43].

Addressing Epistemological Differences: An important finding from preliminary PD implementation is that faculty across disciplines conceptualize appropriate AI use differently, reflecting disciplinary epistemologies. STEM faculty often view AI as a tool for computational efficiency; Humanities faculty prioritize AI as a dialectical partner for developing arguments; VET faculty emphasize AI for procedure generation and troubleshooting. Rather than imposing a unified "AI literacy" definition, RAPA's flexible constraint system accommodates these epistemological differences. This flexibility prevents the common problem where technology integration initiatives designed for STEM become poorly-fitting [28], low-engagement exercises when mandated across the entire institution.

C. Critical Thinking and Metacognitive Development

The framework's solution to the critical thinking deficit is architectural: it makes the AI assistant's reasoning process transparent and subject to academic review [39], directly counteracting observed AI weakness in fostering practical problem-solving ability and generating nuanced output.

Critical Thinking Development Through Architectural Scaffolding: By mandating explicit CoT reasoning steps and verifiable source citations (Step 7), the RAPA system transforms the student's learning task from a simple answer retrieval into a critical validation exercise [7][45]. The student's goal shifts: rather than "use AI to answer my question," it becomes "analyze the AI's reasoning, verify its claims, identify its limitations, and propose improvements." This represents a fundamental pedagogical shift toward what we might call “educated skepticism,” learning to use powerful tools while maintaining critical evaluation.

Importantly, this architectural enforcement creates consistency. In systems where CoT reasoning is optional or probabilistic, students receive varying levels of reasoning transparency; some responses include reasoning, others don't. RAPA's mandatory CoT ensures that every answer includes

visible reasoning, making critical analysis a consistent assignment expectation rather than leaving it to the system to generate [7].

Mitigating Bias and Hallucination Through Multi-Layered Defense: The system employs multiple defenses against inaccuracies and ethical bias:

- Technical Defense: Robust Fine-Tuning (RbFT) trains the LLM to actively detect and ignore counterfactual or noisy context [6]. When students verify AI claims against sources (as part of the Critical AI Analysis Assignment), they find that the AI's claims are grounded in evidence rather than hallucinations.
- Evaluation Defense: Critical AI Analysis Assignments ensure human judgment remains the final safeguard [36][46]. Rubrics are customized to penalize outputs that lack nuance, complexity, and originality—precisely the areas where AI outputs are substandard. This rubric design creates incentive alignment: students are rewarded for identifying exactly what AI does poorly and for developing expertise in recognizing AI limitations [36].
- Pedagogical Defense: Faculty constraint definition can explicitly require acknowledgment of limitations, alternative viewpoints, or nuance. A lecturer can constrain the system: "Always acknowledge opposing viewpoints before presenting the main argument," or "Identify assumptions underlying this analysis." These constraints, enforced during generation, structurally reduce the bias and narrow-mindedness common in unconstrained AI outputs [25].

Rubric Design and AI Weakness Targeting: Rubrics for Critical AI Analysis Assignments are intentionally designed to target AI weaknesses:

- Shallow Analysis: Students receive points for identifying areas where the AI oversimplified complex issues
- Lack of Nuance: Students earn credit for recognizing where the AI presented single perspectives without acknowledging complexity
- Unsupported Generalizations: Assessment rewards students for catching claims lacking sufficient evidence
- Missing Ethical Considerations: Rubrics specifically assess whether student analysis identifies ethical dimensions that the AI overlooked

This rubric design aligns learning objectives (developing critical thinking) with assessment (students demonstrating critical thinking by critiquing AI output) [36]. The rubric becomes a scaffold helping students recognize sophisticated critique.

V. Conclusion and Future Work

The RAPA methodology provides a verifiable, architecturally advanced framework for integrating domain-specific AI in education. By committing Hybrid RAG for performance [53], local hosting for compliance, and the DVC model for pedagogical competence [29], the framework establishes a pathway to foster critical thinking and ensure equitable AI literacy across all academic disciplines [54].

A. Strategic Recommendations

- Adopt Modular Architecture: Future deployments should prioritize Modular RAG frameworks, integrating efficiency modules (PROXIMITY [31], Oreo [56]) with iterative reasoning modules (ITER-RETGEN) [7] to ensure systems can reliably handle high-volume queries and complex synthesis tasks.
- Mandate Reflection-Based PD: The continued efficacy of RAPA hinges on institutionalizing the DVC-inspired PD cycle [25][57], requiring faculty to use AI output logs as core reflective material to continuously refine their Prompt Engineering (rules) and pedagogical strategies [35].

B. Future Research

Future research must focus on the longitudinal, empirical validation of the framework's pedagogical components:

1) Multimodal RAG extension: Future research should extend RAPA to include Multimodal RAG capabilities for integrating non-textual data—engineering diagrams, art history images, code snippets, video lectures [58][59]. This is required to fully validate equitable integration across disciplines that do not rely solely on text. Establishing a clear technical framework will be essential, including outlining data formats and sources across diverse disciplines, implementing data preprocessing techniques, and developing cross-modal retrieval algorithms enabling seamless integration of text with other data types [58][59]. Additionally, pedagogical strategies must guide educators in leveraging multimodal capabilities effectively, ensuring faculty across fields can incorporate visual, tactile, or auditory elements to enhance learning outcomes and inclusivity [58][59].

2) Cultural contexts and institutional culture: An important future research question should explore the role of cultural contexts in shaping the effectiveness of Professional Development (PD) over time [57]. Identifying variables that capture how institutional culture influences PD could open valuable comparative studies across universities, enhancing our understanding of global educational environments. Possible candidate variables include leadership style, faculty autonomy, resource allocation, decision-making processes, organizational climate, and communication channels. These variables will help frame comparative research and develop hypotheses.

3) Causal pathway analysis: A long-term quasi-experimental study is needed, utilizing structural equation modeling (PLS-PM) to definitively verify the indirect causal pathway: PD Intervention → Improved Teacher Competence → Improved Student Critical Thinking → Academic Achievement Gains

Each arrow represents an empirical claim requiring validation: Does PD improve teacher competence? Does improved teaching develop students' critical thinking? Does

critical thinking translate to improved academic outcomes? Longitudinal data spanning 2 to 3 years across multiple cohorts would enable robust path analysis [27].

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REFERENCES

[1] Budakoglu, Gülsüm, and Hakan Emekci. "Unveiling the Power of Large Language Models: A Comparative Study of Retrieval-Augmented Generation, Fine-Tuning and Their Synergistic Fusion for Enhanced Performance." IEEE Access (2025).

[2] Ravi, Manoj. "Using the TPACK Framework for Gen-AI Enabled Learning Activities: Design, Delivery and Evaluation." Journal of Engineering Education Transformations (2025): 175-181.

[3] Kahl, Sebastian, Felix Löffler, Martin Maciol, Fabian Ridder, Marius Schmitz, Jennifer Spanagel, Jens Wienkamp, Christopher Burgahn, and Malte Schilling. "Evaluating the Impact of Advanced LLM Techniques on AI Lecture Tutors for a Robotics Course." In International Workshop on AI in Education and Educational Research, pp. 149-160. Cham: Springer Nature Switzerland, 2024.

[4] Nguyen, Zooey, Anthony Annunziata, Vinh Luong, Sang Dinh, Quynh Le, Anh Hai Ha, Chanh Le, Hong An Phan, Shruti Raghavan, and Christopher Nguyen. "Enhancing Q&A with domain-specific fine-tuning and iterative reasoning: A comparative study." arXiv preprint arXiv:2404.11792 (2024).

[5] Weyssow, Martin, Xin Zhou, Kisub Kim, David Lo, and Houari Sahraoui. "Exploring parameter-efficient fine-tuning techniques for code generation with large language models." ACM Transactions on Software Engineering and Methodology 34, no. 7 (2025): 1-25.

[6] Tu, Yiteng, Weihang Su, Yujia Zhou, Yiqun Liu, and Qingyao Ai. "Robust Fine-tuning for Retrieval Augmented Generation against Retrieval Defects." In Proceedings of the 48th International ACM SIGIR Conference on Research and Development in Information Retrieval, pp. 1272-1282. 2025.

[7] Shao, Zhihong, Yeyun Gong, Yelong Shen, Minlie Huang, Nan Duan, and Weizhu Chen. "Enhancing retrieval-augmented large language models with iterative retrieval-generation synergy." arXiv preprint arXiv:2305.15294 (2023).

[8] Cheng, Rong, Jinyi Liu, Yan Zheng, Fei Ni, Jiazhen Du, Hangyu Mao, Fuzheng Zhang, Bo Wang, and Jianye Hao. "DualRAG: A Dual-Process Approach to Integrate Reasoning and Retrieval for Multi-Hop Question Answering." arXiv preprint arXiv:2504.18243 (2025).

[9] Yang, Ruiyi, Hao Xue, Imran Razzak, Hakim Hacid, and Flora D. Salim. "Beyond Single Pass, Looping Through Time: KG-IRAG with Iterative Knowledge Retrieval." arXiv preprint arXiv:2503.14234 (2025).

[10] Hackl, Veronika, Alexandra Mueller, and Maximilian Sailer. "The AI Literacy Heptagon: A Structured Approach to AI Literacy in Higher Education." arXiv preprint arXiv:2509.18900 (2025).

[11] Koehler, Matthew J., Punya Mishra, and William Cain. "What is technological pedagogical content knowledge (TPACK)?." Journal of education 193, no. 3 (2013): 13-19.

[12] Saylor, Laura Lackner, and Carla C. Johnson. "The role of reflection in elementary mathematics and science teachers' training and development: A meta-synthesis." School Science and Mathematics 114, no. 1 (2014): 30-39.

[13] Garet, Michael S., Andrew C. Porter, Laura Desimone, Beatrice F. Birman, and Kwang Suk Yoon. "What makes professional development effective? Results from a national sample of teachers." American educational research journal 38, no. 4 (2001): 915-945.

[14] Roberts, Jonathan C., Hanan Alnjar, Aron E. Owen, and Panagiotis D. Ritsos. "Critical design strategy: a method for heuristically evaluating visualisation designs." arXiv preprint arXiv:2508.05325 (2025).

[15] Desimone, Laura M. "Improving impact studies of teachers' professional development: Toward better conceptualizations and measures." Educational researcher 38, no. 3 (2009): 181-199.

[16] Weinert, Dane A., and Andreas M. Rauschecker. "Enhancing large language models with retrieval-augmented generation: a radiology-specific approach." Radiology: Artificial Intelligence 7, no. 3 (2025): e240313.

[17] Grabuloski, Marko, Aleksandar Karadimce, Anis Sefidanoski, and NORTH MACEDONIA. "Enhancing Language Models with Retrieval-Augmented Generation A Comparative Study on Performance." WSEAS Transactions on Information Science and Applications 22 (2025): 272-297.

[18] RAINA, Ashutosh, Kushal MUNDRA, Prajish PRASAD, and Shitanshu MISHRA. "Fostering ethics in AI: perceptions from the Indian AI curriculum." In International Conference on Computers in Education. 2023.

[19] Anichkov, Yegor, Victor Popov, and Sergey Bolovtsov. "Retrieval Poisoning Attacks Based on Prompt Injections into Retrieval-Augmented Generation Systems that Store Generated Responses." In International Conference on Distributed Computer and Communication Networks, pp. 417-429. Cham: Springer Nature Switzerland, 2024.

[20] Gummadi, Venkata, Pamula Udayaraju, Venkata Rahul Sarabu, Chaitanya Ravulu, Dhanunjay Reddy Seelam, and S. Venkataramana. "Enhancing communication and data transmission security in rag using large language models." In 2024 4th International Conference on Sustainable Expert Systems (ICSES), pp. 612-617. IEEE, 2024.

[21] Ching, Anthony Chun Hin, Sau Wai Law, and Davy Tsz Kit Ng. "Evaluating a global citizenship course on developing business students' AI literacy skills." In Effective Practices in AI Literacy Education: Case Studies and Reflections, pp. 91-99. Emerald Publishing Limited, 2024.

[22] dos Santos Junior, José Cassio, Rachel Hu, Richard Song, and Yunfei Bai. "Domain-driven LLM development: insights into rag and fine-tuning practices." In Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, pp. 6416-6417. 2024.

[23] Adhikari, Manoj, Puskar Joshi, Gabriel Vieira Ramos, Ahmad Al Doulat, and Shehenaz Shaik. "AIDE: Leveraging Retrieval-Augmented Generation for Context-Aware Educational Data Retrieval and Dialogue." In 2025 International Conference on Smart Applications, Communications and Networking (SmartNets), pp. 1-7. IEEE, 2025.

[24] Zeng, Shenglai, Jiankun Zhang, Pengfei He, Yue Xing, Yiding Liu, Han Xu, Jie Ren et al. "The good and the bad: Exploring privacy issues in retrieval-augmented generation (rag)." arXiv preprint arXiv:2402.16893 (2024).

[25] Landry, Susan H., Paul R. Swank, Jason L. Anthony, and Michael A. Assel. "An experimental study evaluating professional development activities within a state funded pre-kindergarten program." Reading and writing 24, no. 8 (2011): 971-1010.

[26] Nguyen, Ha-Thanh, and Ken Satoh. "ConsRAG: Minimize LLM Hallucinations in the Legal Domain."

[27] Wan, Yu, Rui Li, Wenjie Li, and Hongbo Du. "Impact Pathways of AI-Supported Instruction on Learning Behaviors, Competence Development, and Academic Achievement in Engineering Education." Sustainability 17, no. 17 (2025): 8059.

[28] Lee, Irene, and Beatriz Perret. "Preparing high school teachers to integrate AI methods into STEM classrooms." In Proceedings of the AAAI conference on artificial intelligence, vol. 36, no. 11, pp. 12783-12791. 2022.

[29] Gröschner, Alexander, Tina Seidel, Katharina Kiemer, and Ann-Kathrin Pehmer. "Through the lens of teacher professional development components: the 'Dialogic Video Cycle' as an innovative program to foster classroom dialogue." Professional development in education 41, no. 4 (2015): 729-756.

[30] Oyetade, Kayode, and Tranos Zuva. "Advancing Equitable Education with Inclusive AI to Mitigate Bias and Enhance Teacher Literacy." Educational Process: International Journal 14 (2025): e2025087.

[31] Yao, Chengyuan, and Satoshi Fujita. "Adaptive control of retrieval-augmented generation for large language models through reflective tags." Electronics 13, no. 23 (2024): 4643.

[32] Bergman, Shai Aviram, Zhang Ji, Anne-Marie Kermarrec, Diana Petrescu, Rafael Pires, Mathis Randl, and Martijn de Vos. "Leveraging Approximate Caching for Faster Retrieval-Augmented Generation." In Proceedings of the 5th Workshop on Machine Learning and Systems, pp. 66-73. 2025.

[33] Tian, Fangzheng, Debasis Ganguly, and Craig Macdonald. "Is Relevance Propagated from Retriever to Generator in RAG?." In European Conference on Information Retrieval, pp. 32-48. Cham: Springer Nature Switzerland, 2025.

[34] Cheng, Chih-Chan, Jeen-Shing Wang, Xiaoming Zhai, and Ya-Ting Carolyn Yang. "AI literacy and gender equity in elementary education: A quasi-experimental study of a STEAM–PBL–AIoT course with questionnaire validation." International Journal of STEM Education 12, no. 1 (2025): 50.

[35] Watson, Goodwin, and Edward M. Glaser. Watson-Glaser critical thinking appraisal: Forms A and B; Manual. Psychological Corporation, 1980.

[36] Hemmat, Arshia, Kianoosh Vadaei, Mohammad Hassan Heydari, and Afsaneh Fatemi. "Leveraging Retrieval-Augmented Generation for Persian University Knowledge Retrieval." In 2024 15th International Conference on Information and Knowledge Technology (IKT), pp. 279-286. IEEE, 2024.

[37] Gargari, Omid Kohandel, and Gholamreza Habibi. "Enhancing medical AI with retrieval-augmented generation: A mini narrative review." Digital health 11 (2025): 20552076251337177.

[38] Daher, Roula. "Integrating AI literacy into teacher education: a critical perspective paper." Discover Artificial Intelligence 5, no. 1 (2025): 217.

[39] Li, Hongming, Yizirui Fang, Shan Zhang, Seiyon M. Lee, Yiming Wang, Mark Trexler, and Anthony F. Botelho. "ARCHED: A Human-Centered Framework for Transparent, Responsible, and Collaborative AI-Assisted Instructional Design." arXiv preprint arXiv:2503.08931 (2025).

[40] Peddi, Sarita, and Geetha Manoharan. "Innovative Approaches to Staff Development in Education Using AI." In Training and Development in Transnational Higher Education, pp. 347-368. IGI Global Scientific Publishing, 2025.

[41] Torrisi-Steele, Geraldine. "Addressing the Digital Divide: Ensuring Equal Access to Al Tools." Foundations and Frameworks for AI in Education (2025): 77.

[42] Mutawa, A. M., and Sai Sruthi. "UNESCO's AI Competency Framework: Challenges and Opportunities in Educational Settings." Impacts of Generative AI on the Future of Research and Education (2025): 75-96.

[43] Kong, Siu-Cheung, Man-Yin William Cheung, and Olson Tsang. "Developing an artificial intelligence literacy framework: Evaluation of a literacy course for senior secondary students using a project-based learning approach." Computers and Education: Artificial Intelligence 6 (2024): 100214.

[44] Williams, Randi, Safinah Ali, Nisha Devasia, Daniella DiPaola, Jenna Hong, Stephen P. Kaputsos, Brian Jordan, and Cynthia Breazeal. "AI+ ethics curricula for middle school youth: Lessons learned from three project-based curricula." International Journal of Artificial Intelligence in Education 33, no. 2 (2023): 325-383.

[45] Abo El-Enen, Mohamed, Sally Saad, and Taymoor Nazmy. "A survey on retrieval-augmentation generation (RAG) models for healthcare applications." Neural Computing and Applications (2025): 1-77.

[46] Lee, Hea-Jin. "Developing an effective professional development model to enhance teachers' conceptual understanding and pedagogical strategies in mathematics." The Journal of Educational Thought (JET)/Revue de la Pensée Educative (2007): 125-144.

[47] Jakesch, Maurice, Jeffrey T. Hancock, and Mor Naaman. "Human heuristics for AI-generated language are flawed." Proceedings of the National Academy of Sciences 120, no. 11 (2023): e2208839120.

[48] Curcio, Eliseo. "Introducing LCOAI: A Standardized Economic Metric for Evaluating AI Deployment Costs." arXiv preprint arXiv:2509.02596 (2025).

[49] Modh, Jatin C., Tejaskumar P. Bhatt, Darshita Kalyani, and Aakanksha Jain. "Foundations of AI Literacy." In Developing AI Literacy in Students, pp. 39-86. IGI Global Scientific Publishing, 2026.

[50] Pan, Guanzhong, and Haibo Wang. "A Cost-Benefit Analysis of On-Premise Large Language Model Deployment: Breaking Even with Commercial LLM Services." arXiv preprint arXiv:2509.18101 (2025).

[51] Zeng, Shenglai, Jiankun Zhang, Pengfei He, Yiding Liu, Yue Xing, Han Xu, Jie Ren et al. "The good and the bad: Exploring privacy issues in retrieval-augmented generation (rag)." In Findings of the Association for Computational Linguistics: ACL 2024, pp. 4505-4524. 2024.

[52] Sawarkar, Kunal, Abhilasha Mangal, and Shivam Raj Solanki. "Blended rag: Improving rag (retriever-augmented generation) accuracy with semantic search and hybrid query-based retrievers." In 2024 IEEE 7th international conference on multimedia information processing and retrieval (MIPR), pp. 155-161. IEEE, 2024.

[53] Yuan, Ye, Chengwu Liu, Jingyang Yuan, Gongbo Sun, Siqi Li, and Ming Zhang. "A hybrid RAG system with comprehensive enhancement on complex reasoning." arXiv preprint arXiv:2408.05141 (2024).

[54] Kim, Kyong-Jee, and Curtis J. Bonk. "The future of online teaching and learning in higher education." Educause quarterly 29, no. 4 (2006): 22-30.

[55] Kalra, Rishi, Zekun Wu, Ayesha Gulley, Airlie Hilliard, Xin Guan, Adriano Koshiyama, and Philip Colin Treleaven. "HyPA-RAG: A hybrid parameter adaptive retrieval-augmented generation system for AI legal and policy applications." In Proceedings of the 1st workshop on customizable nlp: Progress and challenges in customizing nlp for a domain, application, group, or individual (customnlp4u), pp. 237-256. 2024.

[56] Li, Sha, and Naren Ramakrishnan. "Oreo: A plug-in context reconstructor to enhance retrieval-augmented generation." In Proceedings of the 2025 International ACM SIGIR Conference on Innovative Concepts and Theories in Information Retrieval (ICTIR), pp. 238-253. 2025.

[57] Velez-Solic, Angela, and Jennifer R. Banas. "Professional development for online educators: Problems, predictions, and best practices." In Adult and Continuing Education: Concepts, Methodologies, Tools, and Applications, pp. 521-544. IGI Global, 2014.

[58] Li, Zongxi, Zijian Wang, Weiming Wang, Kevin Hung, Haoran Xie, and Fu Lee Wang. "Retrieval-augmented generation for educational application: A systematic survey." Computers and Education: Artificial Intelligence (2025): 100417.

[59] Xia, Peng, Kangyu Zhu, Haoran Li, Tianze Wang, Weijia Shi, Sheng Wang, Linjun Zhang, James Zou, and Huaxiu Yao. "Mmed-rag: Versatile multimodal rag system for medical vision language models." arXiv preprint arXiv:2410.13085 (2024)

[60] Lin, Xuefei, Guangyu Xu, and Bin Xiong. "Artificial intelligence literacy, sustainability of digital learning and practice achievement: A study of vocational college students." *Plos one* 20, no. 10 (2025): e0332175.

Automated Quality Evaluation of Panoramic Dental Radiographs Using a Domain-Adapted Transfer Learning

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***Abstract*—Assessing the quality of panoramic dental radiographs is essential to ensure diagnostic accuracy and patient safety. However, existing CNN-based approaches for radiograph quality assessment often emphasize architectural comparisons, while providing limited discussion on training stability and generalization, particularly when applied to relatively small and heterogeneous datasets. To address this gap, this study proposes a transfer learning-based framework that integrates Global Average Pooling (GAP) and Batch Normalization (BN) to enhance feature robustness and reduce overfitting in panoramic dental radiograph quality classification. Three pretrained CNN architectures: ResNet50, VGG16, and VGG19 were evaluated using panoramic radiographs collected from two tertiary hospitals in Indonesia. Experimental results using *k*-fold cross-validation indicate that the proposed GAP+BN refinement improves classification consistency across models, with VGG16 demonstrating the most stable and reliable performance. These findings suggest that domain-adapted transfer learning with appropriate feature aggregation and normalization can support the development of automated and clinically reliable quality assurance systems for panoramic dental imaging.**

***Keywords*—Batch Normalization; image quality; panoramic radiograph; transfer learning**

I. Introduction

Panoramic radiography is one of the most widely used imaging modalities in dentistry because it provides comprehensive visualization of maxillary and mandibular structures with relatively low radiation exposure. However, the diagnostic reliability of panoramic radiographs is strongly dependent on image quality, which can be adversely affected by patient positioning errors, improper exposure parameters, and technical disturbances. Poor-quality radiographs reduce diagnostic accuracy and increase the likelihood of retakes, thereby exposing patients to unnecessary additional radiation. Consequently, systematic quality assessment of panoramic radiographs is a critical aspect of dental radiology practice.

Previous studies have evaluated panoramic radiograph quality from both technical and diagnostic perspectives. Comparative analysis of different imaging devices has shown relatively small variations in image quality, indicating that multiple systems may be clinically acceptable [1],[2]. Other investigations reported that positioning errors, including head tilt and patient movement, occur in up to 95% of panoramic radiographs and represent the primary contributors to reduced diagnostic quality [3]. Although these studies provide valuable insights into common sources of image degradation, quality assessment in routine clinical practice still relies heavily on manual evaluation by operators and radiologists, which is inherently subjective and time-consuming.

Several studies have emphasized the role of operator training and quality control in improving panoramic radiograph quality. Investigations conducted in South Wales and other dental institutions revealed that a large proportion of panoramic radiographs failed to meet national quality standards, primarily due to patient positioning errors and insufficient operator instructions [4],[5],[6]. In addition, improper tongue positioning against the palate has been identified as one of the most frequent errors, leading to radiolucent artifacts in the maxillary region and compromising diagnostic interpretation [7], [8]. These findings consistently highlight that human-related factors remain the dominant cause of poor panoramic radiograph quality.

With the advancement of artificial intelligence, deep learning, particularly Convolutional Neural Networks (CNNs), has shown promising performance in automating image quality assessment across various radiographic modalities. CNN-based approaches have achieved high accuracy in evaluating diagnostic quality in ankle radiographs [9], and have been successfully applied to automated quality control in chest and elbow radiography [10], [11]. In the context of dental imaging, recent studies utilizing YOLOv8 and Generative Adversarial Networks have primarily focused on image enhancement or anatomical anomaly detection rather than explicitly addressing acquisition-related errors as indicators of panoramic radiograph quality [12], [13]. Despite these advances, several challenges remain unresolved. Reviews have reported inconsistencies in labeling strategies and dataset utilization for machine learning-based panoramic

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radiograph quality assessment, which limits model generalization and reproducibility [14]. Moreover, most deep learning applications in panoramic radiography continue to prioritize anomaly detection or disease diagnosis, such as osteoporosis assessment, rather than systematic quality evaluation based on acquisition technique and patient positioning errors [15], [16], [17]. This indicates that research specifically targeting automated panoramic radiograph quality evaluation remains limited, particularly in terms of methodological robustness and clinical applicability.

To address these limitations, this study proposes a transfer learning-based CNN framework for panoramic radiograph quality classification by systematically comparing three widely used architectures: ResNet50, VGG16, and VGG19. These models were selected due to their proven effectiveness in medical image classification tasks and their distinct feature representation capabilities. Previous studies have demonstrated the strong performance of VGG16 in binary medical image classification tasks, achieving high accuracy and F1-scores [18], while ResNet50 is known for its ability to mitigate the vanishing gradient problem through residual connections. Building upon these findings, the present study integrates Global Average Pooling (GAP) and Batch Normalization (BN) to enhance training stability and generalization, particularly when dealing with limited datasets.

Unlike previous research that focused on dental anomaly detection or disease diagnosis using CNN-based models with Batch Normalization [16], This study emphasizes the evaluation of panoramic radiograph quality based on acquisition-related errors. The main contributions of this research are threefold: 1) providing a comparative analysis of popular pretrained CNN architectures for panoramic radiograph quality assessment, 2) demonstrating the effectiveness of GAP and BN in improving training stability and classification performance on limited datasets, and 3) presenting empirical evidence from multi-institutional panoramic radiographs collected from Universitas Gadjah Mada and Universitas Airlangga hospitals in Indonesia to support the development of AI-based automatic quality assurance systems in dental radiology.

This study is organized as follows: Section II presents a review of related literature. Section III describes the dataset used in this research and explains the proposed method in detail. Section IV discusses the experimental results and findings. Finally, Section V concludes the study and outlines directions for future research.

II. Literature Review

The quality of panoramic radiographs determines the diagnostic value and reliability of image interpretation. Several research have evaluated the consistency and quality of images obtained from different radiographic machines and the factors influencing them. An early research [1] compared two panoramic units and found that both produced equivalent diagnostic results for anatomical evaluation, with negligible differences in image quality, indicating that both devices were clinically acceptable. This suggests that technical acquisition parameters and patient positioning have a greater impact on diagnostic quality than differences between imaging devices.

Automated approaches have also been introduced to assess radiographic acceptability. In [2], the authors developed an automated CNN-based framework to determine whether panoramic radiographs were suitable for further analysis. The system demonstrated high accuracy and showed potential to support diagnostic workflows, particularly in regions with limited access to orthodontic radiologists.

Further applications of deep learning have extended to non-panoramic radiographs. For example, research [9] evaluated the diagnostic quality of ankle radiographs based on anatomical features, achieving 94.1% accuracy, surpassing average radiologist performance. Similarly, research [19] proposed a CNN with multi-scale feature extraction to automatically assess panoramic radiograph quality, outperforming conventional methods. Several studies have also focused on improving image quality. Research [20] introduced a Multi-Scale Top-Hat with Geodesic Reconstruction (MSTHGR) method to enhance image contrast and detail, while research [13] used a Generative Adversarial Network (Pix2Pix) to correct blurred and noisy images, significantly improving PSNR and SSIM metrics. Another research [21] employed a deep learning-based super-resolution technique (LTE) to enhance image resolution with visually and quantitatively superior results.

Panoramic radiography plays an essential role in dental diagnosis; however, patient positioning errors frequently occur due to equipment complexity and anatomical variations, leading to reduced image quality and diagnostic accuracy. Research developed a deep learning model to detect six common positioning errors: slumped posture, low chin, open lips, head rotation, head tilt, and tongue not against the palate, using 552 panoramic radiographs. Six CNN architectures were employed for feature extraction, and the extracted features were fused and classified using a Support Vector Machine (SVM). The model achieved an accuracy of 0.832 with high precision and recall, proving effective for automatic identification of patient positioning errors and improving diagnostic reliability.

Positioning errors are among the main causes of reduced diagnostic quality in panoramic imaging. Research [3] reported that 95% of 500 radiographs contained one or more positioning errors, particularly head tilt. Similarly, research [4] found that 54.6% of radiographs in South Wales exhibited positioning errors and 47.9% were affected by poor patient preparation or instruction. Research [5], which analyzed 1,000 panoramic radiographs, found that the most common error was the tongue not being pressed against the palate (69.5%), followed by patient motion (0.4%). Research [6] involving 2,629 patients revealed that only 32.8% of radiographs were error-free, with tongue positioning errors being the most prevalent. Research [7] compared image quality across three radiographic technicians and found significant inter-operator variation, with the “gazebo effect” and condyle positioning errors being the most frequent findings.

In Indonesia, research [8] reported that 98.78% of panoramic radiographs exhibited patient positioning errors, most commonly due to the tongue not adhering to the palate (49.68%), although the overall diagnostic quality remained

acceptable. Similar errors have been reported in other research [22], [23], [24], [25], where head alignment, lateral rotation, and palatoglossal air space were identified as the primary factors reducing image quality [26].

Several studies have highlighted the impact of imaging technique and operator skill on radiographic quality. In [27], the authors emphasized the importance of head positioning, occlusal plane orientation, mandibular condyle alignment, and metal artifact control in producing symmetric and diagnostically acceptable panoramic images. Research [28] added that horizontal spatial distortion up to ≤20% remains clinically acceptable, while a minimum spatial resolution of 1.88 lp/mm is necessary to maintain anatomical readability.

In [9], the authors showed that while radiographic quality did not vary significantly among technicians, the types of errors did, indicating that operator training and experience play a major role. This finding was supported by research [23], which concluded that radiographic errors are not directly correlated with professional experience but are influenced by patient cooperation and attentiveness during image acquisition. In addition to operator-related issues, technical parameters such as exposure settings and image processing also affect diagnostic quality. In [24], [25], the authors found that post-trauma radiographs frequently suffered from exposure errors, out-of-focus positioning, and metal artifacts, which limited diagnostic interpretation.

Efforts to improve radiographic quality control have increasingly employed deep learning methods. In [12], the authors developed a YOLOv8-based model to assess panoramic radiograph quality using five clinical visual criteria, achieving an overall accuracy of 81.4%. Similar approaches have been applied to chest [10] and elbow [11] radiographs, demonstrating strong potential for automated medical image quality assessment.

Moreover, research [14] conducted a systematic review of 41 research on panoramic radiograph image quality for machine learning model training. The review found that most research lacked standardized image quality criteria, and defective images were often excluded from datasets without detailed analysis. This practice introduces bias and reduces model generalizability, emphasizing the need for automated methods to assess and manage radiograph quality consistently.

The quality of panoramic radiographs is predominantly affected by acquisition technique and patient positioning, with the latter being the leading cause of diagnostically unacceptable images. Although deep learning systems have been widely used for image enhancement and quality evaluation, research that integrates expert clinical annotations with CNN models for objective assessment of panoramic radiograph quality remains limited.

This highlights an existing research gap that needs to be addressed through the development of CNN-based automated systems capable of accurately identifying technical and positioning errors while providing feedback to improve image acquisition quality. Table I summarizes the key differences between the present research and the work of [12].

TABLE I. COMPARISON BETWEEN THE PROPOSED MODEL AND PREVIOUS RESEARCHES

Aspect	Research [12]	Proposed	Contribution/Difference
Objective	Automated assessment of panoramic radiograph quality based on four criteria (artifacts, coverage area, patient positioning, and contrast/density) and clinical acceptability (acceptable vs. not acceptable).	Development of a CNN-based panoramic radiograph quality evaluation model using a domain-adapted ResNet50 to classify image quality into good and poor categories.	Both assess image quality; however, the proposed research focuses on optimizing a domain-adapted CNN and evaluating inter-architecture performance rather than single-model classification using YOLO.
Model	YOLOv8 (single-stage real-time classifier with 141 layers, Adam-W optimizer, learning rate=0.0001).	Domain-adapted ResNet50 architecture with additional Global Average Pooling (GAP) and Batch Normalization (BN) layers for improved stability and generalization.	The proposed research presents a transfer learning-based modification of a classical CNN architecture, which is referred to as a domain-adapted transfer learning to emphasize its adaptation to the specific characteristics of panoramic dental radiographs. This adaptation was achieved through architectural modification (GAP and BN layers) and fine-tuning on domain-specific data.
Evaluation Criteria	Four aspects (artifacts, coverage, positioning, contrast/density) plus overall image quality.	Focuses on overall radiograph quality (good or poor) based on coverage, vertical and horizontal distortion, detail and sharpness, artifacts and ghost images, and radiolucent areas in the anterior maxillary apical region.	The proposed method performs holistic radiograph quality assessment rather than per-aspect evaluation, providing faster and more efficient results for clinical application.
Accuracy	74.1-97.9% per criterion, with an average of 81.4% for clinical classification.	Domain-adapted ResNet50 achieved 82-85% accuracy and the highest F1-score compared to baseline CNNs (VGG architectures).	The proposed model delivers comparable or slightly higher performance with lower model complexity than YOLOv8.
Optimization	Strategy Data augmentation, Adam-W optimizer, and automatic mixed precision.	Transfer learning, Batch Normalization, and adaptive learning rate scheduler.	The proposed approach emphasizes training efficiency and domain adaptability without requiring high-end GPU resources.
Clinical Contribution	Provides a real-time radiograph quality control system and an educational tool for dental students.	Offers a lightweight CNN model for automated radiograph quality evaluation in resource-limited institutions.	The proposed method is easier to implement in local dental clinics without the need for high computational infrastructure.

A. Conventional Approaches and Their Limitations

Early research relied on manual visual inspection by radiologists, which is subjective and time-consuming. Later, rule-based metrics such as contrast, entropy, or edge sharpness were used to quantify quality, but these fail to capture anatomical distortion or exposure errors. Classical machine-learning models (e.g., SVM, *k*-NN) using handcrafted texture or wavelet features improved objectivity but depended heavily on feature design and were sensitive to acquisition variability. Recent deep-learning approaches applied CNNs for anomaly detection or anatomy segmentation rather than direct good/poor quality classification, and often used single-center data without cross-institution validation. This research differs by applying a transfer-learning CNN (ResNet50, VGG16, VGG19) directly to the binary quality classification task of panoramic radiographs, reducing the need for handcrafted features and improving robustness for small, domain-specific datasets.

III. Methods

A. Dataset

The dataset used in this research was obtained from the Dental and Oral Hospital (RSGM) of Universitas Airlangga, Surabaya, and the Dental and Oral Hospital of Universitas Gadjah Mada, Yogyakarta. Ethical approval for the use of radiographic data was granted by both institutions under approval numbers 0910/HRECC.FODM/VIII/2025 and 158/UNI/KEP/FKG-RSGM/EC/2025, respectively. In total, 1,285 panoramic radiographic images were collected, consisting of 820 images from Universitas Airlangga and 465 images from Universitas Gadjah Mada.

Each radiograph was independently evaluated by four dental radiology experts based on five key diagnostic quality aspects (see Table II), with a maximum total score of five. Radiographs with a total score of five were categorized as good quality, indicating no retake was required, while radiographs with a score below five were categorized as poor quality, indicating a retake was recommended. To ensure annotation reliability and reduce label ambiguity, only radiographs with full consensus among all four experts were included in the final dataset used for model training and evaluation.

Based on this strict selection criterion, 442 panoramic radiographs were retained, including 221 good-quality and 221 poor-quality images (see Table III). Specifically, 105 good-quality and 105 poor-quality radiographs were obtained from Universitas Airlangga, while 116 good-quality and 116 poor-quality radiographs were obtained from Universitas Gadjah Mada. This balanced class distribution was intentionally maintained to prevent model bias towards a dominant class.

Examples of panoramic radiographs used in this study are shown in Fig. 1. Good-quality radiographs exhibit complete anatomical coverage, clear visualization of the maxillomandibular structures, sharp anatomical details, and the absence of distortion or artifacts that may interfere with diagnosis. In contrast, poor-quality radiographs are characterized by positioning-related distortions, asymmetry, reduced sharpness due to patient movement, and the presence of artifacts such as ghost images or extensive radiolucent regions that compromise diagnostic reliability.

TABLE II. Image Quality Assessment Criteria

No.	Aspect	1	0
1	Coverage	The image includes the lower border of the mandible, both right and left condyles, and the lower border of the orbits.	One or more of these anatomical areas are not included in the image.
2	Vertical and Horizontal Distortion	No vertical or horizontal distortion is observed.	Distortion interferes with interpretation (e.g., inverted or V-shaped dental arch, asymmetrical mandibular shape).
3	Detail and Sharpness	The image shows clear anatomical detail and sharpness.	Image detail is unclear or overlapping due to patient head movement during exposure.
4	Artifacts and Ghost Images	No artifacts or ghost images interfere with diagnostic interpretation.	Ghost images from foreign objects or large radiolucent areas (air spaces) obscure dental or maxillofacial structures.
5	Radiolucent Area in the Anterior Maxillary Apical Region	No radiolucent area interferes with interpretation.	A radiolucent area is present in the anterior maxillary apical region, reducing diagnostic clarity.

TABLE III. Dataset Distribution

Class	Training	Testing	Total
Good	170	51	221
Poor	170	51	221
Total	340	102	442

Although the final dataset used in this study consists of 442 curated panoramic radiographs, which may be considered relatively small for deep learning applications, this reflects realistic clinical constraints where high-quality, expert-labeled radiographic data are limited. The reduced dataset size increases the risk of overfitting; therefore, several mitigation strategies were employed. First, transfer learning from pretrained CNN models was used to leverage previously learned generic visual features. Second, Global Average Pooling (GAP) was applied to reduce the number of trainable parameters, while Batch Normalization (BN) was incorporated to stabilize training and improve generalization. In addition, *k*-fold cross-validation was adopted to maximize data utilization and provide a more robust estimate of model performance across different data partitions.

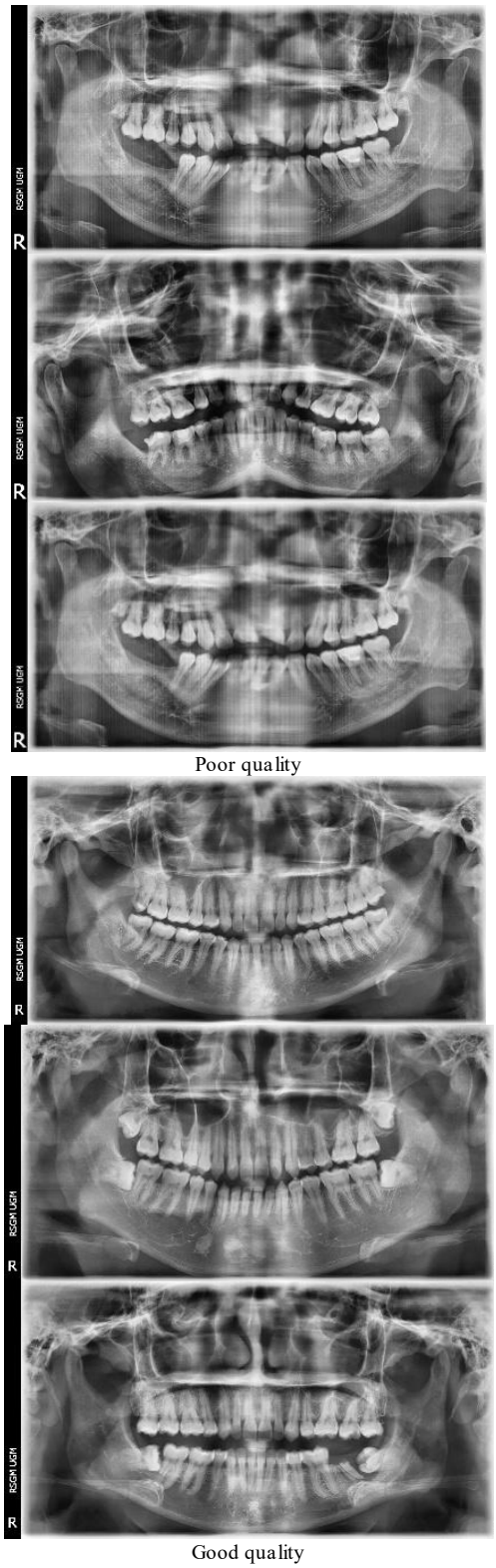


Fig. 1. Examples of panoramic radiographs.

Although the final dataset size is relatively limited, this scenario reflects realistic clinical conditions where curated, high-quality labeled radiographic data are often scarce. To mitigate the risk of overfitting associated with limited data, this study employed a transfer learning strategy using pretrained CNN models, combined with Global Average Pooling and Batch Normalization to enhance feature robustness and training stability. Furthermore, *k*-fold cross-validation was applied to maximize data utilization and provide a more reliable estimation of model generalization performance across different data splits.

B. Proposed Method

This research proposes a transfer learning-based approach using three CNN architectures: ResNet50, VGG16, and VGG19 to classify the quality of panoramic dental radiographs into two classes: good and poor (Fig. 2). All pretrained models were initialized with ImageNet weights and modified by adding Global Average Pooling (GAP) and Batch Normalization (BN) layers to improve adaptability to the specific characteristics of dental radiographs. In this context, the term domain-adapted refers to the adaptation of a pretrained network through transfer learning and fine-tuning using dental imaging data, rather than an explicit domain adaptation mechanism such as adversarial alignment or feature distribution matching. The proposed method aims to automate the panoramic radiograph quality assessment process and empirically verify the reliability of ResNet50 compared to the other architectures. Model performance was evaluated using *k*-fold cross-validation to ensure robustness and reduce sampling bias. The main stages of the proposed method include the following steps (as illustrated in Fig. 2):

a) Preprocessing data: All panoramic radiograph images were converted into RGB format with a resolution of 512×512 pixels and normalized to a range of [0,1].

b) Feature extraction (transfer learning): Three pretrained CNN models were employed as feature extractors: ResNet50, which utilizes residual connections to preserve gradient flow and is well-suited for detecting complex radiographic textures; VGG16 and VGG19, which employ simple stacked convolutional layers effective for capturing edge and shape representations.

c) Architecture modification: To enhance model performance, several layers were added: Global Average Pooling (GAP) to reduce feature dimensions while retaining essential spatial information; Batch Normalization (BN) to stabilize inter-layer activation distributions and accelerate convergence; and Dense Layers (128-256 units) with ReLU activation as the classifier head. The models were optimized using the Adam or AdamW optimizer with a learning rate of 0.0001, batch size of 2, and 30 training epochs.

d) Training and evaluation: The models were trained on a labeled dataset of 442 panoramic radiographs (340 for training and 102 for testing). Evaluation metrics included accuracy [Eq. (1)], precision [Eq. (2)], recall (sensitivity) [Eq. (3)], specificity [Eq. (4)], and F1-Score [Eq. (5)] analysis [18]. These metrics were selected to provide a comprehensive understanding of diagnostic reliability, particularly regarding false negatives, which may correspond to clinically unacceptable images being classified as acceptable. This evaluation framework supports the model's applicability for clinical quality assurance and radiation dose reduction in dental radiology workflows.

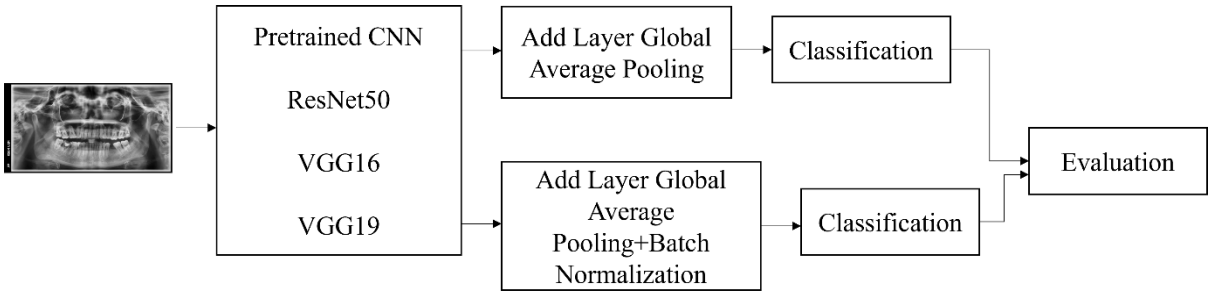


Fig. 2. Proposed method framework.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP+TN}{TP+FN} \quad (3)$$

$$Specificity = \frac{TN}{TP+FP} \quad (4)$$

$$F1-Score = \frac{2.TP}{2.TP+FP+FN} \quad (5)$$

IV. Results and Discussion

Tables IV to XII summarize the class-wise evaluation metrics obtained from *k*-fold cross-validation for all evaluated models. Rather than focusing solely on absolute metric values, the results reveal clear performance trends across architectures and configurations. Overall, VGG16-based models consistently demonstrated more stable and balanced performance compared to ResNet50 and VGG19, particularly when combined with Global Average Pooling (GAP) and Batch Normalization (BN).

ResNet50 achieved relatively high AUC values in several folds, indicating strong discriminative potential. However, its performance exhibited substantial variability in recall and specificity across folds (Tables IV to VI and Tables XIII to XV). This instability suggests sensitivity to data partitioning and potential overfitting, which can be attributed to the model's higher architectural complexity relative to the limited size of the curated panoramic radiograph dataset. Although residual connections are designed to facilitate deeper feature learning, they may lead to unstable optimization when the available training data are insufficient to support robust parameter estimation.

In contrast, VGG16 demonstrated consistently lower variance across folds and more balanced class-wise performance (Tables VII to IX and Tables XVI to XVIII). The integration of GAP reduced the number of trainable parameters, while BN improved gradient flow and training stability. These architectural refinements enabled VGG16 to achieve the most reliable overall performance, with an average accuracy of 85.00% and an AUC of 94.72%. The relatively shallow and uniform convolutional structure of VGG16 appears to be better suited for capturing global structural distortions and acquisition-related artifacts commonly observed in panoramic radiographs.

TABLE IV. ResNet50 (GAP) Evaluation Results for Each Class

k-fold=1	Recall	Precision	F1-score	Specificity
Good	55.56	80.00	65.57	84.38
Poor	84.38	62.79	72.00	55.56
mean	69.97	71.40	68.79	69.97
std	20.38	12.17	4.54	20.38
k-fold=2	Recall	Precision	F1-score	Specificity
Good	28.57	58.82	38.46	78.79
Poor	78.79	50.98	50.98	28.57
mean	53.68	54.90	44.72	53.68
std	35.51	5.55	8.85	35.51
k-fold=3	Recall	Precision	F1-score	Specificity
Good	71.88	62.16	66.67	61.11
Poor	61.11	70.97	65.67	71.88
mean	66.49	66.56	66.17	66.49
std	7.61	6.23	0.70	7.61
k-fold=4	Recall	Precision	F1-score	Specificity
Good	100.00	52.94	69.23	0.00
Poor	0.00	0.00	0.00	100.00
mean	50.00	26.47	34.62	50.00
std	70.71	37.44	48.95	70.71
k-fold=5	Recall	Precision	F1-score	Specificity
Good	100.00	60.78	75.61	45.95
Poor	45.95	100.00	62.96	100.00
mean	72.97	80.39	69.29	72.97
std	38.22	27.73	8.94	38.22

TABLE V. ResNet50 (GAP+BN) Evaluation Results for Each Class

k-fold=1	Recall	Precision	F1-score	Specificity
Good	66.67	88.89	76.19	90.63
Poor	90.63	70.73	79.45	66.67
mean	78.65	79.81	77.82	78.65
std	16.94	12.84	2.31	16.94
k-fold=2	Recall	Precision	F1-score	Specificity
Good	22.86	88.89	36.36	96.97

Poor	96.97	54.24	54.24	22.86
mean	59.91	71.56	45.30	59.91
std	52.41	24.50	12.64	52.41
k-fold=3	Recall	Precision	F1-score	Specificity
Good	0.00	0.00	0.00	100.00
Poor	100.00	52.94	69.23	0.00
mean	50.00	26.47	34.62	50.00
std	70.71	37.44	48.95	70.71
k-fold=4	Recall	Precision	F1-score	Specificity
Good	100.00	52.94	69.23	0.00
Poor	0.00	0.00	0.00	100.00
mean	50.00	26.47	34.62	50.00
std	70.71	37.44	48.95	70.71
k-fold=5	Recall	Precision	F1-score	Specificity
Good	100.00	45.59	62.63	0.00
Poor	0.00	0.00	0.00	100.00
mean	50.00	22.79	31.31	50.00
std	70.71	32.24	44.28	70.71

TABLE VI. RESNET50 (GAP+BN) OPTIMIZER ADAMW EVALUATION RESULTS FOR EACH CLASS

k-fold=1	Recall	Precision	F1-score	Specificity
Good	100.00	61.02	75.79	28.13
Poor	28.13	100.00	43.90	100.00
mean	64.06	80.51	59.85	64.06
std	50.82	27.57	22.55	50.82
k-fold=2	Recall	Precision	F1-score	Specificity
Good	100.00	51.47	67.96	0.00
Poor	0.00	0.00	0.00	100.00
mean	50.00	25.74	33.98	50.00
std	70.71	36.40	48.06	70.71
k-fold=3	Recall	Precision	F1-score	Specificity
Good	0.00	0.00	0.00	100.00
Poor	100.00	52.94	69.23	0.00
mean	50.00	26.47	34.62	50.00
std	70.71	37.44	48.95	70.71
k-fold=4	Recall	Precision	F1-score	Specificity
Good	97.22	62.50	76.09	34.38
Poor	34.38	91.67	50.00	97.22
mean	65.80	77.08	63.04	65.80
std	44.44	20.62	18.45	44.44
k-fold=5	Recall	Precision	F1-score	Specificity
Good	100.00	45.59	62.63	0.00
Poor	0.00	0.00	0.00	100.00
mean	50.00	22.79	31.31	50.00
std	70.71	32.24	44.28	70.71

TABLE VII. VGG16 (GAP) EVALUATION RESULTS FOR EACH CLASS

k-fold=1	Recall	Precision	F1-score	Specificity
Good	86.11	72.09	78.48	62.50
Poor	62.50	80.00	70.18	86.11
mean	74.31	76.05	74.33	74.31
std	16.70	5.59	5.87	16.70
k-fold=2	Recall	Precision	F1-score	Specificity
Good	60.00	87.50	71.19	90.91
Poor	90.91	68.18	77.92	60.00
mean	75.45	77.84	74.55	75.45
std	21.86	13.66	4.76	21.86
k-fold=3	Recall	Precision	F1-score	Specificity
Good	84.38	64.29	72.97	58.33
Poor	58.33	80.77	67.74	84.38
mean	71.35	72.53	70.36	71.35
std	18.41	11.66	3.70	18.41
k-fold=4	Recall	Precision	F1-score	Specificity
Good	97.22	67.31	79.55	46.88
Poor	46.88	93.75	62.50	97.22
mean	72.05	80.53	71.02	72.05
std	35.60	18.70	12.05	35.60
k-fold=5	Recall	Precision	F1-score	Specificity
Good	93.55	69.05	79.45	64.86
Poor	64.86	92.31	76.19	93.55
mean	79.21	80.68	77.82	79.21
std	20.28	16.45	2.31	20.28

TABLE VIII. VGG16 (GAP+BN) EVALUATION RESULTS FOR EACH CLASS

k-fold=1	Recall	Precision	F1-score	Specificity
Good	69.44	100.00	81.97	100.00
Poor	100.00	74.42	85.33	69.44
mean	84.72	87.21	83.65	84.72
std	21.61	18.09	2.38	21.61
k-fold=2	Recall	Precision	F1-score	Specificity
Good	62.86	95.65	75.86	96.97
Poor	96.97	71.11	82.05	62.86
mean	79.91	83.38	78.96	79.91
std	24.12	17.35	4.38	24.12
k-fold=3	Recall	Precision	F1-score	Specificity
Good	96.88	81.58	88.57	80.56
Poor	80.56	96.67	87.88	96.88
mean	88.72	89.12	88.23	88.72
std	11.54	10.67	0.49	11.54
k-fold=4	Recall	Precision	F1-score	Specificity
Good	100.00	83.72	91.14	78.13
Poor	78.13	100.00	87.72	100.00
mean	89.06	91.86	89.43	89.06
std	15.47	11.51	2.42	15.47
k-fold=5	Recall	Precision	F1-score	Specificity
Good	93.55	76.32	84.06	75.68
Poor	75.68	93.33	83.58	93.55
mean	84.61	84.82	83.82	84.61
std	12.64	12.03	0.34	12.64

TABLE IX. VGG16 (GAP+BN) OPTIMIZER ADAMW EVALUATION RESULTS FOR EACH CLASS

k-fold=1	Recall	Precision	F1-score	Specificity
Good	63.89	95.83	76.67	96.88
Poor	96.88	70.45	81.58	63.89
mean	80.38	83.14	79.12	80.38
std	23.32	17.95	3.47	23.32
k-fold=2	Recall	Precision	F1-score	Specificity
Good	97.14	73.91	83.95	63.64
Poor	63.64	95.45	76.36	97.14
mean	80.39	84.68	80.16	80.39
std	23.69	15.23	5.36	23.69
k-fold=3	Recall	Precision	F1-score	Specificity
Good	90.63	74.36	81.69	72.22
Poor	72.22	89.66	80.00	90.63
mean	81.42	82.01	80.85	81.42
std	13.01	10.82	1.20	13.01
k-fold=4	Recall	Precision	F1-score	Specificity
Good	100.00	80.00	88.89	71.88
Poor	71.88	100.00	83.64	100.00
mean	85.94	90.00	86.26	85.94
std	19.89	14.14	3.71	19.89
k-fold=5	Recall	Precision	F1-score	Specificity
Good	16.13	100.00	27.78	100.00
Poor	100.00	58.73	74.00	16.13
mean	58.06	79.37	50.89	58.06
std	59.31	29.18	32.68	59.31

TABLE X. VGG19 (GAP) EVALUATION RESULTS FOR EACH CLASS

k-fold=1	Recall	Precision	F1-score	Specificity
Good	72.22	74.29	73.24	71.88
Poor	71.88	69.70	70.77	72.22
mean	72.05	71.99	72.00	72.05
std	0.25	3.24	1.75	0.25
k-fold=2	Recall	Precision	F1-score	Specificity
Good	80.00	70.00	74.67	63.64
Poor	63.64	75.00	68.85	80.00
mean	71.82	72.50	71.76	71.82
std	11.57	3.54	4.11	11.57
k-fold=3	Recall	Precision	F1-score	Specificity
Good	90.63	65.91	76.32	58.33
Poor	58.33	87.50	70.00	90.63
mean	74.48	76.70	73.16	74.48
std	22.83	15.27	4.47	22.83
k-fold=4	Recall	Precision	F1-score	Specificity
Good	88.89	68.09	77.11	53.13
Poor	53.13	80.95	64.15	88.89
mean	71.01	74.52	70.63	71.01
std	25.29	9.10	9.16	25.29
k-fold=5	Recall	Precision	F1-score	Specificity
Good	77.42	77.42	77.42	81.08
Poor	81.08	81.08	81.08	77.42
mean	79.25	79.25	79.25	79.25
std	2.59	2.59	2.59	2.59

TABLE XI. VGG19 (GAP+BN) EVALUATION RESULTS FOR EACH CLASS

k-fold=1	Recall	Precision	F1-score	Specificity
Good	86.11	79.49	82.67	75.00
Poor	75.00	82.76	78.69	86.11
mean	80.56	81.12	80.68	80.56
std	7.86	2.31	2.81	7.86
k-fold=2	Recall	Precision	F1-score	Specificity
Good	100.00	59.32	74.47	27.27
Poor	27.27	100.00	42.86	100.00
mean	63.64	79.66	58.66	63.64
std	51.43	28.76	22.35	51.43
k-fold=3	Recall	Precision	F1-score	Specificity
Good	96.88	50.00	65.96	13.89
Poor	13.89	83.33	23.81	96.88
mean	55.38	66.67	44.88	55.38
std	58.68	23.57	29.80	58.68
k-fold=4	Recall	Precision	F1-score	Specificity
Good	72.22	86.67	78.79	87.50
Poor	87.50	73.68	80.00	72.22
mean	79.86	80.18	79.39	79.86
std	10.80	9.18	0.86	10.80
k-fold=5	Recall	Precision	F1-score	Specificity
Good	87.10	90.00	88.52	91.89
Poor	91.89	89.47	90.67	87.10
mean	89.49	89.74	89.60	89.49
std	3.39	0.37	1.51	3.39

TABLE XII. VGG19 (GAP+BN) OPTIMIZER ADAMW EVALUATION RESULTS FOR EACH CLASS

k-fold=1	Recall	Precision	F1-score	Specificity
Good	72.22	86.67	78.79	87.50
Poor	87.50	73.68	80.00	72.22
mean	79.86	80.18	79.39	79.86
std	10.80	9.18	0.86	10.80
k-fold=2	Recall	Precision	F1-score	Specificity
Good	100.00	70.00	82.35	54.55

Poor	54.55	100.00	70.59	100.00
mean	77.27	85.00	76.47	77.27
std	32.14	21.21	8.32	32.14
k-fold=3	Recall	Precision	F1-score	Specificity
Good	90.63	80.56	85.29	80.56
Poor	80.56	90.63	85.29	90.63
mean	85.59	85.59	85.29	85.59
std	7.12	7.12	0.00	7.12
k-fold=4	Recall	Precision	F1-score	Specificity
Good	86.11	83.78	84.93	81.25
Poor	81.25	83.87	82.54	86.11
mean	83.68	83.83	83.74	83.68
std	3.44	0.06	1.69	3.44
k-fold=5	Recall	Precision	F1-score	Specificity
Good	19.35	100.00	32.43	100.00
Poor	100.00	59.68	74.75	19.35
mean	59.68	79.84	53.59	59.68
std	57.02	28.51	29.92	57.02

TABLE XIII. RESNET50 (GAP) *K*-FOLD CROSS-VALIDATION RESULTS

k-fold	Accuracy	Precision	Recall	F1-score	AUC	Specificity
1	69.12	62.79	84.38	72.00	78.21	55.56
2	52.94	50.98	78.79	61.90	69.52	28.57
3	66.18	70.97	61.11	65.67	72.92	71.88
4	52.94	0.00	0.00	0.00	76.39	100.00
5	70.59	100.00	45.95	62.96	92.07	100.00
max	70.59	100.00	84.38	72.00	92.07	100.00
mean	62.35	56.95	54.05	52.51	77.82	71.20
std	8.74	36.62	33.80	29.61	8.63	30.50

TABLE XIV. RESNET50 (GAP+BN) *K*-FOLD CROSS-VALIDATION RESULTS

k-fold	Accuracy	Precision	Recall	F1-score	AUC	Specificity
1	77.94	70.73	90.63	79.45	91.58	66.67
2	58.82	54.24	96.97	69.57	91.26	22.86
3	52.94	52.94	100.00	69.23	90.23	0.00
4	52.94	0.00	0.00	0.00	87.85	100.00
5	45.59	0.00	0.00	0.00	93.98	100.00
max	77.94	70.73	100.00	79.45	93.98	100.00
mean	57.65	35.58	57.52	43.65	90.98	57.91
std	12.28	33.23	52.62	40.06	2.22	45.28

TABLE XV. RESNET50 (GAP+BN) OPTIMIZER ADAMW *K*-FOLD CROSS-VALIDATION RESULTS

k-fold	Accuracy	Precision	Recall	F1-score	AUC	Specificity
1	66.18	100.00	28.13	43.90	86.20	100.00
2	51.47	0.00	0.00	0.00	89.61	100.00
3	52.94	52.94	100.00	69.23	93.06	0.00
4	67.65	91.67	34.38	50.00	89.06	97.22
5	45.59	0.00	0.00	0.00	95.90	100.00
max	67.65	100.00	100.00	69.23	95.90	100.00
mean	56.77	48.92	32.50	32.63	90.77	79.44
std	9.68	48.06	40.90	31.22	3.77	44.43

TABLE XVI. VGG16 (GAP) *K*-FOLD CROSS-VALIDATION RESULTS

k-fold	Accuracy	Precision	Recall	F1-score	AUC	Specificity
1	75.00	80.00	62.50	70.18	78.21	86.11
2	75.00	68.18	90.91	77.92	85.45	60.00
3	70.59	80.77	58.33	67.74	74.48	84.38
4	73.53	93.75	46.88	62.50	86.89	97.22
5	77.94	92.31	64.86	76.19	85.00	93.55
max	77.94	93.75	90.91	77.92	86.89	97.22
mean	74.41	83.00	64.70	70.91	82.01	84.25
std	2.67	10.44	16.20	6.29	5.38	14.55

TABLE XVII. VGG16 (GAP+BN) *K*-FOLD CROSS-VALIDATION RESULTS

k-fold	Accuracy	Precision	Recall	F1-score	AUC	Specificity
1	83.82	74.42	100.00	85.33	95.75	69.44
2	79.41	71.11	96.97	82.05	96.19	62.86
3	88.24	96.67	80.56	87.88	94.88	96.88
4	89.71	100.00	78.13	87.72	94.79	100.00
5	83.82	93.33	75.68	83.58	91.98	93.55
max	89.71	100.00	100.00	87.88	96.19	100.00
mean	85.00	87.11	86.27	85.31	94.72	84.55
std	4.08	13.35	11.34	2.55	1.64	17.11

TABLE XVIII.VGG16 (GAP+BN) OPTIMIZER ADAMW *K*-FOLD CROSS-VALIDATION RESULTS

k-fold	Accuracy	Precision	Recall	F1-score	AUC	Specificity
1	79.41	70.45	96.88	81.58	95.05	63.89
2	80.88	95.45	63.64	76.36	95.93	97.14
3	80.88	89.66	72.22	80.00	93.84	90.63
4	86.76	100.00	71.88	83.64	90.00	100.00
5	61.76	58.73	100.00	74.00	91.63	16.13
max	86.76	100.00	100.00	83.64	95.93	100.00
mean	77.94	82.86	80.92	79.12	93.29	73.56
std	9.47	17.57	16.39	3.91	2.45	35.14

TABLE XIX. VGG19 (GAP) *K*-FOLD CROSS-VALIDATION RESULTS

k-fold	Accuracy	Precision	Recall	F1-score	AUC	Specificity
1	72.06	69.70	71.88	70.77	84.38	72.22
2	72.06	75.00	63.64	68.85	80.26	80.00
3	73.53	87.50	58.30	70.00	72.60	90.63
4	72.06	80.95	53.13	64.15	77.08	88.89
5	79.41	81.08	81.08	81.08	88.14	77.42
max	79.41	87.50	81.08	81.08	88.14	90.63
mean	73.82	78.85	65.61	70.97	80.49	81.83
std	3.19	6.76	11.09	6.21	6.07	7.79

TABLE XX. VGG19 (GAP+BN) *K*-FOLD CROSS-VALIDATION RESULTS

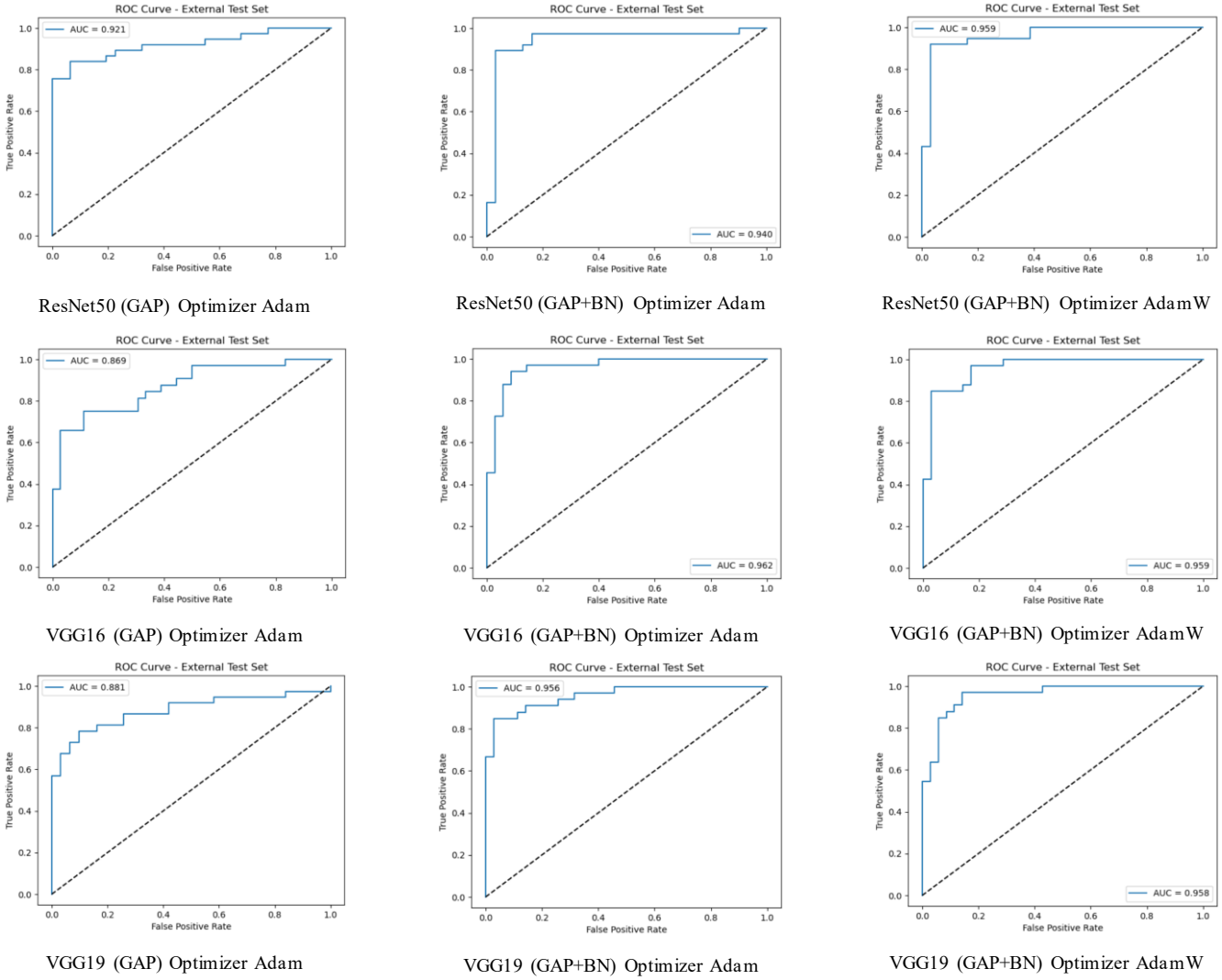
k-fold	Accuracy	Precision	Recall	F1-score	AUC	Specificity
1	80.88	82.76	75.00	78.69	86.72	86.11
2	64.71	100.00	27.27	42.86	95.58	100.00
3	52.94	83.33	13.89	23.81	92.27	96.88
4	79.41	73.68	87.50	80.00	92.71	72.22
5	89.71	89.47	91.89	90.67	93.46	87.10
max	89.71	100.00	91.89	90.67	95.58	100.00
mean	73.53	85.85	59.11	63.21	92.15	88.46
std	14.60	9.71	36.03	28.47	3.29	10.90

TABLE XXI. VGG19 (GAP+BN) OPTIMIZER ADAMW *K*-FOLD CROSS-VALIDATION RESULTS

k-fold	Accuracy	Precision	Recall	F1-score	AUC	Specificity
1	79.41	73.68	87.50	80.00	89.15	72.22
2	77.94	100.00	54.55	70.59	95.76	100.00
3	85.29	90.63	80.56	85.29	91.93	90.63
4	83.82	83.87	81.25	82.54	92.88	86.11
5	63.24	59.68	100.00	74.75	93.55	19.35
max	85.29	100.00	100.00	85.29	95.76	100.00
mean	77.94	81.57	80.77	78.63	92.65	73.66
std	8.76	15.56	16.60	5.94	2.41	31.97

VGG19 exhibited competitive discriminative performance, with mean AUC values around 92% (Table X to Table XII and Table XIX to Table XXI). However, its deeper architecture resulted in slightly higher performance variability compared to VGG16, suggesting increased sensitivity to limited data and fold composition. Among VGG19 variants, the use of adaptive optimization (AdamW) improved convergence consistency, reinforcing the importance of optimizer selection in small-scale medical imaging datasets.

Fig. 3 illustrates the ROC curves for all evaluated configurations, further confirming that VGG16 with GAP and BN achieved superior and more consistent discrimination between good- and poor-quality radiographs. The proximity of the ROC curve to the upper-left corner indicates a favorable balance between sensitivity and specificity, which is critical in quality assessment tasks where both false positives and false negatives carry clinical consequences.



ResNet50 (GAP) Optimizer Adam | ResNet50 (GAP+BN) Optimizer Adam | ResNet50 (GAP+BN) Optimizer AdamW

VGG16 (GAP) Optimizer Adam | VGG16 (GAP+BN) Optimizer Adam | VGG16 (GAP+BN) Optimizer AdamW

VGG19 (GAP) Optimizer Adam | VGG19 (GAP+BN) Optimizer Adam | VGG19 (GAP+BN) Optimizer AdamW

Fig. 3. ROC-AUC curves of transfer learning models.

From an error analysis perspective, false negatives where poor-quality radiographs are misclassified as good quality pose a greater clinical risk than false positives. Such errors may result in diagnostically inadequate images being accepted, potentially leading to misdiagnosis or delayed treatment. The VGG16 (GAP+BN, Adam) model exhibited a

lower false-negative rate compared to other configurations, suggesting improved reliability for clinical deployment. False positives, while less critical from a safety standpoint, may still contribute to unnecessary retakes and workflow inefficiencies; however, these errors are generally preferable to false negatives in radiographic quality assurance.

A comparative evaluation with previous studies (Table XXII) demonstrates that the proposed VGG16-based approach achieves competitive performance relative to more complex frameworks such as CNN-SVM hybrids or object detection-based models (e.g., YOLOv8). Importantly, the proposed method maintains a lightweight architecture and efficient training process, making it more practical for real-world clinical implementation.

Overall, these findings indicate that domain-adapted transfer learning, when combined with architectural simplification and normalization strategies, can effectively enhance model generalization for automatic panoramic radiograph quality assessment. By providing reliable differentiation between diagnostically acceptable and poor-quality images, the proposed approach has the potential to reduce unnecessary retakes, improve patient safety by minimizing radiation exposure, and support standardized quality control in dental radiology practice.

Despite the promising results, this study has several limitations. The relatively small dataset, although carefully curated with expert consensus, may limit the generalizability of the proposed models to broader clinical settings. While the use of transfer learning, GAP, BN, and *k*-fold cross-validation helps mitigate overfitting, external validation using independent datasets from additional institutions would provide stronger evidence of generalizability. Furthermore, ablation studies investigating the effects of dataset size and class balance were not conducted and will be considered in future research.

TABLE XXII. CITATION-ONLY CONTEXTUAL COMPARISON

No	Model	Research Focus	Evaluation Results
1	Model CNN feature fusion+SVM [28]	Patient positioning errors (multi-class)	Accuracy=83.2%, AUC up to 0.998
2	YOLOv8 Classification Model [12]	Radiograph quality	Artifacts (Accuracy=87.2%, Precision=88.9%, F1-Score=0.864-0.943); Coverage area (Accuracy=74.1%, Precision =83.3-91.3%, F1-Score=0.769-0.941); Patient positioning (Accuracy=77.3%, Precision=76.9%, F1-Score=0.72-0.67); Contrast/Density (Accuracy=97.9%, Precision=83.3-84.6%, F1-Score=0.782-0.765); Overall image quality (Accuracy=79.3%, Precision=81.4%, F1-Score=0.809-0.820)
3	Proposed Method	Radiograph quality (good and poor)	Accuracy=85.00%, Precision=87.11%, Recall=86.27%, F1-score=85.31%, AUC=94.72%, Specificity=84.55%

V. CONCLUSION

Based on the experimental results and analysis, the proposed transfer learning-based CNN models demonstrated promising performance in the automatic quality classification of panoramic dental radiographs. Among the evaluated architectures, the VGG16 model enhanced with Global Average Pooling (GAP) and Batch Normalization (BN) and optimized using the Adam optimizer achieved the best overall performance under *k*-fold cross-validation, with an average accuracy of 85.00%, precision of 87.11%, recall of 86.27%, F1-score of 85.31%, AUC of 94.72%, and specificity of 84.55%. The integration of GAP and BN effectively improved training stability and reduced overfitting, allowing the model to generalize well across folds. These findings confirm that the domain-adapted transfer learning approach can provide a stable and reliable framework for automated panoramic radiograph quality assessment. In the future, expanding the dataset and incorporating external validation across multiple institutions will further strengthen model generalizability and clinical applicability. This study contributes to advancing AI-based quality assurance systems in dental radiology, enabling more consistent diagnostic outcomes and reducing retake rates in clinical practice.

Based on these findings, several directions for future research are recommended: Increasing data quantity and diversity to improve model robustness and generalization. Further fine-tuning of pretrained models to better adapt to radiographic features. System implementation and integration into clinical workflows for real-time image quality assessment.

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REFERENCES

[1] G. Kaeppler, D. Axmann-Krcmar, I. Reuter, J. Meyle, and G. Gómez-Román, "A clinical evaluation of some factors affecting image quality in panoramic radiography," Dentomaxillofacial Radiology, vol. 29, no. 2, 2000, doi: 10.1038/sj.dmfr.4600505.

[2] J. Faure and A. Engelbrecht, "A Convolutional Neural Network for Dental Panoramic Radiograph Classification," in ACM International

Conference Proceeding Series, Association for Computing Machinery, Apr. 2021, pp. 54–59. doi: 10.1145/3461598.3461607.

[3] A. Khator, M. Motwani, and A. Choudhary, "A study for determination of various positioning errors in digital panoramic radiography for evaluation of diagnostic image quality," Indian Journal of Dental Research, vol. 28, no. 6, 2017, doi: 10.4103/ijdr.IJDR_781_16.

[4] A. Loughlin, N. Drage, C. Greenall, and D. J. J. Farnell, "An investigation in to the impact of acquisition location on error type and rate when undertaking panoramic radiography," Radiography, vol. 23, no. 4, 2017, doi: 10.1016/j.radi.2017.07.004.

[5] N. Kumar, "Assessment of common errors and subjective quality of digital panoramic radiographs in a dental institution," Dentistry and Medical Research, vol. 8, no. 1, 2020, doi: 10.4103/dmr.dmr_22_19.

[6] A. S. Lingam, P. Koppolu, R. Abdulsalam, R. L. Reddy, A. Anwarullah, and D. Koppolu, "Assessment of common errors and subjective quality of digital panoramic radiographs in dental institution, Riyadh," Ann Afr Med, vol. 22, no. 1, 2023, doi: 10.4103/aam.aam_213_21.

[7] H. Abdul-Wahab, D. J. Ferguson, and N. Abou-Kheir, "Assessment of panoral radiograph quality in a dental treatment center," APOS Trends in Orthodontics, vol. 6, 2016, doi: 10.4103/2321-1407.177960.

[8] N. R. Suparno, A. Faizah, and A. N. Nafisah, "Assessment of Panoramic Radiograph Errors: An Evaluation of Patient Preparation and Positioning Quality at Soelastri Dental and Oral Hospital," Open Dent J, vol. 17, no. 1, 2023, doi: 10.2174/0118742106261974230925073155.

[9] H. Sun et al., "An AI-Based Image Quality Control Framework for Knee Radiographs," J Digit Imaging, vol. 36, no. 5, 2023, doi: 10.1007/s10278-023-00853-6.

[10] K. Nousiainen, T. Mäkelä, A. Piilonen, and J. I. Peltonen, "Automating chest radiograph imaging quality control," Physica Medica, vol. 83, 2021, doi: 10.1016/j.ejmp.2021.03.014.

[11] Q. Lai et al., "Quality control of elbow joint radiography using a YOLOv8-based artificial intelligence technology," Eur Radiol Exp, vol. 8, no. 1, Dec. 2024, doi: 10.1186/s41747-024-00504-7.

[12] N. Ameli, M. Miri Moghaddam, H. Lai, and C. Pacheco-Pereira, "Automated quality evaluation of dental panoramic radiographs using deep learning," Imaging Sci Dent, vol. 55, no. 2, p. 175, 2025, doi: 10.5624/isd.20240232.

[13] H. S. Kim et al., "Refinement of image quality in panoramic radiography using a generative adversarial network," Dentomaxillofacial Radiology, vol. 52, no. 5, 2023, doi: 10.1259/dmfr.20230007.

[14] E. Delamare, X. Fu, Z. Huang, and J. Kim, "Panoramic imaging errors in machine learning model development: a systematic review," Dentomaxillofac Radiol, vol. 53, no. 3, 2024, doi: 10.1093/dmfr/twae002.

[15] M. Y. Ichahane and N. Assad, "Multi-Model Attention-Enhanced CNN Ensemble for Automated Osteoporosis Detection in Radiographic Knee Images," International Journal of Intelligent Engineering and Systems, vol. 18, no. 3, pp. 177–194, 2025, doi: 10.22266/ijies2025.0430.13.

[16] A. Fariza, R. Asmara, E. R. Astuti, and R. H. Putra, "Tooth and Supporting Tissue Anomalies Detection from Panoramic Radiography Using Integrating Convolution Neural Network with Batch Normalization," International Journal of Intelligent Engineering and Systems, vol. 17, no. 2, 2024, doi: 10.22266/ijies2024.0430.19.

[17] N. Nafi'iyah, C. Fatichah, D. Herumurti, E. R. Astuti, R. H. Putra, and A. S. Akbar, "Automatic for Generating Landmark Mandibular Panoramic Radiography Image," International Journal of Intelligent Engineering and Systems, vol. 17, no. 1, pp. 584–595, 2024, doi: 10.22266/ijies2024.0229.49.

[18] Kamal and H. Ez-zahraouy, "A comparison between the VGG16, VGG19 and ResNet50 architecture frameworks for classification of normal and CLAHE processed medical images," Res Sq, 2023.

[19] J. Lin, Y. Ma, W. Lu, Z. Qu, Z. Jin, and J. Zhou, "Panoramic radiograph quality assessment: Database and algorithm," Displays, vol. 82, 2024, doi: 10.1016/j.displa.2023.102625.

[20] J. C. Mello Román et al., "Panoramic dental radiography image enhancement using multiscale mathematical morphology," Sensors, vol. 21, no. 9, 2021, doi: 10.3390/s21093110.

[21] H. Mohammad-Rahimi et al., "Super-Resolution of Dental Panoramic Radiographs Using Deep Learning: A Pilot Study," Diagnostics, vol. 13, no. 5, 2023, doi: 10.3390/diagnostics13050996.

[22] A. C. Subbulakshmi, N. Mohan, R. Thiruneervannan, S. Naveen, and S. Gokulraj, "Positioning errors in digital panoramic radiographs: A study," J Orofac Sci, vol. 8, no. 1, 2016, doi: 10.4103/0975-8844.181922.

[23] H. Maghbuli, T. Razi, E. Banakar, P. Emamverdizadeh, and S. Razi, "Positioning Errors in Panoramic Images Based on the Dentition Type of Patients Referring to the Oral and Maxillofacial Radiology Department of Tabriz Dental School During 2017-2018," Avicenna Journal of Dental Research, vol. 15, no. 2, 2023, doi: 10.34172/ajdr.2023.535.

[24] O. Almășan et al., "Post-Traumatic-Related Technical Errors in Orthopantomographic Imaging," Medicines, vol. 9, no. 12, 2022, doi: 10.3390/medicines9120063.

[25] E. D. Costa, W. G. Cral, F. P. Murad, M. L. Oliveira, G. M. B. Ambrosano, and D. Q. Freitas, "Prevalence of Errors and Number of Retakes in Panoramic Radiography: Influence of Professional Training and Patient Characteristics," International journal of odontostomatology, vol. 15, no. 3, 2021, doi: 10.4067/s0718-381x2021000300719.

[26] R. Izzetti, M. Nisi, G. Aringhieri, L. Crocetti, F. Graziani, and C. Nardi, "Basic knowledge and new advances in panoramic radiography imaging techniques: A narrative review on what dentists and radiologists should know," Applied Sciences (Switzerland), vol. 11, no. 17, 2021, doi: 10.3390/app11177858.

[27] H. G. Yeom et al., "Correlation between spatial resolution and ball distortion rate of panoramic radiography," BMC Med Imaging, vol. 20, no. 1, 2020, doi: 10.1186/s12880-020-00472-5.

[28] H. Y. Su et al., "Fusion extracted features from deep learning for identification of multiple positioning errors in dental panoramic imaging," J Xray Sci Technol, vol. 31, no. 6, 2023, doi: 10.3233/XST-230171.

A Multi-View Classification Method for Distribution Network Towers Based on Improved EfficientNet

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***Abstract*—View recognition of distribution network towers is a key technology in UAV intelligent inspection. To address the problem of low accuracy of existing deep learning methods in complex background interference, this paper proposes a tower view classification method based on EfficientNet that integrates foreground perception, multi-scale feature fusion, and dual-dimensional attention. First, a Mask-Guided Fusion Module (MGFM) is designed to extract tower foreground masks using the BiRefNet network, enhancing foreground representation and suppressing background interference through a two-stage fusion strategy. Second, a Multi-Scale Attention Aggregation Module (MSAA) is constructed to achieve efficient cross-layer feature fusion through parallel multi-scale convolution, fully integrating shallow details and deep semantic information. Finally, the Convolutional Block Attention Module (CBAM) is introduced to adaptively strengthen view-discriminative features through channel and spatial dual-attention mechanisms, significantly improving the recognition capability for small-sample categories such as top views. Ablation experiments on a self-built multi-view tower dataset show that the proposed method can effectively distinguish different views such as top view, front view, and side view, with significantly improved accuracy compared to other deep learning models, providing technical support for intelligent inspection of transmission lines.**

***Keywords*—Multi-view classification of power towers; mask-guided feature fusion; BirefNet; multi-scale feature fusion; convolutional block attention**

I. Introduction

Transmission lines constitute a critical component of modern power systems, and their safe and stable operation is essential for national economic development and public quality of life [1, 2]. Owing to the vast geographical coverage of transmission networks—often deployed across complex terrains such as mountainous regions and river crossings—traditional manual inspection methods are increasingly constrained by low efficiency, high operational costs, and potential safety risks. In recent years, the rapid development of unmanned aerial vehicle (UAV) technology has enabled vision-based intelligent inspection to emerge as a promising alternative for power infrastructure monitoring [3].

As the primary load-bearing structures of transmission lines, towers play a decisive role in ensuring system reliability. During UAV-based inspection, accurately recognizing the shooting viewpoint of a tower (e.g., front, side, or top view) provides essential spatial context for subsequent inspection tasks, including defect detection, component localization, and three-dimensional reconstruction [4, 5]. Moreover, reliable viewpoint information can facilitate inspection path planning and improve the overall efficiency and consistency of automated inspection workflows. Consequently, high-accuracy and robust tower viewpoint recognition is of significant practical importance for intelligent power inspection systems.

Existing inspection solutions have achieved notable progress by leveraging advances in computer vision and deep learning. Nevertheless, real-world UAV inspection scenes remain highly challenging. Images are frequently captured under complex natural backgrounds, varying illumination conditions, and occlusions, which can severely degrade recognition performance. In addition, inspection data often exhibit strong viewpoint imbalance, where certain viewpoints—such as top views—are underrepresented, further limiting the robustness of conventional recognition pipelines. These practical constraints highlight the need for viewpoint recognition approaches that are not only accurate but also resilient to background interference and data imbalance.

Recent research trends indicate that enhancing visual recognition performance often relies on improved foreground perception, multi-scale feature representation, and attention-based feature refinement. While these directions have demonstrated effectiveness in general vision tasks, they are typically explored in isolation or adopted as generic components without being explicitly tailored to the characteristics of UAV-based tower inspection. As a result, existing approaches struggle to jointly address background suppression, cross-scale feature interaction, and viewpoint-discriminative enhancement within a unified framework, particularly under complex inspection scenarios.

To bridge this gap, this paper investigates the following research question: how can foreground awareness, multi-scale feature interaction, and attention-driven discrimination be systematically integrated into a unified, task-oriented framework to improve tower viewpoint recognition under real UAV inspection conditions? To address these issues, this paper proposes a task-oriented and stage-wise tower viewpoint recognition framework based on EfficientNet-B4. The proposed approach organizes viewpoint recognition as a progressive enhancement process, explicitly strengthening foreground guidance, adaptive multi-scale interaction, and viewpoint-discriminative attention in a coordinated manner.

The main contributions of this work are summarized as follows: 1) A task-oriented, stage-wise viewpoint recognition

framework is developed to systematically integrate foreground-guided perception, adaptive multi-scale feature fusion, and attention-based discrimination for UAV-based tower inspection. 2) A Mask-Guided Fusion Module (MGFM) is introduced to enhance tower foreground perception and suppress complex background interference through a two-stage fusion strategy. 3) A Multi-scale Attention Aggregation Module (MSAA) and a dual-dimensional attention mechanism are incorporated to strengthen cross-scale feature interaction and improve recognition robustness for minority viewpoints. The remainder of this paper is organized as follows. Section II reviews related work on UAV-based inspection, viewpoint recognition, and feature enhancement strategies. Section III details the proposed framework and its constituent modules. Section IV presents the experimental setup and comprehensive performance evaluation is given in Section V. Finally, Section VI concludes the paper and discusses future research directions.

II. Related Work

A. UAV-Based Intelligent Inspection of Power Infrastructure

Unmanned aerial vehicles (UAVs) have been increasingly adopted in power infrastructure inspection due to their flexibility, low operational cost, and capability to access complex terrains that are difficult for manual inspection. Existing UAV-based inspection systems mainly focus on tasks such as transmission line detection, tower localization, and defect identification. Early studies relied on handcrafted visual features and traditional image processing techniques to extract tower or line structures from aerial images. However, these methods generally exhibit limited robustness under complex backgrounds, illumination variations, and occlusion.

With the advancement of deep learning, convolutional neural networks (CNNs) have become the dominant paradigm in UAV-based power inspection. Shajahan et al. [6] proposed a ROS-based computer vision framework to automatically locate tower regions of interest in UAV images, while Manninen et al. [7] developed a multi-stage deep learning network for automated assessment of transmission infrastructure using fly-by images. These approaches demonstrate the effectiveness of data-driven feature learning for inspection tasks. Nevertheless, in most existing works, viewpoint information is treated as an implicit factor rather than an explicit recognition objective. In practical inspection workflows, viewpoint recognition can provide reliable spatial priors for downstream tasks such as defect detection, component localization, and three-dimensional reconstruction. Despite its practical significance, tower viewpoint recognition has received comparatively limited attention as an independent and systematically studied problem in UAV inspection literature.

B. Viewpoint Recognition and Multi-View Classification

Viewpoint recognition and multi-view classification have been widely studied in computer vision, aiming to learn discriminative representations across different observation angles. Recent studies indicate that exploiting viewpoint diversity plays a crucial role in enhancing feature discrimination. Liu et al. [8] explored trusted multi-view deep learning frameworks and demonstrated that effective aggregation of multi-view information can significantly improve classification robustness and accuracy. Yan et al. [9] provided a comprehensive review of deep multi-view learning methods, highlighting the importance of self-attention and cross-attention mechanisms in aligning cross-view representations and modeling inter-view dependencies.

In the context of power infrastructure inspection, viewpoint information has also been recognized as an important factor for improving downstream perception tasks. Luo et al. [10] conducted a comprehensive survey of UAV-based intelligent transmission line inspection systems and emphasized that viewpoint awareness is critical for subsequent tasks such as defect detection and three-dimensional reconstruction. Furthermore, Faisal et al. [11] pointed out in their recent review that although traditional inspection methods may still be effective under constrained conditions, their generalization capability is significantly inferior to that of end-to-end deep learning models, particularly in complex real-world environments.

Despite these advances, existing multi-view learning and inspection-oriented approaches are mostly designed for generic scenarios or treat viewpoint as auxiliary information rather than an explicit recognition target. When directly applied to UAV-based tower inspection, such methods often struggle with severe background interference, viewpoint ambiguity, and class imbalance, especially for minority viewpoints. These limitations highlight the necessity of developing task-specific viewpoint recognition frameworks that explicitly model viewpoint discrimination under realistic UAV inspection conditions.

Meanwhile, generic image classification architectures have evolved rapidly, from classical convolutional neural networks to modern transformer-based models. Architectures such as Inception, ResNet, and VGG have achieved strong performance on large-scale benchmarks, while Vision Transformer (ViT) and Swin Transformer further improve global modeling capability through self-attention mechanisms. Although these models provide powerful feature extractors, they are primarily designed for generic object recognition tasks. When directly applied to UAV-based tower viewpoint recognition, their performance may be limited by severe background interference, viewpoint ambiguity, and class imbalance commonly encountered in real inspection scenarios. These characteristics distinguish tower viewpoint recognition from conventional multi-view benchmarks and call for task-specific modeling strategies.

C. Foreground Perception, Multi-Scale Feature Fusion, and Attention Mechanisms

Foreground perception and background suppression are essential for visual recognition in complex scenes. Segmentation-based methods have been widely used to obtain object-level priors that help reduce background interference, among which encoder–decoder architectures such as U-Net demonstrate the effectiveness of explicitly modeling foreground regions for complex visual environments [12]. Such priors are particularly valuable in UAV inspection images, where the target tower often occupies only a small portion of the image and is surrounded by cluttered natural backgrounds.

However, in many recognition pipelines, foreground extraction and classification are treated as separate stages, and the segmentation prior is not explicitly integrated into the feature learning hierarchy.

Multi-scale feature fusion is another key strategy for improving recognition robustness, as shallow features capture fine-grained spatial details while deep features encode high-level semantic information. Feature pyramid networks (FPN) explicitly construct hierarchical feature representations across multiple scales, highlighting the importance of structured cross-scale interaction for robust visual recognition [13]. In practice, various fusion strategies, including feature concatenation, weighted summation, and pyramid-based architectures, have been explored to exploit cross-scale complementarity. At the same time, attention mechanisms have been extensively investigated to enhance feature representation by emphasizing informative channels or spatial regions.

Despite these advances, existing fusion and attention mechanisms are typically applied as generic plug-and-play components. They are often optimized independently and lack a unified, task-oriented design that jointly considers foreground perception, cross-scale interaction, and viewpoint-discriminative enhancement. In the context of UAV-based tower inspection, this limitation becomes more pronounced under complex backgrounds and severe viewpoint imbalance. Consequently, there remains a gap in developing a coordinated and hierarchical framework that systematically integrates these techniques for robust tower viewpoint recognition.

III. Improved EfficientNet Algorithm

Unlike existing approaches that treat foreground perception, multi-scale fusion, and attention mechanisms as independent components, the proposed framework organizes these processes into a progressive enhancement pipeline specifically tailored for viewpoint recognition. The EfficientNet model [14] consists of three parts: input, backbone, and classification head. This paper selects EfficientNet-B4 as the baseline model with an input resolution of 380×380. The backbone starts with a Stem module (a stride=2, 3×3 standard convolution) followed by multiple MBConv modules. The MBConv module expands channels via a 1×1 convolution, extracts spatial features through depthwise separable convolution, integrates an SE module for adaptive channel recalibration, and finally restores the dimension via a 1×1 convolution with a residual connection to the input (see Fig. 1). The model employs a compound scaling strategy to jointly adjust network depth, width, and resolution, and applies stochastic depth regularization to enhance generalization, achieving an optimal balance between accuracy and efficiency.

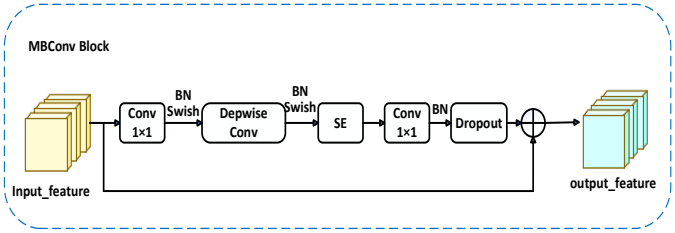


Fig. 1. The structure of MBConv.

Despite EfficientNet's strong performance in various vision tasks, it still faces challenges in the specific context of distribution network tower viewpoint recognition, including severe background interference, insufficient multi-scale feature fusion, and weak discriminative capability for minority viewpoints. To address this, a multi-module collaborative framework is proposed, in which three innovative modules are embedded at different stages of the backbone network to construct a progressive feature learning and enhancement mechanism. The overall framework adopts a "Foreground Guidance — Multi-scale Feature Fusion — Dual-dimensional Attention Modulation" three-stage enhancement strategy: First, the Mask-Guided Fusion Module (MGFM) is introduced at the shallow layer (Layer2). It uses a foreground mask extracted by BiRefNet [15] to spatially guide shallow features, enabling the network to focus on the tower body region early in feature learning and effectively suppress complex background noise. Second, the Multi-scale Attention Aggregation Module (MSAA) is deployed between the middle-deep layers (Layer3 and Layer5). It achieves intra-branch addition fusion and inter-layer feature concatenation through parallel multi-scale convolutions and channel attention weighting, fully integrating shallow details and deep semantic information. Finally, the Convolutional Block Attention Module (CBAM) is applied to the global features. Through dual channel and spatial attention mechanisms, it adaptively strengthens the feature response of viewpoint-discriminative regions, significantly enhancing the recognition robustness for minority classes like the top view. The overall architecture of the proposed model is illustrated in Fig. 2.

The three modules work synergistically to form a complete feature enhancement chain: MGFM solves the background interference problem at the source of feature extraction, providing high-quality foreground-enhanced features for subsequent modules; MSAA achieves efficient and complementary multi-scale feature fusion in the intermediate stage, breaking the limitations of traditional unidirectional propagation or simple concatenation; CBAM performs channel-spatial joint modulation at the decision front-end, ensuring the network can adaptively focus on the most discriminative regions and channels for different viewpoints. This hierarchical, progressive design philosophy closely aligns with the requirements of tower viewpoint recognition, enabling the model to receive targeted optimization at different abstraction levels, thereby achieving high-accuracy and robust multi-view classification performance.

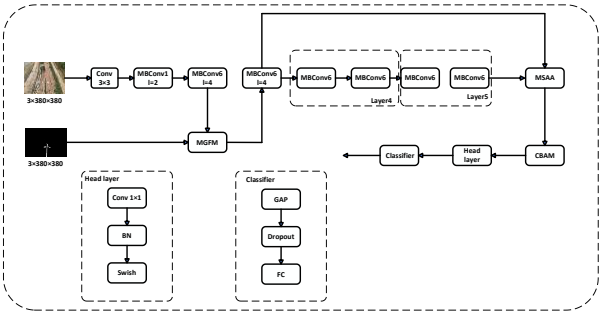


Fig. 2. The overall structure of the model.

A. MGFM Module

The Mask-Guided Fusion Module (MGFM) is designed to address the issue of foreground-background confusion in shallow feature extraction by traditional convolutional neural networks. In viewpoint classification tasks, objects under different viewpoints exhibit significant differences in foreground-background distribution. Conventional methods often treat foreground and background information equally, causing key foreground features to be corrupted by background noise and degrading subsequent viewpoint discrimination performance. Regarding the choice of the foreground segmentation network, this paper systematically evaluated several candidates and ultimately selected BiRefNet as the core component of the MGFM module. Compared to mainstream salient object detection networks such as U²-Net [16] and ISNet [17], BiRefNet demonstrates significant advantages in the power tower scenario. First, BiRefNet employs an innovative bidirectional refinement mechanism that leverages both top-down and bottom-up pathways in a collaborative manner, enabling it to simultaneously capture global semantic context and fine-grained local details. This characteristic is particularly crucial for power towers: as a structured object, a tower exhibits a clear topological hierarchy, which the top-down pathway effectively models through global contextual reasoning. Meanwhile, critical small-scale components (e.g., bolts, grading rings) possess strong discriminative power, and the bottom-up pathway ensures these fine details are preserved during segmentation. Second, BiRefNet achieves high segmentation accuracy while maintaining exceptional computational efficiency, with only 27.8 million parameters—significantly fewer than U²-Net or ISNet.

To leverage this high-quality prior, the MGFM module integrates the foreground mask generated by BiRefNet as spatial guidance. It is inserted after Layer2 of EfficientNet-B4 and employs a two-stage fusion strategy to enhance foreground representation and suppress background interference. The detailed structure of the MGFM is shown in Fig. 3.

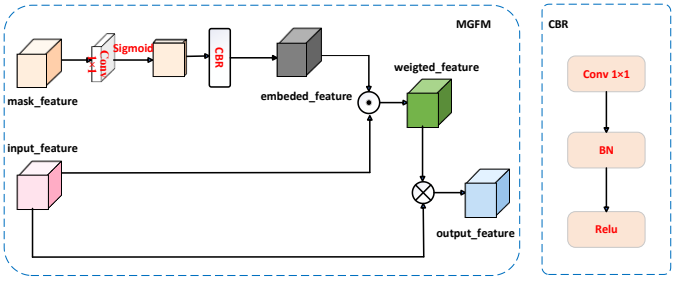


Fig. 3. The structure of MGFM.

The complete MGFM pipeline is as follows: 1) Mask Channel Compression: The three-channel RGB-format mask is first passed through a 1×1 convolutional layer to compress it into a single-channel grayscale map, which is then constrained to the [0,1] range via a Sigmoid activation function to generate a spatial attention prior. 2) Mask Resolution Alignment: The single-channel mask is upsampled/downsampled via bilinear interpolation to match the spatial resolution (H'×W') of the backbone feature map. 3) Mask Channel Embedding: The aligned single-channel mask is passed through another 1×1 convolutional layer, combined with Batch Normalization (BN) and ReLU activation, to map it to the same C-dimensional channel space as the backbone feature, generating the embedded mask Embedded_Mask. 4) Spatial Guidance Fusion: Embedded_Mask is element-wise multiplied (broadcasting) with the original feature Input_Feature to obtain the foreground-enhanced Weighted_Feature. 5) Adaptive Weighted Fusion: A learnable scalar parameter $\alpha \in [0,1]$ (constrained by Sigmoid) is introduced to linearly weight Weighted_Feature and the original Input_Feature.

The core advantage of the MGFM module lies in its efficient foreground perception capability. The mask embedding mechanism accurately identifies foreground regions, avoiding the negative impact of background interference on feature learning. The single learnable fusion parameter α allows the network to adaptively adjust the intensity of foreground enhancement based on task requirements, providing sufficient flexibility while maintaining model lightweightness.

B. MSAA Module

The Multi-scale Attention Aggregation Module (MSAA) is designed to address the limitations of traditional convolutional neural networks in cross-layer feature fusion, specifically the insufficient information interaction and limited multi-scale modeling capability. In deep networks, shallow features contain rich spatial details, while deep features encode stronger semantic information. However, these two types of features are often difficult to effectively collaborate due to their differing receptive fields and levels of abstraction. To this end, the MSAA module employs parallel multi-scale convolutional pathways combined with a channel attention mechanism to achieve efficient and complementary cross-layer feature fusion. Fig. 4 depicts the architecture of the proposed MSAA module. It is deployed after the outputs of Layer3 and Layer5 in EfficientNet-B4 to enhance the model's joint representation capability for both local details and global structures of the power tower.

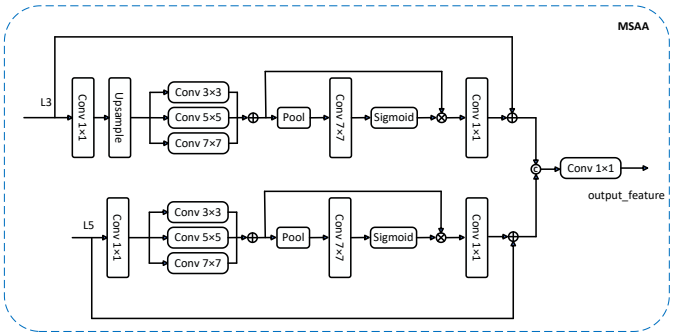


Fig. 4. The structure of MSAA.

The MSAA module's core pipeline consists of two main branches processing features from Layer3 and Layer5, respectively. For each input feature map, it is first mapped to a unified intermediate channel dimension via a Conv1×1, then replicated into three copies and fed into three parallel convolutional branches using Conv3×3, Conv5×5, and Conv7×7 kernels to cover a range of receptive fields from small to large. Within each parallel branch, channel attention

weights are generated through global average pooling, a 1×1 convolution (implemented as 7×7 due to 1×1 input), and Sigmoid activation, which are then used to modulate the original features. The channel-modulated feature maps are element-wise added to the original features to obtain the final output feature map for that branch. Finally, the final output feature maps from the Layer3 and Layer5 branches are concatenated along the channel dimension and compressed to produce the final fused feature map.

C. CBAM Module

To achieve finer feature selection and viewpoint-discriminative enhancement at the decision front-end, this paper introduces the Convolutional Block Attention Module (CBAM) [18] after global feature fusion. CBAM is a lightweight, plug-and-play attention mechanism that sequentially applies Channel Attention Mechanism (CAM) and Spatial Attention Mechanism (SAM) to doubly modulate the input feature map, thereby adaptively enhancing the response intensity of key regions and channels. The serial structure of CBAM is presented in Fig. 5.

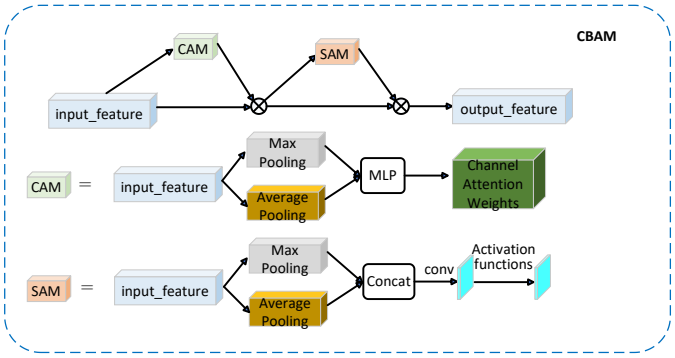


Fig. 5. The structure of CBAM.

The CBAM module adopts a serial structure of CAM and SAM to doubly modulate the input feature map. Its processing flow is as follows: First, the channel attention mechanism compresses the input feature map through Global Average Pooling (GAP) and Global Max Pooling (GMP) to generate two channel descriptors. These descriptors are then processed by a shared Multi-Layer Perceptron (MLP) for feature interaction and nonlinear transformation. Their outputs are summed and passed through a Sigmoid activation function to obtain the final channel attention weight map, which is element-wise multiplied with the original feature map to complete channel-wise adaptive recalibration. Next, the spatial attention mechanism takes the output from the previous step, performs max and average pooling along the channel dimension, concatenates the resulting two spatial maps, fuses them through a 7×7 convolutional layer, and applies a Sigmoid activation function to generate the spatial attention weight map. Finally, this spatial weight map is element-wise multiplied with the current feature map to achieve spatial focusing enhancement, yielding the final feature after dual channel-spatial attention modulation.

The core advantage of the CBAM module lies in its simple structure, high computational efficiency, and no requirement for additional annotations. In this work, the module is applied to the final feature map of the backbone network (before global average pooling). Its functions are: 1) highlighting key channel features relevant to viewpoint discrimination through channel attention; 2) focusing on the most discriminative regions in the image through spatial attention, thereby effectively suppressing background interference; 3) being particularly suitable for solving the recognition problem of minority viewpoints like the top view, as it can adaptively amplify the discriminative feature responses of these rare viewpoints.

IV. Experimental Setup

A. Experimental Environment and Dataset

The experimental hardware environment is shown in Table I. All experiments were conducted on a single server equipped with an NVIDIA GeForce RTX 3090, with CUDA 12.1 driver installed. The software environment uses Ubuntu 20.04 OS, Python 3.10, and deep learning frameworks PyTorch 2.2.1 and Torchvision 0.17.1. The ablation experiments used the AdamW optimizer with momentum parameters beta1 and beta2 set to 0.9 and 0.999, respectively. The model was trained for 30 epochs with a cosine annealing learning rate scheduler (maximum learning rate: 0.001), a batch size of 8, and a weight decay of 0.01.

TABLE I. Experimental Hardware Environment

Hardware	Model	Quantity
CPU	Intel Xeon 6148 Processor	1
Memory	Samsung DDR4 16GB	8
GPU	NVIDIA GeForce RTX 3090	1
Storage	Samsung SSD 980 PRO 2TB	1

The dataset was collected during routine UAV inspections conducted by a power grid company in real operational environments. All images were captured under clear weather conditions with sufficient natural illumination, which is representative of typical inspection scenarios. The UAV flight altitude ranged approximately from 11 m to 50 m, covering different observation distances and view scales. The dataset mainly includes two common structural types of distribution network towers, namely reinforced concrete towers and angle steel towers. In addition, multiple functional tower categories are involved, including straight-line towers, strain towers, and angle towers. Such diversity in acquisition conditions and tower configurations contributes to the robustness and generalization ability of the proposed method. The dataset used in this paper is a distribution network tower dataset captured by a power grid company, containing 5,268 multi-view tower images. There are three viewpoint types: front/back, side, and top. The dataset was randomly split into training and validation sets at a 7:3 ratio, with the validation set also serving as the test set, resulting in 3,686 training images and 1,582 validation/test images.

B. Evaluation Metrics

1) Top-1 accuracy: Accuracy is the most intuitive and commonly used evaluation metric in classification tasks, measuring the proportion of samples correctly predicted by the model. In viewpoint classification, accuracy reflects the

model's overall performance in recognizing different viewpoints (front/back, side, top). The formula is:

$$Accuracy = \frac{\sum_{i=1}^{C} TP_i}{N} \quad (1)$$

where C is the number of classes, N is the total number of samples, and TP_i is the number of true positives for class i. While accuracy provides an intuitive measure of overall performance, it can be misleading under class imbalance.

2) Macro-F1 score: To fairly evaluate the model's performance on each class (especially minority classes), this paper adopts the Macro-F1 Score. The F1 score is the harmonic mean of Precision and Recall:

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} = \frac{2TP}{2TP + FP + FN} \quad (2)$$

Where, FP and FN are the false positives and false negatives for class, respectively. The Macro-F1 Score is the arithmetic mean of the F1 scores of all classes, independent of the number of samples per class:

$$F1_{\text{macro}} = \frac{1}{C} \sum_{i=1}^{C} F1_i \quad (3)$$

V. Experiments and Results Analysis

A. Ablation Study on Individual Modules

To validate the effectiveness of each proposed module, a systematic ablation study is conducted on a self-built multi-view tower dataset. The results are summarized in Table II.

TABLE II. Ablation Study on Individual Modules

Model	Top-1/%	$F1_{\text{macro}}$/%
EfficientNet-B4	88.56	66.40
EfficientNet-B4+MGFM	89.82	69.97
EfficientNet-B4+MGFM+MSAA	90.71	71.75
EfficientNet-B4+MGFM+ MSAA+CBAM	92.38	72.26

The results demonstrate that each module contributes positively to model performance, and their combination yields strong synergistic effects. The MGFM module, serving as the foundation for foreground-aware perception, leverages high-quality foreground masks generated by BiRefNet to effectively suppress complex background interference. It improves Top-1 accuracy by 1.26% and boosts Macro-F1 by 3.57%, confirming the efficacy of foreground guidance in addressing background noise. Building upon this, the MSAA module further refines multi-scale feature fusion. Although it only increases Top-1 accuracy by 0.91%, it significantly raises Macro-F1 by 1.78%, indicating that its parallel multi-scale convolutions and channel-wise attention weighting effectively enhance the complementary representation between shallow details and deep semantics, thereby improving the model's joint modeling of local structures and global layouts of towers. Finally, the CBAM module, acting as a dual-modulation mechanism at the decision front-end, further elevates Top-1 accuracy by 1.65%, achieving a final accuracy of 92.38%. Its channel-spatial dual attention adaptively focuses on viewpoint-discriminative regions, substantially enhancing robustness for minority classes (e.g., top view) while maintaining class balance. Together, these three modules form a complete feature enhancement chain following the hierarchical design principle of "Foreground Guidance — Multi-scale Feature Fusion — Dual-dimensional Attention Modulation", effectively addressing the core challenges in distribution network tower viewpoint classification and validating the superiority of progressive feature enhancement in power vision tasks.

B. Comparison of Different Attention Mechanisms

To investigate the impact of attention mechanisms on classification performance, four representative attention modules—SE [19], ECA [20], EMA [21], and CBAM—are integrated before the classification head of the baseline model. The results are shown in Table III.

TABLE III. Comparison of Different Attention Mechanisms

Attention	Top-1/%	$F1_{\text{macro}}$/%
SE	87.73	66.38
ECA	88.59	64.46
EMA	88.25	65.15
CBAM	89.41	68.19

As shown, CBAM outperforms all other attention mechanisms in both Top-1 accuracy and Macro-F1. While SE, ECA, and EMA primarily operate in the channel dimension, CBAM's incorporation of spatial attention enables more comprehensive feature recalibration. This dual-dimensional modulation not only improves overall performance but also significantly enhances recognition of minority classes. The results confirm that, in tower viewpoint classification, spatial localization is as critical as channel-wise feature selection, and their joint optimization leads to more discriminative feature representations.

C. Comparison of Experiments

The full model is further compared with several mainstream deep learning architectures, including classical CNNs (Inception V3 [22], ResNet50 [23], VGGNet [24]) and modern vision transformers (ViT [25], Swin Transformer [26]). The results are presented in Table IV.

TABLE IV. Comparison of Experiments

Model	Top-1/%	$F1_{\text{macro}}$/%
EfficientNet-B4	88.56	66.40
MobileNetV3	88.75	77.08
ShuffleNetV2	85.30	63.57
Inception V3	83.43	64.69
Resnet 50	85.24	67.20
VggNet	83.18	64.72
Vision Transformer	88.57	67.42
Swin Transformer	90.42	70.35
Ours	92.38	72.26

The proposed method achieves a Top-1 accuracy of 92.38%, significantly outperforming all baseline approaches. Notably, it surpasses the second-best model (Swin Transformer) by 1.96% in accuracy and 1.91% in Macro-F1. This consistent improvement across both metrics—particularly the higher

Macro-F1—demonstrates that the proposed approach not only attains superior overall performance but also exhibits stronger robustness under class imbalance, which is a critical requirement for real-world power inspection scenarios.

To further evaluate the effectiveness of the proposed method under resource-constrained settings, a comparison is conducted with representative lightweight architectures, including MobileNetV3 and ShuffleNetV2. As shown in Table Ⅳ, MobileNetV3 achieves a Top-1 accuracy of 88.75% with a Macro-F1 of 77.08%, while ShuffleNetV2 attains 85.30% Top-1 accuracy and 63.57% Macro-F1. These results indicate that although lightweight models offer advantages in computational efficiency, their discriminative capability for viewpoint recognition—especially under class imbalance—remains limited.

D. Scalability Analysis Across Different EfficientNet Variants

To evaluate the scalability of the proposed modules, experiments are further conducted by integrating them into different EfficientNet variants. The results are shown in Table V.

TABLE V. PERFORMANCE COMPARISON ACROSS DIFFERENT EFFICIENTNET VARIANTS

Backbone	Baseline		Ours	
	Top-1(%)	*$F1_{macro}$(%)*	*Top-1(%)*	*$F1_{macro}$(%)*
Efficient-B0	90.77	70.47	92.58	74.68
Efficient-B1	87.62	66.37	89.35	68.13
Efficient-B2	87.41	66.29	89.93	67.82
Efficient-B3	89.43	68.37	93.16	70.46
Efficient-B4	88.56	66.40	92.38	72.26
Efficient-B5	87.27	67.38	88.15	68.29
Efficient-B6	89.49	69.41	91.24	71.31
Efficient-B7	86.43	66.15	86.19	65.32

As shown in Table V, the proposed method consistently improves performance over the corresponding baselines across most backbone scales. Notable gains in both Top-1 accuracy and Macro-F1 are observed for EfficientNet-B0 to B6, indicating that the proposed foreground-guided and multi-scale attention mechanisms generalize well across different model capacities.

In particular, the improvements in Macro-F1 demonstrate enhanced class-balanced recognition performance, suggesting that the proposed framework effectively alleviates viewpoint imbalance regardless of backbone depth. Although marginal performance saturation or slight fluctuation is observed on the largest backbone (EfficientNet-B7), the overall trend confirms that the proposed method is not limited to a specific EfficientNet configuration. These results validate the scalability and robustness of the proposed framework across a wide range of network capacities.

E. Confusion Matrix

To gain deeper insight into the model's classification performance for each individual category, particularly its error patterns, this section employs confusion matrices for visual analysis. In addition to the visual analysis, quantitative confusion-matrix-derived statistics are reported to further clarify class-wise misclassification behavior. Table VI summarizes the class-wise precision and recall of the baseline model and the proposed method, providing a quantitative comparison of classification performance across different viewpoints.

TABLE VI. CLASS-WISE PRECISION AND RECALL COMPARISON BETWEEN BASELINE AND PROPOSED METHOD

Class	Baseline		Ours	
	Precision(%)	*Recall(%)*	*Precision(%)*	*Recall(%)*
Front/Back	90.44	93.96	93.52	96.23
Side	92.26	89.07	96.76	90.86
Top	17.24	15.63	24.71	32.81

The confusion matrix clearly illustrates the model's classification and misclassification situations for each viewpoint category. The diagonal elements represent the proportion of correctly classified samples, while the off-diagonal elements reveal the category pairs that the model tends to confuse. The confusion matrices of the baseline model (EfficientNet-B4) and the models with the proposed modules incrementally integrated on the test set are compared, as shown in Fig. 6 to Fig. 9.

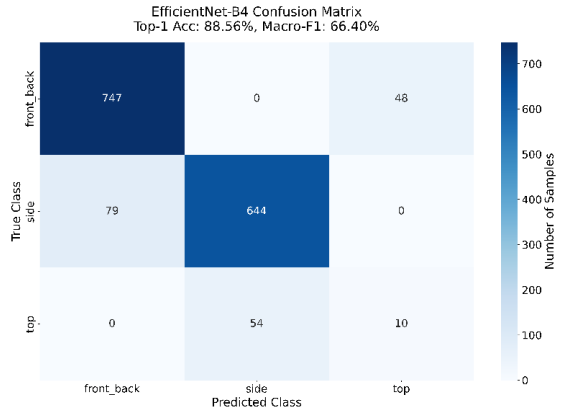


Fig. 6. Confusion matrix of the baseline model (EfficientNet-B4).

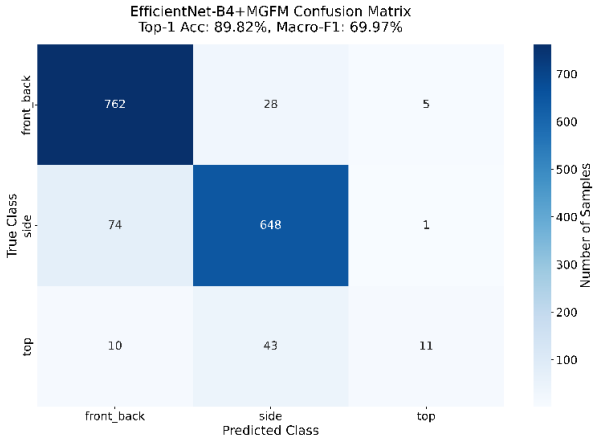


Fig. 7. Confusion matrix of the baseline model with MGFM.

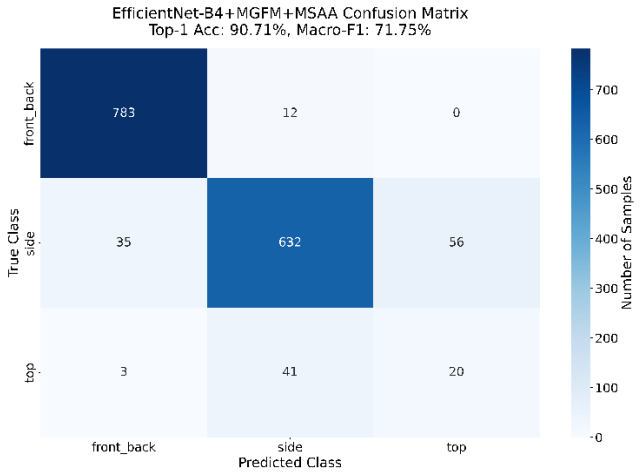


Fig. 8. Confusion matrix of the baseline model with MGFM and MSAA.

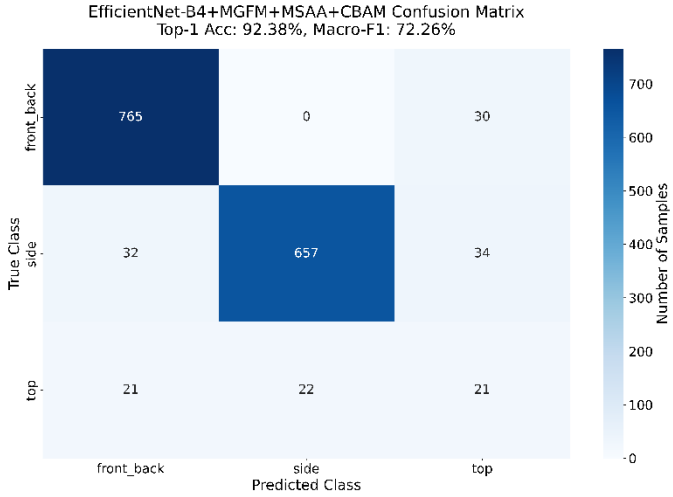


Fig. 9. Confusion matrix of the proposed full model (with MGFM, MSAA, and CBAM).

Fig. 6 illustrates the confusion matrix of the baseline EfficientNet-B4 model. Although satisfactory performance is achieved for the front/back and side viewpoints, severe misclassification is observed for the top view. A large proportion of top-view samples are incorrectly predicted as side view, resulting in extremely low recall for the top category. This indicates that the baseline model struggles to capture discriminative features for minority viewpoints under complex backgrounds, which directly contributes to the low Macro-F1 score. As shown in Fig. 7, after introducing the Mask-Guided Fusion Module (MGFM), the classification performance for front/back and side views is moderately improved, and background-induced misclassification is partially suppressed. However, confusion between the top and side viewpoints remains prominent, suggesting that foreground guidance alone is insufficient to resolve viewpoint ambiguity caused by scale variation and limited semantic discrimination. Fig. 8 presents the confusion matrix of the model with both MGFM and MSAA integrated. Compared with the previous configurations, the number of top-view samples correctly classified increases noticeably, while misclassification into the side category is reduced. This improvement demonstrates that multi-scale feature aggregation effectively enhances the representation of viewpoint-sensitive structural cues, particularly for small-scale and underrepresented viewpoints. Finally, Fig. 9 shows the confusion matrix of the full model incorporating MGFM, MSAA, and CBAM. The results reveal a substantial reduction in cross-view confusion across all categories. In particular, the recall of the top view is significantly improved, indicating that the attention-based modulation further strengthens viewpoint-discriminative regions in both channel and spatial dimensions. The overall confusion pattern becomes more compact along the diagonal, which is consistent with the highest Top-1 accuracy and Macro-F1 score achieved by the proposed method.

Overall, the progressive reduction of misclassification errors from the baseline to the full model validates the complementary roles of foreground guidance, multi-scale feature fusion, and dual-dimensional attention modulation. These results confirm that the proposed framework effectively alleviates viewpoint imbalance and enhances classification robustness in real UAV-based tower inspection scenarios.

F. Overall Experimental Discussion

Overall, the experimental results demonstrate that the proposed method achieves consistent and substantial performance improvements across different evaluation metrics and backbone configurations. Compared with the baseline model, the proposed framework improves Top-1 accuracy by up to 3.82% and Macro-F1 by more than 6%, with particularly notable gains observed on the minority top-view category. These improvements are most evident under challenging conditions, such as complex backgrounds and severe class imbalance, which commonly occur in real UAV-based power inspection scenarios. Consequently, the proposed method provides a more reliable and robust solution for tower viewpoint recognition, facilitating downstream inspection tasks and supporting practical deployment in real-world power grid applications.

VI. Conclusion

To address the key challenges in multi-view classification of distribution network towers—such as severe background interference, difficulty in recognizing minority viewpoints, and insufficient cross-scale feature interaction—this paper presents an improved EfficientNet-B4-based viewpoint recognition framework. A progressive three-stage enhancement mechanism, consisting of foreground-guided perception, adaptive multi-scale feature fusion, and dual-dimensional attention modulation, is constructed to systematically enhance viewpoint-discriminative representations.

Extensive experimental results on a self-built multi-view tower dataset demonstrate that the proposed method achieves consistent and significant performance improvements under challenging UAV inspection conditions, including complex natural backgrounds and pronounced class imbalance. Specifically, foreground-guided feature extraction effectively suppresses background noise and emphasizes tower body regions, while adaptive multi-scale fusion fully exploits the complementary characteristics of shallow structural details and deep semantic information. In addition, the dual attention modulation mechanism further strengthens viewpoint-sensitive

regions, leading to substantial robustness gains for minority viewpoints, particularly the top view.

Beyond the specific application of tower viewpoint recognition, this work provides a generalizable framework for multi-view visual classification under challenging conditions. By organizing foreground guidance, multi-scale feature interaction, and attention-based discrimination into a unified progressive pipeline, the proposed method establishes a reusable design paradigm that can be extended to other UAV inspection tasks and viewpoint-sensitive recognition problems. Owing to its stage-wise and task-oriented design, the framework exhibits strong generality and transferability across different backbone configurations.

From a practical perspective, the consistent improvements in both Top-1 accuracy and Macro-F1—especially under complex backgrounds and severe class imbalance—directly translate into more reliable perception in real inspection scenarios. The robust viewpoint recognition results provide stable spatial priors for downstream tasks such as tower defect detection, component localization, inspection path planning, and three-dimensional reconstruction, thereby supporting real-world deployment beyond performance-driven architectural refinements. Future work will focus on three directions: (1) expanding the dataset scale and viewpoint diversity to further improve model generalization; (2) investigating lightweight deployment strategies to enable real-time inference on edge devices; and (3) exploring end-to-end joint optimization of viewpoint recognition and defect detection to construct a more integrated and efficient inspection perception pipeline.

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REFERENCES

[1] T. Aziz, Z. Lin, M. Waseem, and S. Liu, "Review on optimization methodologies in transmission network reconfiguration of power systems for grid resilience," *Int. Trans. Electr. Energy Syst.*, vol. 30, no. 12, p. e12704, Dec. 2020.

[2] B. Lu, Z. Yang, M. Ding, J. Ma, D. Sun, W. Li, and X. Zhao, "Vision-based transmission tower strain monitoring using industrial camera module and slider strain sensing mechanism," *J. Civ. Struct. Health Monit.*, vol. 15, no. 3, pp. 2419–2432, Mar. 2025.

[3] S. Zhang, Z. Li, L. Huang, K. Jia, and D. Zhang, "UAV transmission line transfer-acceptance technology based on vision," in *Proc. Int. Conf. Algorithm, Imaging Process., Mach. Vis. (AIPMV)*, Qingdao, China, 2023, pp. 129692S.

[4] Y. He, Z. Liu, Y. Guo, Q. Zhu, Y. Fang, and Y. Yin, "UAV based sensing and imaging technologies for power system detection, monitoring and inspection: a review," *Nondestruct. Test. Eval.*, vol. 40, no. 1, pp. 1–25, Nov. 2024.

[5] E. Pastucha, E. Puniach, A. Ścisłowitz, P. Ćwiąkała, and W. Niewiem, "3D Reconstruction of Power Lines Using UAV Images to Monitor Corridor Clearance," *Remote Sens.*, vol. 12, no. 22, p. 3698, Nov. 2020.

[6] N. M. Shajahan, A. Sasikumar, T. Kuruvila, and D. Davis, "Automated inspection of monopole tower using drones and computer vision," in *Proc. 2nd Int. Conf. Intell. Auton. Syst. (ICoIAS)*, Kollam, India, 2019.

[7] H. Manninen, C. J. Ramlal, A. Singh, J. Kilter, and M. Landsberg, "Multi-stage deep learning networks for automated assessment of electricity transmission infrastructure using fly-by images," *Electr. Power Syst. Res.*, vol. 209, p. 107948, Aug. 2022.

[8] W. Liu, X. Yue, Y. Chen, and T. Denoeux, "Trusted multi-view deep learning with opinion aggregation," in *Proc. 36th AAAI Conf. Artif. Intell. (AAAI)*, Vancouver, Canada, 2022, pp. 1–8.

[9] X. Yan, S. Hu, Y. Mao, Y. Ye, and H. Yu, "Deep multi-view learning methods: A review," *Neurocomputing*, vol. 448, pp. 106–129, Aug. 2021.

[10] Y. Luo, X. Yu, D. Yang, and B. Zhou, "A survey of intelligent transmission line inspection based on unmanned aerial vehicle," *Artif. Intell. Rev.*, vol. 56, no. 1, pp. 173–201, Apr. 2022.

[11] M. A. A. Faisal, I. Mecheter, Y. Qiblawey, J. Hernandez Fernandez, M. E. H. Chowdhury, and S. Kiranyaz, "Deep learning in automated power line inspection: A review," *Appl. Energy*, vol. 385, p. 125507, May 2025.

[12] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional networks for biomedical image segmentation," in Proc. Int. Conf. Medical Image Computing and Computer-Assisted Intervention (MICCAI), Munich, Germany, 2015, pp. 234–241.

[13] T.-Y. Lin, P. Dollár, R. Girshick, K. He, B. Hariharan, and S. Belongie, "Feature pyramid networks for object detection," in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 2017, pp. 2117–2125.

[14] M. Tan and Q. V. Le, "EfficientNet: Rethinking model scaling for convolutional neural networks," in *Proc. 36th Int. Conf. Mach. Learn. (ICML)*, vol. 97, pp. 6105–6114, 2019.

[15] P. Zheng, D. Gao, D.-P. Fan, L. Liu, J. Laaksonen, W. Ouyang, and N. Sebe, "Bilateral reference for high-resolution dichotomous image segmentation," *CAAI Artif. Intell. Res.*, vol. 3, p. 9150038, 2024.

[16] X. Qin, Z. Zhang, C. Huang, M. Dehghan, O. R. Zaiane, and M. Jagersand, "U²-Net: Going deeper with nested U-structure for salient object detection," *Pattern Recognit.*, vol. 106, p. 107404, Oct. 2020.

[17] M. Zhang, R. Zhang, Y. Yang, H. Bai, J. Zhang, and J. Guo, "ISNet: Shape matters for infrared small target detection," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2024.

[18] S. Woo, J. Park, J.-Y. Lee, and I. S. Kweon, "CBAM: Convolutional block attention module," in *Proc. 15th Eur. Conf. Comput. Vis. (ECCV)*, Munich, Germany, 2018, pp. 3–19.

[19] J. Hu, L. Shen, and G. Sun, "Squeeze-and-excitation networks," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2018, pp. 7132–7141.

[20] Q. Wang, B. Wu, P. Zhu, et al., "ECA-Net: Efficient channel attention for deep convolutional neural networks," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, pp. 11534–11542, 2020.

[21] D. Ouyang, S. He, G. Zhang, M. Luo, H. Guo, J. Zhan, and Z. Huang, "Efficient multi-scale attention module with cross-spatial learning," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, Vancouver, Canada, 2023, pp. 1–5.

[22] C. Szegedy, V. Vanhoucke, S. Ioffe, et al., "Rethinking the inception architecture for computer vision," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, pp. 2818–2826, 2016.

[23] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, pp. 770–778, 2016.

[24] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," in *Proc. Int. Conf. Learn. Represent. (ICLR)*, 2015.

[25] A. Dosovitskiy, L. Beyer, A. Kolesnikov, et al., "An image is worth 16x16 words: Transformers for image recognition at scale," in *Proc. Int. Conf. Learn. Represent. (ICLR)*, 2021.

[26] Z. Liu, Y. Lin, Y. Cao, et al., "Swin Transformer: Hierarchical vision transformer using shifted windows," in *Proc. IEEE/CVF Int. Conf. Comput. Vis. (ICCV)*, pp. 10012–10022, 2021.

Accessible Application Prototype for Improving Digital Reading in People with Dyslexia: User-Centered Design and Usability Validation

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***Abstract*—Digital reading remains a challenge for individuals with dyslexia due to the limited availability of accessible tools tailored to their cognitive and perceptual needs. Although many digital reading applications offer basic personalization options, they often lack integrated mechanisms to support reading comprehension and user autonomy. This study presents the design and usability validation of an accessible mobile application prototype aimed at improving the digital reading experience for people with dyslexia using a user-centered design approach. The research followed a design thinking methodology that included a systematic literature review, analysis of documented user needs from peer-reviewed studies and dyslexia support communities, personas development based on published user profiles, and a competitive analysis of existing accessible reading applications. The design process focused on identifying key pain points and developing interactive prototypes that integrate advanced text personalization, visual and auditory supports, text difficulty analysis, and intelligent accessibility suggestions. The proposed prototype enables users to customize font type and size, color, and spacing; activate text-to-speech functionality; highlight words or lines; upload and edit texts in multiple formats; and receive automated recommendations to enhance accessibility. Usability and accessibility were evaluated through expert heuristic assessment using established usability principles and WCAG 2.1 guidelines. Results indicate strong adherence to usability standards, with experts highlighting effective feature integration and identifying the need for additional instructional support for advanced functions. Overall, the proposed application addresses key gaps in digital reading accessibility and provides a foundation for future empirical validation with end users.**

***Keywords*—Dyslexia; digital accessibility; digital reading; usability; user-centered design**

I. Introduction

In the digital age, reading texts on electronic devices has become a fundamental activity in both education and professional life. However, for individuals with dyslexia, digital reading continues to pose a significant challenge due to the lack of truly accessible tools tailored to their specific needs [1]. Dyslexia is a neurobiological learning difficulty that affects the accuracy and fluency of word recognition as well as reading comprehension. It is estimated that around 10% of the world's population has some degree of dyslexia, making it one of the most common learning difficulties [2]. Furthermore, dyslexia accounts for up to 80% of diagnosed cases of reading-related learning disorders [1]. Scientific evidence shows that these difficulties persist into adulthood, being especially noticeable in reading and writing speed, while reading comprehension is usually less affected; the severity of symptoms may vary depending on the orthographic transparency of the language, but in all cases, there is a significant impact on the academic and social life of those affected [3]. These findings highlight the importance of developing inclusive and technologically advanced solutions that enable equal opportunities in access to information and education for people with dyslexia.

Despite technological advances and growing awareness of inclusion, many digital platforms still do not offer features adapted to the needs of people with dyslexia. Text personalization options, such as changing font, color, size, or spacing, are often limited or nonexistent. In addition, the integration of assistive technologies such as text-to-speech (TTS), word or line highlighting, and accessible navigation is absent in most digital reading applications. This lack of adequate tools can lead to frustration, low motivation, and difficulties in reading comprehension, affecting users' academic performance and autonomy [3].

User-centered design and user experience (UX) are fundamental approaches for the development of inclusive technological solutions. Understanding the documented needs and experiences of people with dyslexia in the design process makes it possible to identify their real requirements, preferences, and pain points, resulting in more effective and satisfactory products. In this context, the present research proposes the development and validation of a digital reading application prototype aimed at people with dyslexia. The application integrates functionalities such as advanced text personalization, guided mode, text-to-speech, difficulty analysis, and the generation of intelligent suggestions to improve accessibility and reading comprehension.

The main objective of this study is to analyze the challenges faced by people with dyslexia in digital reading and to evaluate the effectiveness and usability of the proposed application. The research questions guiding this work are:

What are the main challenges and needs of people with dyslexia when interacting with digital texts according to existing literature?

What features should be integrated into a digital reading application to improve accessibility and user experience based on evidence-based design principles?

How can heuristic evaluation validate the usability and accessibility of the proposed application design for people with dyslexia?

II. Literature Review

To achieve the objectives of this study, an exhaustive review of previous literature was conducted, focusing on existing problems and solutions related to digital reading accessibility for people with dyslexia. Keywords such as dyslexia, digital accessibility, digital reading, assistive technology, and user experience were used to search for relevant studies in academic databases such as ResearchGate, ScienceDirect, and Springer. Eighteen pertinent research articles were identified, addressing topics ranging from the characterization of reading difficulties in people with dyslexia to the analysis of technological tools and pedagogical strategies aimed at improving reading comprehension.

The literature review highlights the importance of text personalization, including font type, size, color, and spacing, as well as the integration of assistive technologies such as text-to-speech and word highlighting. These features are fundamental to facilitating digital reading for individuals with dyslexia. Additionally, studies were identified that analyze how age, educational level, and familiarity with technology influence the adoption and effectiveness of digital solutions. The reviewed articles also emphasize the need for intuitive interfaces, active user participation in the design process, and usability evaluation as key factors for the success of applications aimed at this group.

The results of the literature review reveal gaps in current digital solutions, especially regarding the absence of comprehensive tools that combine personalization, accessibility, and intelligent support. These findings underscore the need to develop and validate a user-centered digital reading application capable of addressing the real needs of people with dyslexia and promoting equal opportunities in access to information and education.

A. Reading Difficulties and Needs of People with Dyslexia

Digital reading represents a considerable challenge for individuals with dyslexia, who must overcome barriers such as word decoding, comprehension of lengthy texts, and visual fatigue. These difficulties not only affect motivation and academic performance but also limit autonomy and full participation in educational and social environments. The specialized literature indicates that dyslexia involves significant variability in the manifestations and needs of each individual, making the development of flexible and customizable solutions essential [4]. Various studies have shown that the ability to modify font type, size, color, and spacing can facilitate comprehension and reduce the cognitive effort required for reading [5]. Additionally, the use of visual supports, such as word or line highlighting and segmenting text into more manageable fragments, contributes to a more positive and effective reading experience [6]. However, the lack of comprehensive and accessible tools remains one of the main barriers for this group.

B. The Role of Technology in Reading Accessibility

Technological advances have enabled the development of digital tools that improve accessibility for people with dyslexia, transforming the way they access and process written information. Digital applications and platforms currently offer features such as text-to-speech, font and color changes, and spacing adjustments, which facilitate the adaptation of text to each user's needs [7]. The integration of these technologies in educational and professional settings has proven to be key in promoting inclusion and equal opportunities, allowing students and workers with dyslexia to actively participate in activities that were previously inaccessible [8]. However, the literature also warns that the effectiveness of these tools largely depends on their ease of use, the quality of personalization, and the training of users and educators in their implementation [9]. Therefore, user-centered design and continuous evaluation of the user experience are fundamental aspects for the success of technological solutions in this field.

C. Challenges in the Adoption of Accessible Digital Solutions

Despite technological advances, there are significant challenges in the adoption and effective use of accessible digital solutions for people with dyslexia. Among the main obstacles are the lack of standardization in accessibility features, limited training for users and educators, and the scarce availability of materials adapted to different levels of reading difficulty [10]. In addition, information overload, the complexity of some interfaces, and the absence of intelligent recommendations can hinder the reading experience and cause frustration among users [11]. The literature suggests that collaboration between developers, educators, and people with dyslexia is essential to identify real needs and design tools that effectively address them [12]. Likewise, the importance of continuous feedback and the adaptation of solutions to changes in users' preferences and abilities over time is emphasized.

D. Diversity of Age and Technological Experience in Usability

Age and technological experience significantly influence the usability and acceptance of accessible digital reading applications. Younger users, who have grown up in digital environments, tend to adapt more easily to new technologies and confidently explore personalization and support options [13]. In contrast, adults and older individuals may require more intuitive interfaces, clear instructions, and additional support to make the most of the available features [14]. The literature highlights the need to design flexible solutions that adapt to different levels of digital literacy and allow personalization according to each user's preferences and needs [15]. Furthermore, the active participation of people with dyslexia of different ages in the design and validation process of the tools helps improve acceptance, satisfaction, and the effectiveness of technological solutions [16].

E. Artificial Intelligence and Personalization in Digital Reading

Artificial intelligence is transforming reading accessibility through automatic content personalization, the generation of recommendations, and predictive analysis of difficulties. Platforms that integrate AI can suggest formatting adjustments, identify complex words, and offer summaries tailored to the user's level, thereby facilitating comprehension and reducing cognitive load [17]. In addition, AI enables real-time feedback, progress tracking, and dynamic adaptation of features according to user performance and preferences [18]. These capabilities contribute to a more autonomous, motivating, and personalized reading experience, allowing people with dyslexia to overcome traditional barriers and access information more equitably [19]. The literature agrees that the integration of AI into digital reading applications represents a key opportunity to advance toward a more inclusive education and society.

III. Methods

This study followed the design thinking process, which encompasses five phases:

1) empathize, 2) define, 3) ideate, 4) prototype, and 5) test.

A. Requirements Analysis

A systematic analysis of user needs was conducted through examination of published research, case studies, and user testimonials from dyslexia support communities. The analysis covered documented experiences from individuals aged between 10 and 55 years, with varying levels of experience with reading technologies, including students from different educational levels, professionals, and young adults. Sources included peer-reviewed articles, accessibility reports, and documented user experiences from dyslexia organizations and online support forums. The synthesis process involved analyzing fifteen key aspects identified in the literature about digital reading experiences, the main challenges faced, and the improvements or supports considered necessary to facilitate reading. The documented profiles represented a wide variety of cases, from individuals diagnosed with dyslexia in childhood to adults who have developed their own strategies to cope with reading. This qualitative information made it possible to accurately identify common user problems and needs, thus guiding the design and development of the proposed application prototype in this study.

B. Contextual Research

A comprehensive literature analysis and synthesis of published research were conducted to understand the reading habits, behaviors, and mental models of people with dyslexia when interacting with digital texts. Different documented user experiences and accessibility studies were analyzed from various perspectives to build a comprehensive understanding. For this study, a cultural model was developed based on established research findings to identify the values, needs, and factors that influence the reading experience of people with dyslexia. The cultural model (see Fig. 1) highlights the complexity and challenges faced by these users, helping to identify the critical points where the greatest difficulties arise. This analysis made it possible to visualize the main problems and provided the foundation for proposing a digital support system, based on an application with intelligent tools, aimed at facilitating and improving the reading experience for people with dyslexia. No direct interviews or surveys with individuals with dyslexia were conducted in this study; all user insights were derived from secondary sources including peer-reviewed publications, accessibility reports, and documented testimonials from established dyslexia organizations.

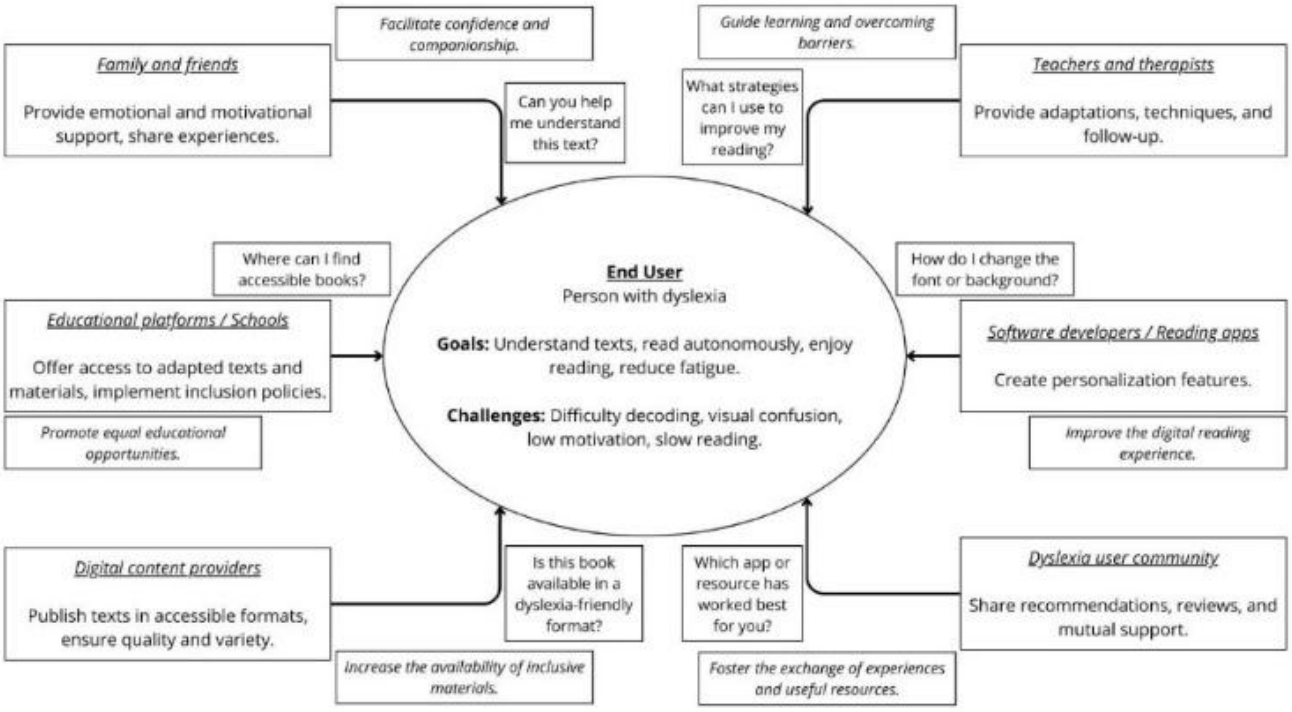


Fig. 1. Cultural model of a person with dyslexia.

C. Problem Definition

Analyzing the results of the literature review and documented user experiences revealed that digital reading represents a significant challenge for people with dyslexia in various aspects. Research indicates that users often face difficulties in understanding texts, maintaining concentration, and adapting materials to their specific needs. Additionally, differences were observed in published studies regarding how people of different ages and educational levels use digital reading tools: for example, younger users tend to explore more personalization options, while adults may feel less familiar with assistive technologies. Documented user feedback also expressed frustration due to the lack of accessible materials, limited text personalization, and the absence of recommendations tailored to their difficulties. To better understand the problem space, a fishbone diagram (see Fig. 2) was used, allowing for an exhaustive analysis of the causes and effects of the problems faced by people with dyslexia when interacting with digital texts.

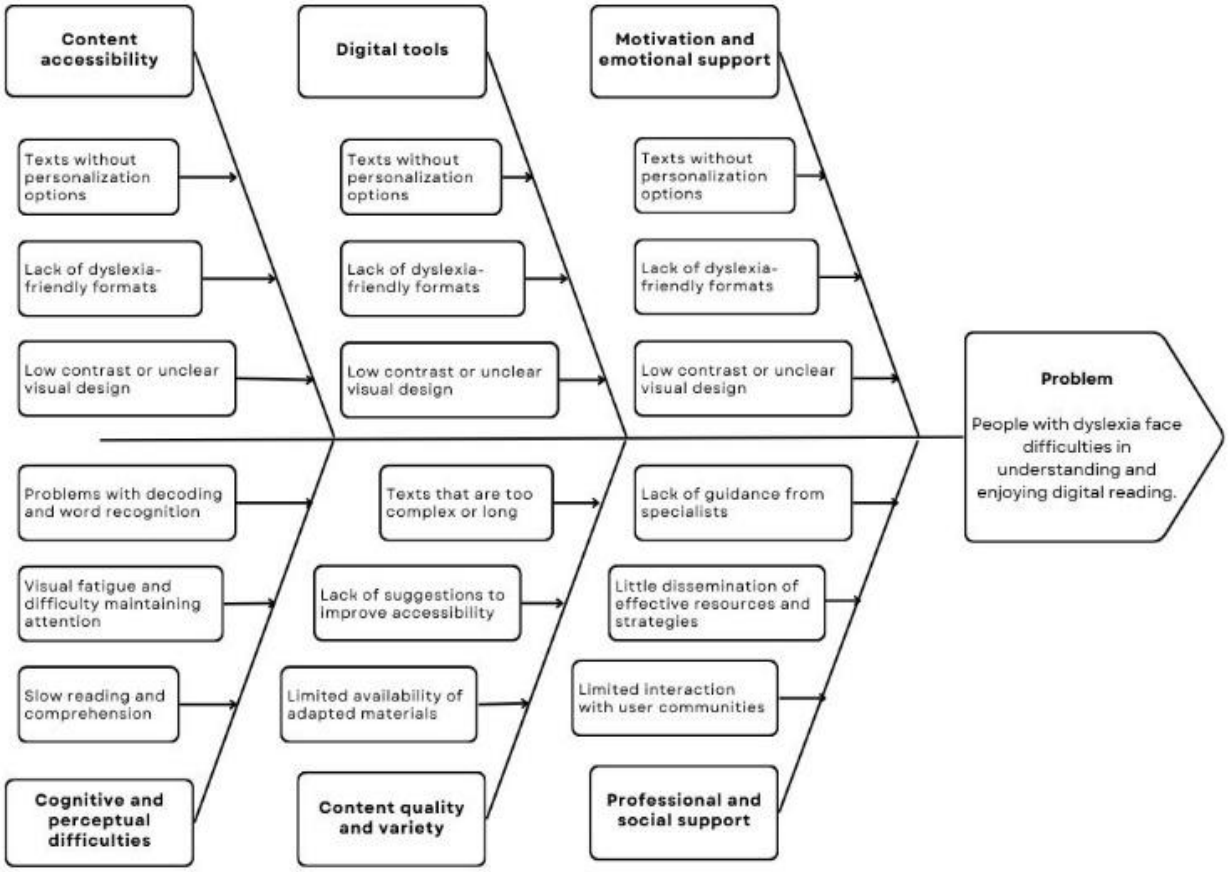


Fig. 2. Fishbone diagram.

D. Competitor Analysis

As shown in Table I, a competitor study was conducted in the field of accessible digital reading for people with dyslexia. The main competitors identified include Microsoft Immersive Reader, ClaroRead, and Voice Dream Reader. Microsoft Immersive Reader offers an inclusive reading experience integrated into various platforms, allowing text personalization, text-to-speech, and translation. ClaroRead is a popular tool that provides text-to-speech, font and color changes, and support for different text formats. Voice Dream Reader is a mobile application that stands out for its customization capabilities, support for multiple voices and formats, and ease of use.

The comparison focuses on essential features to improve accessibility and the reading experience, such as font and color personalization, text-to-speech, difficulty analysis, accessibility suggestions, and ease of use. Each platform has its strengths and limitations, which are summarized in Table I. The analysis shows that, although most applications offer personalization options and TTS, few include text difficulty analysis or intelligent suggestions to improve accessibility. Furthermore, not all platforms allow users to upload and edit texts in different formats or have an interface truly centered on accessibility.

E. Final Concept

Finally, the conceptual framework of the proposed application was consolidated as a comprehensive solution to enhance the digital reading experience for individuals with dyslexia. The app addresses the most common challenges faced by these users, such as difficulties in text customization, lack of support tools, and limited accessibility of materials. It offers advanced personalization options, read-aloud functionality, word or line highlighting, and text difficulty analysis. Additionally, it includes intelligent suggestions to improve accessibility and allows users to upload, edit, or write texts in various formats. The application also incorporates social

features, such as the ability to share adapted texts and recommendations within a user community. The final concept provides people with dyslexia an all-in-one, user-friendly tool focused on their needs, facilitating comprehension and enjoyment of digital reading. Table II presents the SCAMPER model used to enhance the accessibility services of the proposed solution. Table III summarizes the main features of the final idea.

TABLE I. COMPARATIVE TABLE OF KEY FEATURES OF THE MAIN COMPETITORS

Features	Competitors		
	Microsoft Immersive Reader	**ClaroRead**	**Voice Dream Reader**
Release year	2015	2004	2011
Main platform	Web, Windows, Office	Windows, Mac, iOS	iOS, Android
Font and color customization	✓	✓	✓
Dyslexia-friendly font	✓	✓	✓
Text-to-speech (TTS)	✓	✓	✓
Spacing and size adjustment	✓	✓	✓
Text highlighting/line guide	✓	✓	✓
Text difficulty analysis	✗	✗	✗
Accessibility suggestions	✗	✗	✗
File upload (PDF, DOCX, TXT)	✓	✓	✓
Text editing	✗	✓	✓
Clean, focused interface	✓	✓	✓
Keyboard navigation	✓	✓	✓
Adequate contrast	✓	✓	✓
ARIA labels and roles	✓	✗	✗
Total key features	11	10	10

TABLE II. SCAMPER MODEL FOR ACCESSIBILITY ENHANCEMENT

SCAMPER	Description
Substitute	• Traditional reading replaced by read-aloud and text highlighting. • Standard fonts substituted with dyslexia-friendly fonts.
Combine	• Combine font, color, and spacing customization in a single interface. • Integrate difficulty analysis and intelligent suggestions into the text editor. • Combine file upload and manual editing functions for greater flexibility.
Adapt	• Adapt gamification techniques to motivate reading (achievements, rewards). • Adapt accessibility strategies from other educational apps.
Modify	• Modify the interface to be cleaner, more focused, and distraction-free. • Improve keyboard navigation and accessibility for screen readers.
Put to another use	• Use the app as a support tool in classrooms or therapy. • Allow non-dyslexic users to customize reading to improve comprehension or language learning.
Eliminate	• Eliminate unnecessary features and complex menus. • Reduce notifications and visual elements that may distract the user.
Reverse	• Reverse the traditional approach of passive reading, promoting active interaction. • Reverse the help flow: the app automatically suggests improvements based on the uploaded text.

TABLE III. MAIN FEATURES OF THE PROPOSED SOLUTION

Main Feature	Description
Advanced text customization	Allows modification of font type and size, text and background color, and line and letter spacing to suit user needs.
Read-aloud (TTS)	Offers the option to read text aloud, with controls to pause, resume, and stop reading, facilitating auditory comprehension.
Guided mode and highlighting	Enables highlighting of the current line or word, helping maintain attention and improve visual tracking during reading.
Text upload and editing	Allows uploading files (PDF, DOCX, TXT), as well as pasting or manually writing text, providing flexibility in content access.
Difficulty analysis and suggestions	Analyzes the text's difficulty level and offers intelligent suggestions to improve accessibility, such as simplifying phrases or words.
Accessible and focused interface	Presents a clean interface focused on the text, with accessible controls, keyboard navigation, adequate contrast, and support for screen readers.

F. Prototype Evaluation

A heuristic evaluation method was employed to assess the usability of the proposed application prototype. Three accessibility experts with experience in assistive technology and dyslexia support tools conducted independent evaluations based on Nielsen's usability heuristics and WCAG 2.1 accessibility guidelines. The evaluation focused on specific interaction scenarios such as customizing text, using the read-aloud function, uploading and editing files, and analyzing text difficulty. Each expert independently assessed the interface against established usability principles, including learnability, efficiency, memorability, error prevention, and user satisfaction. The experts analyzed the prototype by simulating typical user tasks and identifying potential usability barriers for individuals with varying levels of technological experience. The evaluation results were consolidated through a structured review session, where findings were discussed and prioritized according to severity and potential impact on the target user experience.

IV. Results

A. Literature-Based User Needs Analysis

Analysis of published literature and documented user experiences revealed key aspects regarding the problems and preferences faced by people with dyslexia when reading digital texts across different age groups (10 to 55 years). Research findings indicate that approximately 60% of documented cases, especially among adults, report difficulties in finding accessible materials and customizing text formatting to their needs. Studies focusing on younger individuals (ages 10–25) consistently show frustration with the lack of intuitive digital tools and the limited integration of features such as read-aloud or word highlighting. According to accessibility research, 65% of reported cases across all ages indicate that visual fatigue and difficulty maintaining attention are frequent obstacles during digital reading. Additionally, 70% of documented user feedback emphasizes the importance of having customization options (font type, color, spacing) and a simple, distraction-free interface. Literature on adult users also highlights the need for suggestions to improve reading comprehension and for materials adapted to different levels of difficulty. Overall, the analysis demonstrated a strong demand for a single platform that facilitates digital reading, offers accessible support tools, and adapts to the needs of people with dyslexia of all ages. Documented user preferences show particular interest in a solution that would allow autonomous and personalized reading experiences.

B. User Interface Design Conceptualization

The idea for the application's user interface (UI) emerged from a systematic design thinking process, always focused on the needs and challenges of people with dyslexia. Initially, paper wireframes were created to represent the main user experiences, which allowed for the optimal placement of key elements such as customization controls, the reading area, and access to support functions. Subsequently, the Figma tool was used to develop high-fidelity interactive prototypes. The main interface and customization options are illustrated in the prototype (see Fig. 3). The reading view and text analysis features are also shown in a separate prototype (see Fig. 4). The design prioritized a clean layout, intuitive interactions, and a high-contrast color scheme, thus ensuring a visually pleasing, accessible, and user-centered experience.

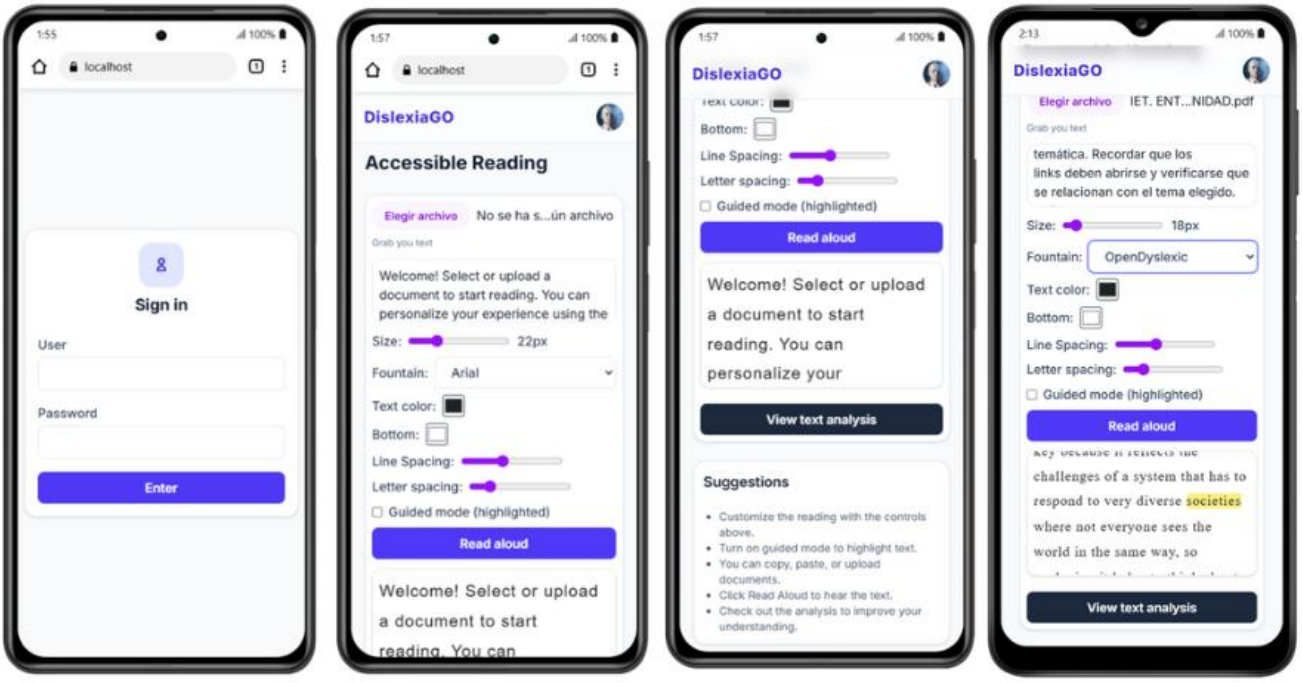


Fig. 3. High-fidelity interactive prototype of the proposed solution: main interface and customization options.

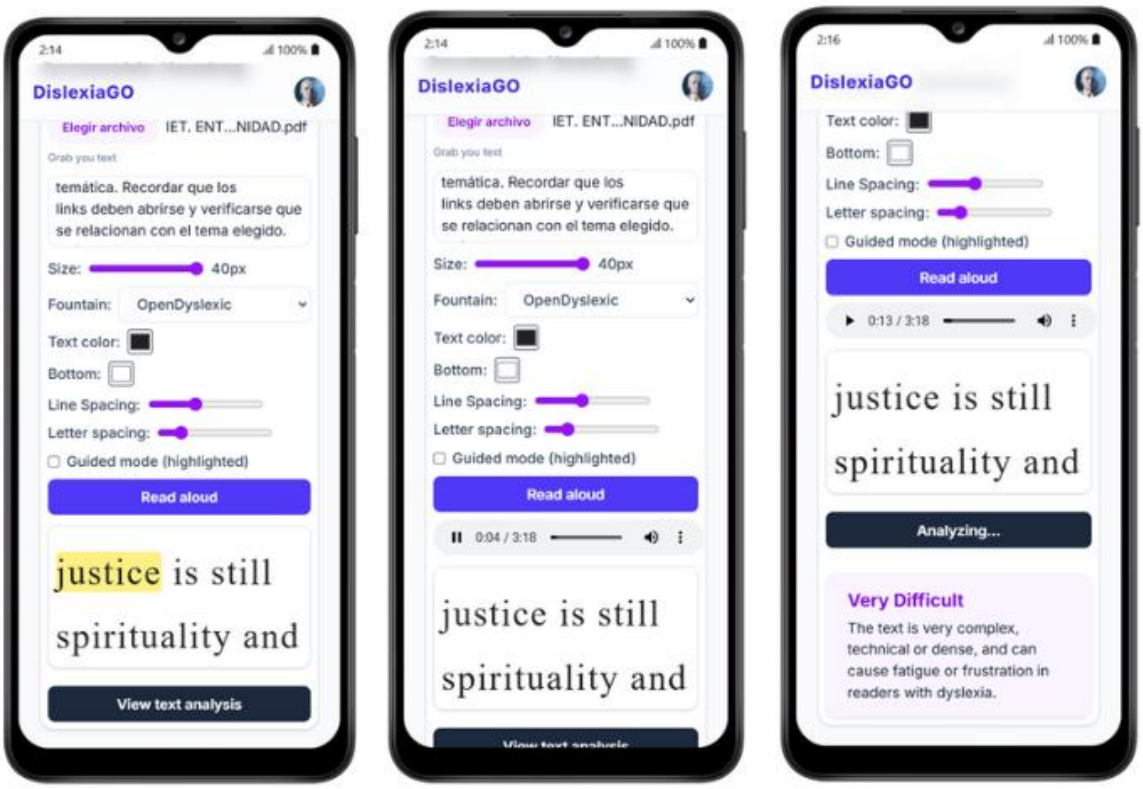


Fig. 4. High-fidelity interactive prototype of the proposed solution: reading view and text analysis features.

C. Usability Testing Information

The expert heuristic evaluation revealed that the application prototype demonstrates strong adherence to established usability principles and accessibility guidelines. The design was assessed as intuitive and accessible according to Nielsen's heuristics and WCAG 2.1 standards. Experts indicated that the interface design would likely encourage frequent use for reading activities among the target population. The organized interface style and the integration of the main features were particularly noted as strengths, especially the ease of customizing text and using the read-aloud function. However, evaluators identified that some advanced features, such as difficulty analysis or file editing, may require additional instructional support, particularly for older adult users with limited technological experience. One usability concern identified was the lack of consistency in some navigation flows, especially when switching between different customization modes. Experts recommended the incorporation of visual cues or interactive tutorials to help clarify the use of certain features. Despite these considerations, the evaluation indicated that the platform design follows user-centered principles and offers advantages over existing digital reading tools. Overall, the expert assessment reflects strong usability potential, although opportunities for improvement were identified to make some features even clearer and more accessible, especially for users with less technological experience. These findings will serve as a basis for future refinements aimed at providing a smoother and more enjoyable experience for all user profiles (Table IV).

TABLE IV. HEURISTIC EVALUATION SUMMARY

Usability Heuristic	Expert Assessment	Priority
Visibility of system status	Strong – Clear feedback on all actions	Low
Match between system and real world	Strong – Intuitive terminology and metaphors	Low
User control and freedom	Good – Undo/redo available, exit options clear	Medium
Consistency and standards	Moderate – Some inconsistencies in navigation flows	High
Error prevention	Strong – Confirmations for critical actions	Low
Recognition rather than recall	Strong – Visual cues and tooltips present	Low
Flexibility and efficiency of use	Good – Customization supports varied user needs	Medium
Aesthetic and minimalist design	Strong – Clean, focused interface	Low
Help users recognize and recover from errors	Good – Clear error messages provided	Medium
Help and documentation	Moderate – Advanced features need more guidance	High

III. Discussion

The use of digital technology has profoundly transformed the way people access information and develop reading skills, especially in educational and professional contexts. For individuals with dyslexia, the emergence of digital tools represents both an opportunity and a challenge. On one hand, technology offers the possibility to personalize the reading experience, facilitating comprehension and autonomy. On the other hand, research indicates that the lack of truly inclusive solutions tailored to the needs of this group can perpetuate barriers and inequalities in access to information.

The objective of this study was to design and develop a prototype of an accessible digital reading application aimed at people with dyslexia, enabling text customization, the use of visual and auditory supports, and the provision of intelligent suggestions to improve reading comprehension. The methodological process was based on design thinking, encompassing the phases of empathizing, defining, ideating, prototyping, and evaluating. Empathy was addressed through comprehensive literature analysis and synthesis of documented user experiences, which made it possible to identify the main pain points and unmet needs in digital reading. Contextual research based on published studies and competitor analysis helped define the problem space and identify the limitations of existing solutions. The use of fishbone diagrams facilitated the visualization of the causes and effects of reading difficulties in people with dyslexia, while the SCAMPER method enabled the ideation of innovative improvements for the proposal.

The application prototype was developed using the Figma tool, prioritizing a clean, accessible, and user-centered design. Features such as advanced text customization, read-aloud functionality, guided mode, and difficulty analysis were incorporated, as well as the ability to upload and edit texts in different formats. The prototype was evaluated through expert heuristic assessment conducted by three accessibility specialists with extensive experience in assistive technology design. The heuristic evaluation results demonstrated strong adherence to established usability and accessibility principles, highlighting the ease of use, the effectiveness of the customization features, and the potential for improving reading comprehension among the target population.

Comparing the proposed design with previous literature, it is observed that most existing applications for people with dyslexia offer basic customization and read-aloud options, but lack difficulty analysis, intelligent suggestions, and seamless integration of all features in a single platform. Recent studies have proposed predictive models and recommendation systems based on artificial intelligence to adapt the reading experience to individual needs, but many of these approaches have not yet been implemented in accessible and user-friendly applications for the general public [20]. Other works have explored gamification, augmented reality, and chatbots as strategies to motivate reading and facilitate interaction, although the evidence regarding their effectiveness in the context of dyslexia is still limited [21], [22].

The user-centered design approach adopted in this study aligns with international best practices for the development of assistive technology. The design process, informed by extensive literature review and analysis of documented user needs, made it possible to identify critical usability considerations and align the application design with the established preferences and expectations of the target population. The heuristic evaluation method demonstrated its effectiveness in identifying usability strengths and priority areas for improvement before implementation [23].

In summary, the proposed application helps bridge the gap between the needs of people with dyslexia and the limitations of current digital solutions. The integration of advanced personalization features, visual and auditory support, and intelligent text analysis, together with an accessible and user-centered interface, represents a significant step forward toward inclusion and equal opportunities in digital reading. However, it is recognized that there is a need to continue researching and refining these tools, incorporating new technologies and expanding validation to different contexts and user groups.

D. Limitations and Scope for Future Research

Although this study employed a systematic method based on design thinking, there are some limitations that should be considered, which open opportunities for future research. While the design of the proposed application prioritizes ease of use, expert evaluation indicated that some advanced options, such as text difficulty analysis or detailed customization, may present a learning curve for users with less technological experience or for older adults. In addition, the evaluation was conducted through heuristic analysis with a limited number of experts; therefore, future research should include empirical validation with actual users from diverse age groups, educational levels, and sociocultural backgrounds to confirm the design effectiveness.

Another relevant aspect is data privacy and security, especially regarding the storage and handling of personal or sensitive texts. Future implementation should incorporate robust data protection mechanisms and consider user perceptions of confidentiality in digital reading applications based on established privacy frameworks. Likewise, it would be valuable to investigate the integration of the application with other educational platforms and support tools, as well as the adaptation of the interface and features to different devices and operating systems to ensure an accessible and consistent experience in any environment.

Finally, future empirical studies are recommended to investigate the actual impact of the implemented application on the long-term development of reading skills, as well as on the motivation and autonomy of people with dyslexia. The incorporation of new technologies, such as artificial intelligence for automatic personalization and progress tracking, represents a promising line for future development aimed at the continuous improvement of accessibility and inclusion in digital reading.

III. Conclusion

In conclusion, the proposed prototype aims to simplify and enhance the digital reading experience for people with dyslexia, addressing the most common challenges such as lack of personalization, limited accessibility, and the absence of

intelligent support. The designed application integrates advanced text customization features, read-aloud functionality, guided mode, and difficulty analysis, with the potential to allow users to adapt reading to their individual needs and preferences. By combining these tools with an intuitive, user-centered interface design, the prototype proposes a smoother, more autonomous, and motivating reading experience.

This study did not involve direct participation of individuals with dyslexia in data collection or evaluation activities. User insights were obtained exclusively from published research and documented experiences. Expert heuristic evaluation was conducted by professional accessibility specialists, not by end users. Therefore, this research did not require ethics committee approval at this stage. Future empirical validation with actual users will require appropriate ethical clearance.

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REFERENCES

[1] N. Değirmenci, B. Bağlama, y Y. Yucesoy, “The Use of Technology in Dyslexia: An Analysis of Recent Trends,” International Journal of Emerging Technologies in Learning (iJET), vol. 15, pp. 30–39, 2020. [Online]. Available: http://doi.org/10.3991/ijet.v15i05.11921.

[2] R. Lerga, S. Čandrlić, y A. Jakupović, “A Review on Assistive Technologies for Students with Dyslexia,” in Proceedings of the 13th International Conference on Computer Supported Education (CSEDU 2021), pp. 64–72, 2021. [Online]. Available: http://doi.org/10.5220/0010434500640072.

[3] A. Reis, S. Araújo, I. Morais, y L. Faísca, “Reading and reading-related skills in adults with dyslexia from different orthographic systems: a review and meta-analysis,” Annals of Dyslexia, vol. 70, pp. 339–368, 2020. [Online]. Available: http://doi.org/10.1007/s11881-020-00205-x.

[4] H. Yaacob, N. Zakariya, y S. Rashid, “Technology-based Interventions for Dyslexic Children: A Systematic Literature Review (SLR),” International Journal of Academic Research in Business and Social Sciences, 2024. [Online]. Available: http://doi.org/10.6007/ijarbss/v14-i2/20826.

[5] A. Watson y S. Wallace, "Improving Reading Outcomes Using Digital Reading Rulers for Readers With & Without Dyslexia," Journal of Vision, vol. 21, no. 9, p. 2650, 2021. [Online]. Available: http://doi.org/10.1167/jov.21.9.2650.

[6] A. Niklaus, T. Cai, Z. Bylinskii, y S. Wallace, "Digital Reading Rulers: Evaluating Inclusively Designed Rulers for Readers With Dyslexia and Without," in Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems, 2023. [Online]. Available: http://doi.org/10.1145/3544548.3581367.

[7] R. Niranchana, P. Karthikeyan, M. Sangeetha, y I. Xavier, “Rehabilitating Reading: Addressing Dyslexia with Innovative Approaches,” International Research Journal on Advanced Engineering Hub (IRJAEH), 2025. [Online]. Available: http://doi.org/10.47392/irjaeh.2025.0057.

[8] M. Mohamad, N. Abdullah, N. Rahim, M. Sanmugam, y H. Takajo, “Mobile Assistive Technology for Dyslexic Children: A Significant Review,” Journal of Advanced Research in Applied Sciences and Engineering Technology, 2024. [Online]. Available: http://doi.org/10.37934/araset.51.2.5770.

[9] M. Schaury R. Koutny, “Dyslexia, Reading/Writing Disorders: Assistive Technology and Accessibility - Introduction to the Special Thematic Session,” pp. 269–274, 2024. [Online]. Available: http://doi.org/10.1007/978-3-031-62849-8_33.

[10] L. Enco-Jáuregui, B. Meneses-Claudio, y M. Auccacusi-Kañahuire, “Web accessibility for people with dyslexia: A systematic literature review,” EAI Endorsed Transactions on Pervasive Health Technology, vol. 9, 2023. [Online]. Available: http://doi.org/10.4108/eetpht.9.4274.

[11] D. Iliska y D. Gudoniene, “Sustainable Technology-Enhanced Learning for Learners with Dyslexia,” Sustainability, 2025. [Online]. Available: http://doi.org/10.3390/su17104513.

[12] J. Hu y J. Hu, “The influence of age at first regular digital device access on digital reading performance: the mediating effect of cognitive flexibility,” Humanities and Social Sciences Communications, vol. 11, pp. 1–18, 2024. [Online]. Available: http://doi.org/10.1057/s41599-024-03292-y.

[13] H. Barrie, T. La Rose, B. Detlor, H. Julien, y A. Serenko, “Because I’m Old: The Role of Ageism in Older Adults’ Experiences of Digital Literacy Training in Public Libraries,” Journal of Technology in Human Services, vol. 39, pp. 379–404, 2021. [Online]. Available: http://doi.org/10.1080/15228835.2021.1962477.

[14] K. Spjeldnæs y F. Karlsen, “How digital devices transform literary reading: The impact of e-books, audiobooks and online life on reading habits,” New Media & Society, vol. 26, pp. 4808–4824, 2022. [Online]. Available: http://doi.org/10.1177/14614448221126168.

[15] A. Shutaleva, E. Kuzminykh, y A. Novgorodtseva, “Youth Practices of Reading as a Form of Life and the Digital World,” Societies, 2023. [Online]. Available: http://doi.org/10.3390/soc13070165.

[16] C. Wagner, “Differentiating Children's Reading Materials with Artificial Intelligence: Exploring Possibilities for Personalized Learning,” The Reading Teacher, 2024. [Online]. Available: http://doi.org/10.1002/trtr.2361.

[17] H. Rad, “Reinforcing L2 reading comprehension through artificial intelligence intervention: refining engagement to foster self-regulated learning,” Smart Learning Environments, vol. 12, p. 23, 2025. [Online]. Available: http://doi.org/10.1186/s40561-025-00377-2.

[18] N. Eziamaka, T. Odonkor, y A. Akinsulire, “AI-Driven accessibility: Transformative software solutions for empowering individuals with disabilities,” International Journal of Applied Research in Social Sciences, 2024. [Online]. Available: http://doi.org/10.51594/ijarss.v6i8.1373.

[19] S. Zhao, S. Xiong, B. Pang, X. Tang, y P. He, “Let AI Read First: Enhancing Reading Abilities for Individuals with Dyslexia through Artificial Intelligence,” in Proceedings of the Extended Abstracts of the CHI Conference on Human Factors in Computing Systems, 2025. [Online]. Available: http://doi.org/10.1145/3706599.3720113.

[20] Y. Kuerban, S. Oyelere, y I. Sanusi, “ReadSmart: Generative AI and Augmented Reality Solution for Supporting Students with Dyslexia Learning Disabilities,” International Journal of Technology in Education and Science, 2025. [Online]. Available: http://doi.org/10.46328/ijtes.599.

[21] A. Zingoni, J. Taborri, y G. Calabrò, “A machine learning-based classification model to support university students with dyslexia with personalized tools and strategies,” Scientific Reports, vol. 14, 2024. [Online]. Available: http://doi.org/10.1038/s41598-023-50879-7.

[22] S. Phatangare, S. Jain, S. Chakrabarty, S. Chougule, y S. Bisen, “LexiEase AI: An AI Powered Dyslexic Support System,” 2025 5th International Conference on Trends in Material Science and Inventive Materials (ICTMIM), pp. 1412–1417, 2025. [Online]. Available: http://doi.org/10.1109/ICTMIM65579.2025.10987997.

[23] M. M. Meenakshi, “Leveraging AI Technologies for Personalized Learning Support in Dyslexic Students,” International Journal for Research in Applied Science and Engineering Technology, 2024. [Online]. Available: http://doi.org/10.22214/ijraset.2024.65734.

Vegetation Identification in Hyperspectral Images of Cartagena City Using the Haar Wavelet Transform

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***Abstract*—Hyperspectral imaging is one of the most widespread remote sensing techniques in earth observation, corresponding to images with high spectral and spatial resolution that enable material detection through the identification of their spectral signature. A key challenge in hyperspectral imaging is the definition of novel and efficient computational methods that contribute to reducing computational cost while maintaining the efficacy and precision in material detection provided by methods such as correlation or machine learning. This study aims to propose a new efficient method for vegetation detection in hyperspectral images based on the similarity between the approximate and detailed components of the Haar wavelet transform of the vegetation spectral signature, with respect to the components of the pixel to be classified in the image. For the development of the present investigation, five methodological phases were defined: P1. Selection of sample pixels for vegetation and other materials; P2. Determination of the characteristic vegetation pixel; P3. Implementation and evaluation of the method with vegetation and non-vegetation pixels; P4. Deployment of the method on the reference hyperspectral image; P5. Comparative evaluation of the proposed method against the correlation method. As a result of this research, a novel computational method for vegetation identification in hyperspectral images was proposed, leveraging the similarity of wavelet transform components. This method demonstrated comparable detection efficacy to the correlation method and proved to be approximately 5% more efficient in the detection process. The proposed method can be suitably integrated into hyperspectral image-based environmental monitoring systems, particularly where images are of considerable size and more efficient methods are required.**

***Keywords*—Vegetation detection; hyperspectral images; remote sensing; wavelet transform; earth observation**

I. Introduction

Remote sensing is a set of techniques that make it possible to observe the Earth's surface without direct contact; sensors on satellites [1], [2], airplanes, drones, or ground-based instruments [3], [4] get electromagnetic energy reflected by different materials, such as visible, infrared, and microwave radiation [5]. These systems provide fast access to large areas and help lower the time and cost of ground measurements [3], [6].

This technology also gives access to information that humans cannot see directly, as it shows soil conditions, vegetation health, and atmospheric properties; such data supports better decisions in natural-resource management [7], [8]. Within remote sensing, hyperspectral imaging has become one of the most used techniques [9] because it includes many narrow spectral bands that let users distinguish materials with high precision [10], [11].

Unlike multispectral images, hyperspectral data cubes have many more bands and show the unique spectral signature of each surface material [12], [13]. A hyperspectral image is a three-dimensional data cube [14], [15], where the first two dimensions show spatial location and the third shows reflectance as a function of wavelength [16], [17].

Hyperspectral imaging plays an important role in environmental and agricultural studies. For example, it helps identify tree species and supports biodiversity planning [18]. It lets researchers detect salt crusts in estuaries and follow climate-related patterns [19]. It also helps monitor vegetation changes through time using multisensor data and clustering methods [20].

Other applications include mapping biodiversity with NDVI and autoencoders [21], detecting microplastics [22] and supporting the management of water resources [23]. In agriculture, hyperspectral images help detect diseases early [24], classify multiple crop types [25], [26], and show product quality in a non-destructive way [27]-[29]. They also support soil and crop characterization tasks [30], [31].

However, hyperspectral images bring several challenges. They contain large volumes of redundant data, which need dimensionality-reduction methods [32], [33]. Machine learning and deep learning methods often get good results but need big annotated datasets, high processing power, and complex architectures [34], [35]; these requirements make them difficult to use in real-time environmental monitoring.

For vegetation detection, correlation-based approaches [36] and learning-based methods [20] seem to be the most common choices. Still, they leave open questions about efficiency, data needs, and operational cost. Because of this, there is a need for solutions that keep detection accuracy while cutting computational load.

Building on this, the present study uses the similarity between the approximate and detailed components of the Haar wavelet transform to detect vegetation in hyperspectral images. The Haar transform provides a simple structure that lets users break a signal into low- and high-frequency components [37], [38], which can show features relevant for material discrimination [39], [40].

This work uses open-source Python libraries (spectral, PyWavelets, numpy, pandas, matplotlib) to evaluate the method

with 100 sample pixels (vegetation and non-vegetation). After estimating the detection threshold, the method is applied to a hyperspectral image from Cartagena City (750×850 pixels, 380 bands) and is compared to the correlation method.

Beyond performance, this method can help researchers and practitioners who need efficient tools for large-scale environmental monitoring systems. The use of open-source libraries makes the method easier to replicate and adopt in academic and commercial settings.

Despite the wide range of applications of hyperspectral imaging, vegetation detection still relies predominantly on correlation-based approaches or machine learning models that require large annotated datasets and high computational cost. These methods are accurate but often inefficient when processing large hyperspectral scenes, which limits their integration into operational environmental monitoring pipelines. Consequently, there is a need for computationally efficient alternatives that preserve detection capability while reducing processing time.

To address this gap, this study proposes a new method for vegetation detection based on the similarity between the approximate and detailed components of the Haar wavelet transform of the vegetation spectral signature. The main contributions of this work are:

1) A wavelet-based vegetation detection strategy that reduces dimensionality while preserving spectral structure;

2) A threshold estimation procedure based on combined similarity metrics; and

3) A comparative evaluation against the widely used correlation method in terms of detection accuracy and computational efficiency.

The remainder of the study is organized as follows: Section II presents the literature review and problem statement. Section III describes the methodological phases considered for the development of this research. Section IV presents the results obtained in this study, including the calculation of the approximate and detailed components of the characteristic vegetation pixel; the implementation and evaluation of the method with vegetation and non-vegetation sample pixels to identify detection thresholds; and the deployment of the method on the reference hyperspectral image, comparing its effectiveness and efficiency with the correlation method. Section V presents a discussion of the results, analyzing them in relation to the reviewed literature. Finally, Section VI outlines the conclusions derived from this research.

II. Literature Review and Problem Statement

Unresolved questions are related to the need for very large annotated datasets. The reason is that collecting and labeling such datasets is costly and often unfeasible in many agricultural contexts.

The study [18] demonstrates hyperspectral imaging for identifying tropical tree species. It is shown that the approach is effective at the local scale, but unresolved issues include transferability, since the method relies on curated spectral libraries that are difficult to build for large and diverse ecosystems.

In [20], the authors introduce a multi-sensor framework for detecting vegetation changes. It is shown that temporal dynamics can be effectively captured. However, unresolved questions arise from operational complexity and costs, because the approach requires repeated multi-temporal acquisitions.

The study [21] combines convolutional autoencoders with vegetation indices to map biodiversity. It is shown that detailed and high-resolution outputs can be obtained, but unresolved questions include the need for intensive computational resources and large labeled datasets, which limit its applicability in practice (see Table I).

TABLE I. Summary of Recent Studies on Hyperspectral Vegetation Analysis

Ref.	Year	Features		
		Method	***Application***	***Limitations***
[32]	2009	General hyperspectral image processing	Foundational techniques	High dimensionality and redundancy
[19]	2014	Hyperion imagery for salt crust mapping	Estuarine monitoring	Dependence on atmospherics correction models
[25]	2015	Non-destructive analysis of agricultural products	Stored food quality	Expensive hardware and limited scalability
[22]	2020	Deep learning on microscopic hyperspectral data	Microplastic detection	Limited generalization to field data
[23]	2021	Multi/hyperspectral analysis for water quality	Aquatic environments	Computational bottlenecks for real-time use
[26]	2021	Deep learning for agricultural hyperspectral data	Crop disease detection	Requires large labeled datasets
[18]	2022	Hyperspectral imaging of tropical trees	Biodiversity analysis	Reliance on curated spectral libraries
[20]	2024	Multi-sensor change detection	Vegetation monitoring	High operational complexity and cost
[21]	2024	Autoencoders vegetation indices	Biodiversity mapping	Intensive computational resources

The above analysis of the literature review allows to argue that it is appropriate to conduct a dedicated study on computationally efficient vegetation detection methods.

Limitations presented in Table I highlight the need for more efficient spectral processing techniques that can maintain analytical accuracy while reducing the time and cost associated with hyperspectral data interpretation.

The approach proposed in this study, based on Haar wavelet decomposition, directly addresses these gaps by offering a balanced, computationally efficient alternative for vegetation detection.

III. METHODOLOGY

The proposed vegetation detection method is designed as a sequential and reproducible workflow. Although the detailed description is presented through five methodological phases, the overall procedure can be summarized as follows: selection of representative vegetation and non-vegetation pixels; construction of a characteristic vegetation spectral signature; wavelet-based decomposition of spectral data; similarity analysis and threshold determination; and pixel-wise deployment of the method on the full hyperspectral image, followed by a comparative evaluation with the correlation method. The complete workflow and its individual phases are detailed below and summarized in Fig. 1.

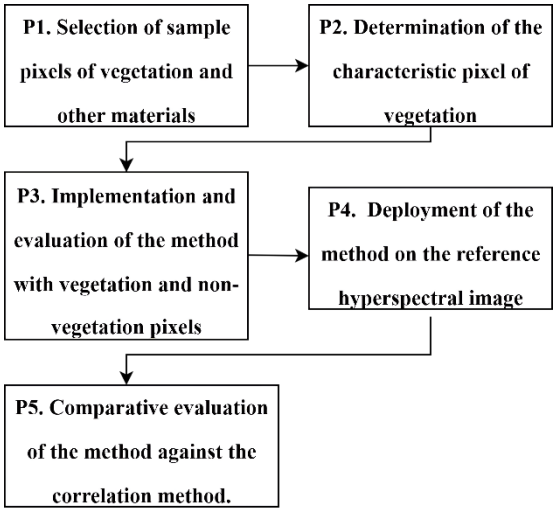


Fig. 1. Considered methodological phases. The diagram summarizes the complete workflow of the proposed vegetation detection approach.

For the development of this research, five methodological phases were defined as follows in Fig. 1. This diagram summarizes the workflow of the proposed approach, allowing one to understand the sequence of processes from data acquisition to vegetation detection and performance evaluation:

- P1. Selection of sample pixels representing vegetation and other materials.
- P2. Determination of the characteristic vegetation pixel.
- P3. Implementation and evaluation of the method using vegetation and non-vegetation pixels.
- P4. Deployment of the method on the reference hyperspectral image.
- P5. Comparative evaluation of the method against the correlation method.

In Phase 1 of the methodology, using a hyperspectral image of the city of Cartagena, Colombia, with 750 x 850 pixels and 380 reflectance bands per pixel, a set of 50 sample pixels corresponding to vegetation and 50 pixels corresponding to other materials were visually inspected and selected. This process aimed to obtain the spectral signature of vegetation and evaluate the method with vegetation and non-vegetation pixels.

The sampling strategy was designed to capture representative spectral signatures while avoiding oversampling effects that may reduce separability in threshold-based similarity analysis.

Once the vegetation and non-vegetation pixels were selected, Phase 2 involved calculating the characteristic vegetation pixel by averaging the normalized reflectance values of the 50 vegetation pixels band by band.

In Phase 3 of the methodology, the determination of the approximate and detailed components of the Haar wavelet transform for the characteristic vegetation pixel was initially performed using Eq. (1) and Eq. (2). The approximate components of the Haar wavelet transform are given by Eq. (1):

$$A_i = \frac{r_{2i-1} + r_{2i}}{\sqrt{2}}, i = 1,2,\ldots,190 \quad (1)$$

where, Eq. (1) defines the approximate components Ai of the Haar wavelet transform, which are derived from an array of 380 values corresponding to the normalized reflectance associated with the 380 bands of the characteristic vegetation pixel or spectral signature ($R = [r_1, r_2, r_3 \ldots, r_{380}]$). It is important to note that, since the Haar wavelet transform operates on consecutive pairs, the array of approximate components Ai consists of a total of 190 elements, equivalent to half of the 380 reflectance bands.

The detailed components of the Haar wavelet transform are expressed as Eq. (2):

$$D_i = \frac{r_{2i-1} - r_{2i}}{\sqrt{2}}, i = 1,2,\ldots,190 \quad (2)$$

Eq. (2) defines the detailed components Di of the Haar wavelet transform, which also begins with an array of 380 normalized reflectance values from the characteristic pixel and produces an array Di consisting of 190 values. This reduction occurs because, for the detailed component as well, the Haar transform operates on consecutive pairs.

Using the components obtained through Eq. (1) and Eq. (2), an iteration was performed over the 50 vegetation sample pixels and the 50 pixels representing other materials, calculating the approximate and detailed components of the wavelet transform for each pixel.

Through the use of Euclidean distance, a similarity percentage was determined for each component of each pixel, and a combined similarity percentage was calculated for both components.

The process aimed to identify the minimum combined similarity percentage with vegetation pixels and the maximum combined similarity percentage with pixels of other materials. These thresholds enable the assessment of potential overlap between the two, and in the absence of overlap, the detection or differentiation capability of the method can be established, along with the threshold to be considered for deploying the method on the entire reference image.

Phase 4 involved deploying the method on each pixel of the reference hyperspectral image (Once the vegetation detection threshold was identified in Phase 3). For each pixel, the wavelet transform components were obtained, and the similarity percentages for each component, as well as the combined

similarity percentage were calculated. The combined percentage was then used to classify each pixel in the image as either vegetation or another material.

Additionally, in this phase, the number of pixels detected by the method was counted, and the percentage of pixels within the hyperspectral image corresponding to this count was calculated.

Finally, in Phase 5, the correlation method was implemented after detecting the reference thresholds, and both the number of vegetation pixels and the percentage corresponding to this pixel count were determined. This allowed for a comparison of the effectiveness of the proposed method with the correlation method.

Furthermore, in this phase, the computational efficiency of both methods was evaluated by performing a total of 20, 40, 60, 80, and 100 executions on a 50x50-pixel region of the image, each pixel containing 380 bands. For each method, the average execution time per number of runs and the total average time were calculated, enabling a comparison of the computational efficiency of one method relative to the other.

IV. Results

A. Selection of Pixels and Construction of a Characteristic Vegetation Signature

A hyperspectral image of Cartagena City with a resolution of 750 by 850 pixels and 380 spectral bands was used. From this image, 50 vegetation pixels and 50 non-vegetation pixels were manually selected for the evaluation phase.

Fig. 2 shows the RGB visualization of the hyperspectral scene with the manually selected vegetation (green) and non-vegetation (blue) pixels. This visual separation allows verifying that both classes are spatially well distributed across the study area, ensuring that the sample is suitable for computing representative spectral signatures and for estimating detection thresholds.

From the 50 manually selected vegetation pixels, individual spectral signatures were extracted to analyze their variability, as shown in Fig. 3. Fig. 3 shows the dispersion of reflectance values across the spectral bands, highlighting the natural spectral variability of vegetation within the study area.

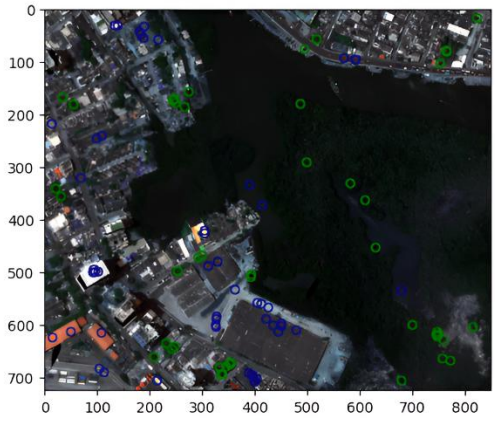


Fig. 2. Selected vegetation and non-vegetation pixels in the RGB rendering of the hyperspectral scene. The labeled samples provide the reference spectral signatures used to estimate similarity thresholds for vegetation detection.

To obtain a stable and representative reference for subsequent analysis, a characteristic vegetation pixel was computed by averaging the spectral signatures of the 50 vegetation samples. The resulting average spectrum, shown in Fig. 4, preserves the general spectral structure of vegetation, while reducing noise and sample-specific fluctuations.

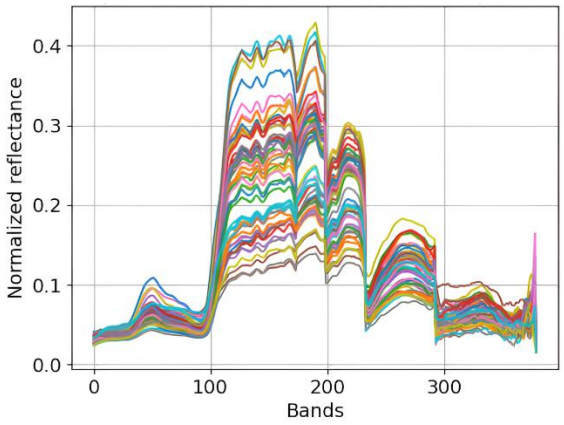


Fig. 3. Spectral signatures of the 50 selected vegetation pixels used to compute a representative reference signature.

The characteristic vegetation pixel shown in Fig. 4 plays a key role in the proposed method, as its wavelet components are compared with those of each pixel in the hyperspectral image (Fig. 1) to determine the presence of vegetation through a similarity analysis.

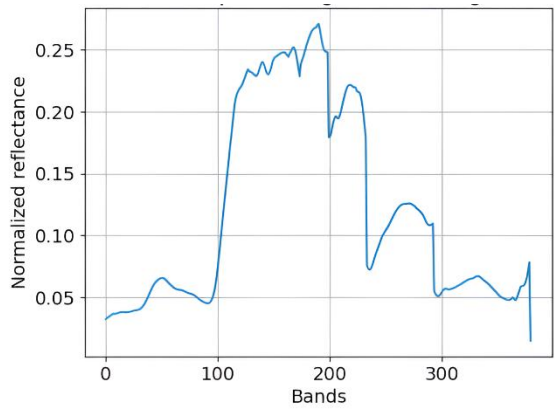


Fig. 4. Spectral signatures of characteristic vegetation pixel used for wavelet decomposition.

B. Wavelet Decomposition

Haar wavelet transform was applied to average (the characteristic) vegetation pixel shown in Fig. 4. This process generated two sets of coefficients: the approximate components (Ai) (see Fig. 5) and the detailed components (Di) (see Fig. 6), which are defined in Eq. (1) and Eq. (2), respectively.

Since the Haar transform operates by pairing consecutive reflectance values, each component contains 190 coefficients, corresponding to half of the original 380 spectral bands. The same transformation was then applied to all 100 sample pixels, including the 50 vegetation and 50 non-vegetation samples, using the characteristic vegetation pixel as the reference for similarity comparisons.

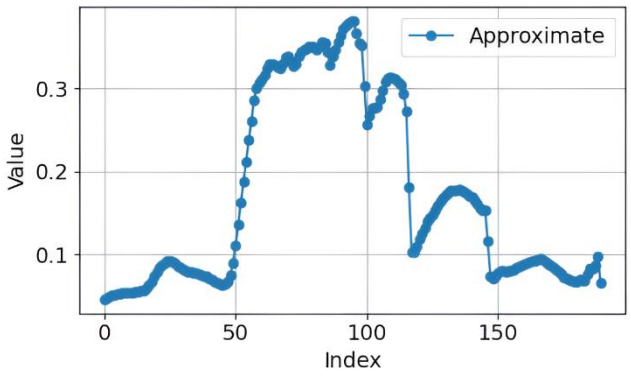


Fig. 5. Approximate component of the characteristic vegetation pixel. It represents the main trend of the vegetation signature after dimensionality reduction.

Fig. 5 shows the approximate component of the characteristic vegetation pixel. This component can be interpreted as a simplified representation of the original spectral signature, as it preserves the low-frequency information and captures the main spectral trend of vegetation while reducing data dimensionality.

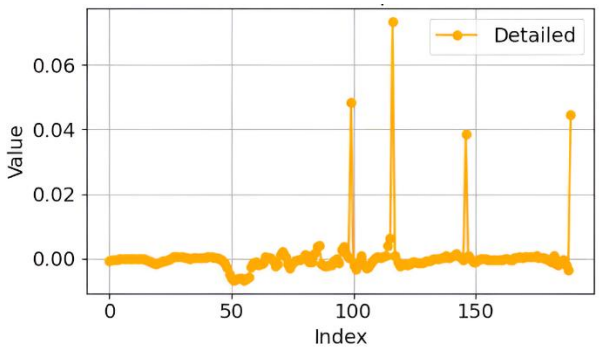


Fig. 6. Detailed component of the characteristic vegetation pixel. It captures local fluctuations between adjacent bands.

Fig. 6 shows the detailed component of the characteristic vegetation pixel. In contrast to the approximation, this component highlights high-frequency information by emphasizing local fluctuations between adjacent spectral bands, allowing the method to capture finer spectral variations relevant for discrimination.

C. Similarity Analysis

Once the transform components of the characteristic pixel were obtained, an iteration was performed over the 50 vegetation pixels and 50 pixels representing other materials to determine the approximate and detailed components for each pixel. Using these components, three similarities were calculated via Euclidean distance: the similarity between approximate components, the similarity between detailed components, and the weighted similarity between components. The results of the similarity analysis for the approximate and detailed components, comparing vegetation pixels with pixels from other materials, are presented in Fig. 7.

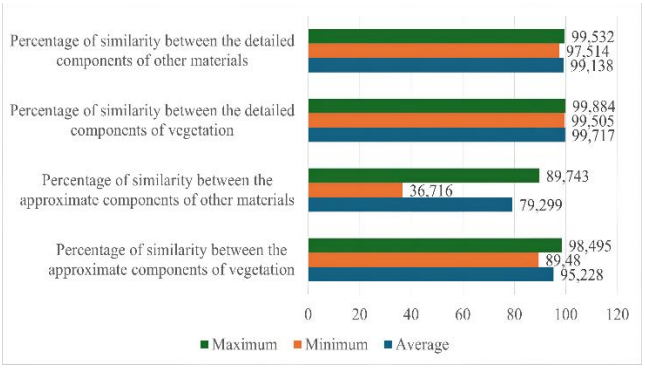


Fig. 7. Similarity percentages obtained for the approximate and detailed wavelet components when comparing vegetation and non-vegetation pixels.

As observed in Fig. 7, for the approximate component, the maximum similarity percentage obtained for non-vegetation pixels (89.743%) exceeds the minimum similarity percentage obtained for vegetation pixels (89.48%). This overlap indicates that the approximate component alone is not sufficient to reliably discriminate vegetation pixels. Similarly, for the detailed component, the maximum similarity percentage for non-vegetation pixels (99.532%) is higher than the minimum similarity percentage for vegetation pixels (99.505%), showing that this component by itself also fails to provide clear separation.

The results presented in Fig. 7 demonstrate that, although the coarse and fine components individually capture relevant spectral information, their isolated use does not allow for accurate vegetation discrimination. When both components are combined and greater weight is assigned to the fine component, the method becomes more sensitive to subtle spectral variations, allowing for more reliable classification and reducing detection errors.

D. Determination of Detection Thresholds

In light of the results presented in Fig. 7, where neither the approximate nor the detailed component alone provided sufficient discrimination, a weighted similarity measure was evaluated. The contribution of the detailed component was varied across different percentages (60%, 70%, 80%, 85%, 90%, 95%, and 98%), while the remaining weight was assigned to the approximate component.

The similarity results obtained for these weighted combinations, comparing vegetation and non-vegetation pixels, are presented in Fig. 8. This analysis allows identifying the weighting configurations that maximize the separation between both classes and serves as the basis for selecting an appropriate detection threshold.

As shown in Fig. 8, the only weighting configuration in which the minimum similarity percentage for vegetation pixels is lower than the maximum similarity percentage for non-vegetation pixels corresponds to a 60% contribution of the detailed component. For higher weight values, a clearer separation between both classes is observed.

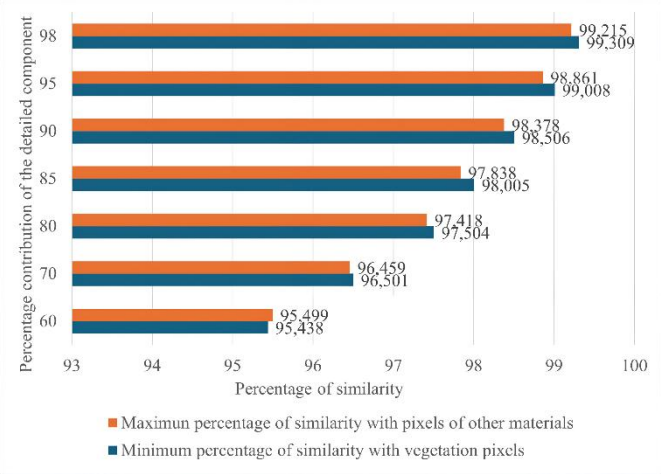


Fig. 8. Similarity percentages obtained for different weightings of the approximate and detailed wavelet components; supports the selection of the detection threshold.

It is noteworthy that the greatest differentiation between vegetation and non-vegetation similarities is achieved when the detailed component has a weight of 95% and the approximate component a weight of 5%, resulting in a percentage difference of 0.147%. Based on this result, the minimum detection threshold for identifying vegetation pixels was established at a similarity value of 99.008%, corresponding to a 95% contribution of the detailed component of the Haar wavelet transform.

Setting this threshold matters, because it turns the method into something practical and measurable. It defines a clear decision line that helps distinguish vegetation from other materials with confidence. The results also show that the Haar based decomposition can create thresholds with very little uncertainty, which is important for building scalable systems that rely on automated classification in environmental monitoring.

E. Large-Scale Deployment and Comparative Evaluation

Using the detection threshold of 99.008% (Fig. 8), the proposed method was deployed across the entire hyperspectral image (Fig. 1) of Cartagena City (750 × 850 pixels, 380 bands).

As shown in Fig. 9, for each pixel in the image, the approximate and detailed components of the wavelet were calculated, similarity scores were calculated with respect to the characteristic vegetation pixel, and a final classification into vegetation or non-vegetation was made.

The implementation was carried out exclusively with open-source Python libraries (spectral, PyWavelets, numpy, pandas, and matplotlib).

As a result, the method determined that 42.95% of the hyperspectral image corresponds to vegetation pixels. Fig. 9 presents the vegetation map generated by the proposed method, where detected vegetation areas are highlighted in blue, visually demonstrating the capability of the Haar wavelet transform measure to discriminate vegetation from other materials.

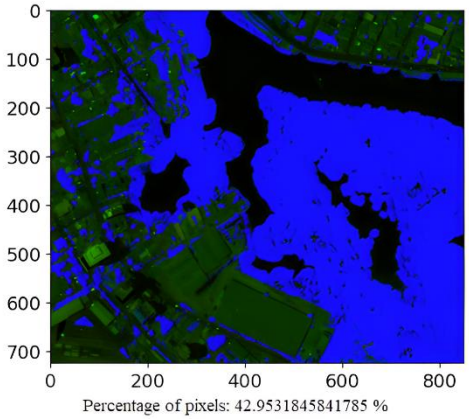


Fig. 9. Vegetation detection method applied to the entire hyperspectral image; final classification is performed.

To evaluate the performance of the proposed method, the traditional correlation-based approach was also applied to the same hyperspectral image (Fig. 1), once its corresponding detection threshold was defined. Fig. 10 illustrates the deployment of the correlation method across the entire scene, while Table II summarizes the vegetation detection results obtained with both techniques.

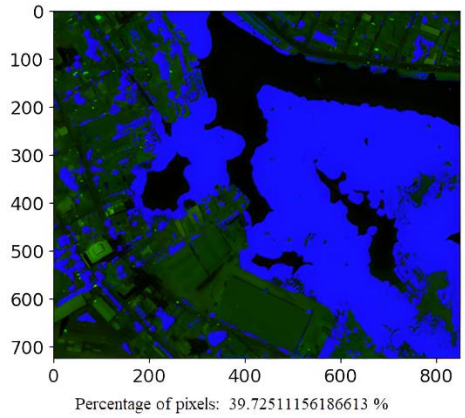


Fig. 10. Vegetation detection map obtained by applying the correlation method to the entire hyperspectral image, used for comparison with the wavelet approach.

The results presented in Fig. 10 and Table II shows that both methods achieve comparable levels of detection accuracy. In particular, the percentage of vegetation pixels detected by the proposed method was 39.72%, which is close to the result obtained with the correlation method, yielding a percentage difference of 3.23%.

TABLE II. VEGETATION DETECTION RESULTS OF THE PROPOSED METHOD VS. CORRELATION METHOD

Method	Vegetation pixels detected	Vegetation percentage
Haar wavelet transform	273488	42.95%
Correlation method	252101	39.72%

The above results indicate that the proposed method provides detection performance comparable to that of the correlation approach, while offering a computationally efficient alternative for environmental monitoring using hyperspectral imagery.

F. Computational Efficiency and Replicability

To evaluate the computational efficiency of the proposed method in comparison with the correlation-based approach, both methods were executed multiple times (20, 40, 60, 80, and 100 executions) on the same reference image region of 50 × 50 pixels with 380 reflectance bands.

The objective of this experiment was to estimate the average execution time as a function of the number of runs for each method, as well as the overall computational behavior under repeated executions. Fig. 11 presents the average execution time curves obtained for both methods.

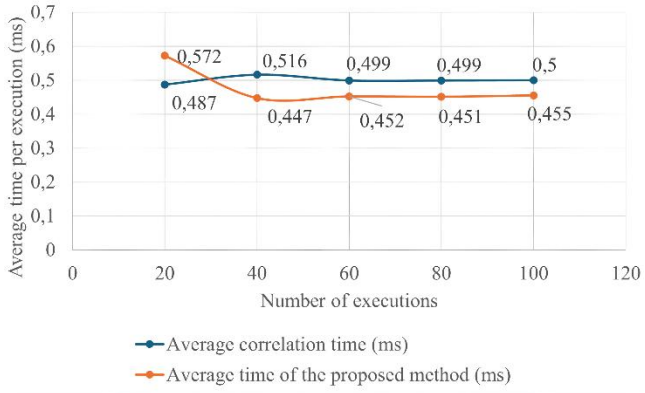


Fig. 11. Average execution time comparison between the proposed wavelet-based method and the correlation-based method for different numbers of executions.

As shown in Fig. 11, the proposed method exhibits a slightly higher average execution time than the correlation method only in the case of 20 executions. For all other evaluated scenarios, the proposed method remains below 0.455 ms and consistently shows lower average execution times as the number of executions increases, indicating better computational efficiency under repeated processing conditions.

It is evident that the average execution time for the correlation method fluctuates around 0.5 ms. By averaging the execution times of both methods and comparing these averages, it is determined that the correlation method is 1.05 times slower than the proposed method, meaning the proposed method is, on average, 4.96% more efficient than the correlation method. While this percentage may be considered small, it could have a greater impact when processing large images, such as those associated with environmental monitoring processes based on hyperspectral imaging.

Centered on the above, Fig. 11 makes it clear that, although the proposed method starts out slightly slower in 20 executions, it becomes increasingly faster as the number of executions increases.

V. Discussion

It is important to highlight that this research contributed a new method for detecting vegetation and materials in hyperspectral images based on the similarity between the approximate and detailed components of the Haar wavelet transform of the characteristic pixel and a given pixel in the image.

From the results obtained during the implementation and evaluation of the method, it was found that, compared to the correlation method, which has been widely disseminated for vegetation detection in hyperspectral images [36], the proposed method was equally effective in detecting vegetation and 4.958% more efficient. This efficiency improvement can result in significant time savings when processing large-volume images, such as those used in environmental monitoring of extensive areas.

From a comparative perspective, the obtained results are consistent with previous studies that have successfully applied similarity-based techniques for vegetation detection in hyperspectral images. Correlation-based approaches have been widely used as reliable baselines in hyperspectral analysis [36], achieving high detection accuracy at the expense of increased computational cost. The comparable detection performance obtained by the proposed method, together with its improved computational efficiency, aligns with recent research efforts focused on reducing processing complexity while preserving spectral discrimination capability.

In contrast to machine learning and deep learning approaches reported in the literature, which often require large annotated datasets and extensive training procedures [34], [35], the proposed method emphasizes interpretability and operational efficiency. Similar trends toward lightweight and data-efficient hyperspectral analysis methods have been reported in studies using dimensionality reduction and transform-based representations [37]–[40], supporting the relevance and practical value of the proposed wavelet-based similarity framework.

From a methodological perspective, in similarity- and threshold-based approaches, increasing the number of sample pixels does not necessarily improve discrimination performance. On the contrary, excessive sampling may lead to saturation of the similarity space and increased overlap between vegetation and non-vegetation classes, making threshold definition more difficult. The sampling strategy adopted in this work was therefore designed to balance representativeness and separability. This explains the stable behavior of the proposed method across different weighting configurations and threshold values, as observed in the experimental results.

Regarding parameter selection, in similarity- and threshold-based detection methods, parameter selection plays a critical role in balancing class separability and robustness. In the proposed approach, the most influential parameters are the weighting coefficients assigned to the approximate and detailed wavelet components, as well as the detection threshold. The results presented in Section IV show that the method exhibits stable behavior within a wide range of weighting configurations for the detailed component (85%–98%), while lower values

increase overlap between vegetation and non-vegetation similarity ranges. This indicates that the method is not overly sensitive to minor parameter variations but operates within a clearly defined and interpretable parameter space. Extreme parameter configurations, such as assigning insufficient weight to the detailed component or relaxing the detection threshold, lead to reduced discrimination capability, which is consistent with the nature of similarity- and threshold-based classification methods.

Also, since the proposed method was implemented using open-source libraries and tools, this research holds significant value both academically and commercially, facilitating the adoption and utilization of these technologies in the processing and analysis of spectral images. This not only reduces the costs associated with proprietary tools but also enables the customization of methods and the hybridization of different techniques to meet specific needs.

In this way, the proposed method serves as a key contribution for research centers and universities in developing countries, promoting the replication and expansion of studies involving hyperspectral images. This is particularly relevant as previous research conducted with proprietary tools such as ENVI has demonstrated their utility in this field [41], [42]. The use of open-source alternatives could further enhance accessibility and foster innovation in such studies.

It is important to note that the objective of this study is not to provide a large-scale benchmark across multiple hyperspectral datasets, but to demonstrate the feasibility and effectiveness of a wavelet-based similarity approach for vegetation detection. The use of a single representative hyperspectral scene and a carefully selected set of sample pixels is consistent with threshold-based methods, where the focus is on spectral behavior and separability rather than statistical learning. While additional scenes could further validate robustness across different conditions, the presented results sufficiently support the methodological contribution and computational advantages of the proposed approach.

Although machine learning and deep learning approaches have shown strong performance in hyperspectral vegetation detection, they typically require large annotated datasets, high computational resources, and complex training procedures. The objective of this work is different: to provide a lightweight, interpretable, and computationally efficient alternative suitable for scenarios where labeled data and processing resources are limited. For this reason, the proposed method was compared against the correlation-based approach, which is one of the most widely used similarity-based techniques in hyperspectral analysis and represents a fair baseline in terms of operational complexity.

Regarding noise and illumination variability, the proposed method relies on normalized spectral signatures and on the Haar wavelet transform, which decomposes the signal into approximate (low-frequency) and detailed (high-frequency) components. This decomposition inherently reduces sensitivity to global illumination variations captured in the low-frequency component, while preserving discriminative spectral patterns in the detailed component. Although an explicit noise robustness analysis is beyond the scope of this study, the wavelet-based representation is known to provide increased robustness against high-frequency noise compared to direct spectral similarity measures.

VI. Conclusion

Considering that vegetation detection in the domain of hyperspectral images has primarily relied on methods based on correlation and machine learning, which, although accurate, require high computational costs, this study proposed a novel computationally efficient method in the same domain. The proposed method is based on the similarity between the wavelet transform components of the characteristic vegetation pixel and the components of the pixel being analyzed in the image. Given the results obtained in terms of both effectiveness and efficiency, the method can be integrated into academic and commercial contexts within systems for monitoring environmental variables using hyperspectral images.

The results obtained in this research determined that, although the similarity between the approximate and detailed components of the characteristic pixel and the sample pixels showed overlap or proved unsuitable for vegetation detection when considered individually, the similarity percentage based on the weighting of the components is more effective and does not exhibit overlap in the thresholds obtained for vegetation and other materials. The best detection threshold is achieved when the weight of the detailed component is 95%, and the weight of the approximate component is 5%. Thus, the proposed method proves effective through the combined weighting of the similarities, establishing 99.008% as the minimum detection threshold for vegetation. Based on this, the proposed method was successfully applied to the entire reference image, yielding detection results comparable to those of the correlation method.

In line with the above, the deployment of the proposed method on the hyperspectral image of a representative area in the city of Cartagena determined that 42.953% of the pixels correspond to vegetation, with a percentage difference of only 3.23% compared to the correlation method. This demonstrates that the proposed method is a valid and reliable alternative for environmental variable monitoring systems, providing results comparable to existing methods. Furthermore, these results are particularly relevant for continuous monitoring of the areas studied in Cartagena, allowing for an accurate assessment of the impact of urban development on vegetation and, by extension, the environment. This highlights the importance of implementing monitoring tools that enable the understanding and mitigation of the effects of urban growth over time.

In evaluating the computational efficiency of the proposed method compared to the correlation-based method, multiple executions (20, 40, 60, 80, 100) were performed on a region of the reference hyperspectral image measuring 50x50 pixels with 380 reflectance bands. The results showed that, on average, the correlation method is 1.05 times slower than the proposed method, indicating that the proposed method is approximately 4.96% more efficient. While this improvement in efficiency may appear modest at first glance, it becomes significant when processing large-volume hyperspectral images, such as those generated by systems monitoring environmental changes or vegetation shifts through remote sensing, enabling optimization of processing times.

This research demonstrated the relevance and feasibility of using open-source tools and technologies for processing and implementing computational methods for detecting vegetation and other materials in the domain of hyperspectral images. In this context, the spectral library proved useful for accessing the reflectance band data of the reference hyperspectral image. The PyWavelets library enabled the implementation of the proposed method by obtaining the approximate and detailed components of the Haar wavelet transform. The numpy library was essential for accessing and handling hyperspectral image data, facilitating data normalization, image iteration, and the implementation of the correlation method. The pandas library supported the loading of points corresponding to vegetation pixels and other materials. Finally, the matplotlib library was used to generate graphs associated with reflectance curves and the curves corresponding to the components of the characteristic pixel. These technologies can thus be employed to replicate experiments with spectral images in academic and commercial domains, while also enabling the development of new detection methods.

As future work derived from this research, the wavelet transform is intended to be used to obtain a condensed representation of the spectral signature, allowing this summarized signature to be hybridized with other detection methods, such as the Fourier similarity method or the differential similarity method. Additionally, the proposed method will be evaluated for detecting water bodies or other types of materials in various application contexts.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

M.O.: conceptualization, writing an original draft, investigation, data curation, reviewing and editing; G.C.: investigation, methodology, reviewing and editing; M.S.: research design, data analysis, funding acquisition, and project administration. All authors have read and agreed to the published version of the manuscript.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work, the authors used Grammarly and ChatGPT to improve their writing. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the publication's content.

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References

[1] J. Sunil and A. Singh, "Evaluation of the Performance of Supervised Classification Alogorithums in Image Classification," Int. J. Curr. Microbiol. Appl. Sci., vol. 8, no. 10, pp. 2634–2643, Oct. 2019, doi: 10.20546/ijcmas.2019.810.304.

[2] J. Awange and J. Kiema, "Fundamentals of Remote Sensing," 2019, pp. 115–123. doi: 10.1007/978-3-030-03017-9_7.

[3] A. A. Misra, "Remote Sensing Fundamentals," in Atlas of Structural Geological and Geomorphological Interpretation of Remote Sensing Images, Wiley, 2022, pp. 7–14. doi: 10.1002/9781119813392.ch1.

[4] A. F. Jiménez-López, M. Jiménez-López, and F. R. Jiménez-López, "Multispectral analysis of vegetation for remote sensing applications," ITECKNE, vol. 12, no. 2, Nov. 2015, doi: 10.15332/iteckne.v12i2.1242.

[5] S. K. Yadav, S. Raj, and S. S. Roy, "Remote sensing technology and its applications," Int. J. Adv. Res. Technol., vol. 2, no. 10, pp. 1–6, 2012.

[6] A. K. Torres Galindo, A. F. Gómez Rivera, and A. F. Jiménez López, "Desarrollo de un sistema multiespectral para aplicaciones en agricultura de precisión usando dispositivos embebidos," Sist. y Telemática, vol. 13, no. 33, pp. 27–44, Jun. 2015, doi: 10.18046/syt.v13i33.2079.

[7] K. Ennouri, M. Ennouri, and M. A. Triki, "Satellite Imagery Used for Analysis of Soil Properties," 2024, pp. 311–334. doi: 10.4018/979-8-3693-6452-9.ch010.

[8] A. Tudor, "Remote sensing in biometeorology," Rev. Air Force Acad., vol. XX, no. 2, pp. 5–14, Feb. 2023, doi: 10.19062/1842-9238.2022.20.2.1.

[9] N. Aburaed, M. Q. Alkhatib, S. Marshall, J. Zabalza, and H. Al Ahmad, "A Review of Spatial Enhancement of Hyperspectral Remote Sensing Imaging Techniques," IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens., vol. 16, pp. 2275–2300, 2023, doi: 10.1109/JSTARS.2023.3242048.

[10] M. J. Khan, H. S. Khan, A. Yousaf, K. Khurshid, and A. Abbas, "Modern Trends in Hyperspectral Image Analysis: A Review," IEEE Access, vol. 6, pp. 14118–14129, 2018, doi: 10.1109/ACCESS.2018.2812999.

[11] Y. Gu et al., "Multimodal hyperspectral remote sensing: an overview and perspective," Sci. China Inf. Sci., vol. 64, no. 2, p. 121301, Feb. 2021, doi: 10.1007/s11432-020-3084-1.

[12] A. S. Gautam, "A Comprehensive Literature Review on Hyperspectral Remote Sensing Techniques and Applications," INTERANTIONAL J. Sci. Res. Eng. Manag., vol. 08, no. 06, pp. 1–5, Jun. 2024, doi: 10.55041/IJSREM35929.

[13] L. Zhang and Y. Zhong, "Analysis of Hyperspectral Remote Sensing Images," in Geospatial Technology for Earth Observation, Boston, MA: Springer US, 2010, pp. 235–269. doi: 10.1007/978-1-4419-0050-0_9.

[14] C. Cucci, J. K. Delaney, and M. Picollo, "Reflectance Hyperspectral Imaging for Investigation of Works of Art: Old Master Paintings and Illuminated Manuscripts," Acc. Chem. Res., vol. 49, no. 10, pp. 2070–2079, Oct. 2016, doi: 10.1021/acs.accounts.6b00048.

[15] M. Caccia, S. Caglio, A. Galli, M. Interlenghi, I. Castiglioni, and M. Martini, "Applying Hyperspectral Reflectance Imaging to Investigate the Palettes and the Techniques of Painters," J. Vis. Exp., no. 172, Jun. 2021, doi: 10.3791/62202.

[16] L. Gao and R. T. Smith, "Optical hyperspectral imaging in microscopy and spectroscopy - a review of data acquisition," J. Biophotonics, vol. 8, no. 6, pp. 441–456, Jun. 2015, doi: 10.1002/jbio.201400051.

[17] J. Burger and A. Gowen, "Data handling in hyperspectral image analysis," Chemom. Intell. Lab. Syst., vol. 108, no. 1, pp. 13–22, Aug. 2011, doi: 10.1016/j.chemolab.2011.04.001.

[18] A. Ramírez et al., "Sistema de visión hiperespectral para el estudio de especies arbóreas tropicales," Rev. Tecnol. en Marcha, Jun. 2022, doi: 10.18845/tm.v35i6.6239.

[19] A. Riaza, E. García-Meléndez, V. Carrère, and A. Mueller, "Cartografía de sales marinas y fluviales en estuarios receptores de aguas ácidas con imágenes hiperespectrales Hyperion (Marismas del río Odiel, Huelva)," Rev. Teledetección, no. 41, p. 1, Jun. 2014, doi: 10.4995/raet.2014.2255.

[20] W. A. Nugraha, P. Wicaksono, and S. Arjasakusuma, "Vegetation Change Detection Analysis Using Multi-sensor Hyperspectral Imagery," J. Geogr. (Geografi Lingkung. Lahan Basah), vol. 5, no. 1, p. 9, Jul. 2024, doi: 10.20527/jgp.v5i1.11709.

[21] G. Nico, M. Monaco, O. Masci, and M. G. C. A. Cimino, "High Resolution Mapping of Vegetation Biodiversity by Hyperspectral Images and Convolutional Autoencoders," in IGARSS 2024 - 2024 IEEE International Geoscience and Remote Sensing Symposium, Jul. 2024, pp. 2247–2250. doi: 10.1109/IGARSS53475.2024.10640541.

[22] H. Chen, "Microscopic Hyperspectral Image Analysis via Deep Learning," Griffith University, 2020. doi: 10.25904/1912/3909.

[23] J. Nalepa, "Recent Advances in Multi- and Hyperspectral Image Analysis," Sensors, vol. 21, no. 18, p. 6002, Sep. 2021, doi: 10.3390/s21186002.

[24] Y. E. García-Vera, A. Polochè-Arango, C. A. Mendivelso-Fajardo, and F. J. Gutiérrez-Bernal, "Hyperspectral Image Analysis and Machine Learning Techniques for Crop Disease Detection and Identification: A Review," Sustain., vol. 16, no. 14, 2024, doi: 10.3390/su16146064.

[25] S. Mahesh, D. S. Jayas, J. Paliwal, and N. D. G. White, "Hyperspectral imaging to classify and monitor quality of agricultural materials," J. Stored Prod. Res., vol. 61, pp. 17–26, Mar. 2015, doi: 10.1016/j.jspr.2015.01.006.

[26] C. Wang et al., "A review of deep learning used in the hyperspectral image analysis for agriculture," Artif. Intell. Rev., vol. 54, no. 7, pp. 5205–5253, Oct. 2021, doi: 10.1007/s10462-021-10018-y.

[27] J. A. Guzman-Alvarez, M. González-Zuñiga, J. A. Sandoval Fernandez, and J. C. Calvo-Alvarado, "Uso de sensores remotos en la agricultura: aplicaciones en el cultivo del banano," Agron. Mesoam., p. 48279, Aug. 2022, doi: 10.15517/am.v33i3.48279.

[28] M. T. Ahmed, A. Villordon, and M. Kamruzzaman, "Comparative analysis of hyperspectral Image reconstruction using deep learning for agricultural and biological applications," Results Eng., vol. 23, p. 102623, Sep. 2024, doi: 10.1016/j.rineng.2024.102623.

[29] B. Jia et al., "Essential processing methods of hyperspectral images of agricultural and food products," Chemom. Intell. Lab. Syst., vol. 198, p. 103936, Mar. 2020, doi: 10.1016/j.chemolab.2020.103936.

[30] B. Lu, P. Dao, J. Liu, Y. He, and J. Shang, "Recent Advances of Hyperspectral Imaging Technology and Applications in Agriculture," Remote Sens., vol. 12, no. 16, p. 2659, Aug. 2020, doi: 10.3390/rs12162659.

[31] B. Wang et al., "The Applications of Hyperspectral Imaging Technology for Agricultural Products Quality Analysis: A Review," Food Rev. Int., vol. 39, no. 2, pp. 1043–1062, Feb. 2023, doi: 10.1080/87559129.2021.1929297.

[32] A. Plaza et al., "Recent advances in techniques for hyperspectral image processing," Remote Sens. Environ., vol. 113, pp. S110–S122, Sep. 2009, doi: 10.1016/j.rse.2007.07.028.

[33] B. Mohan and A. Porwal, "Hyperspectral Image Processing and Analysis," Curr. Sci., vol. 108, pp. 833–841, 2015, doi: https://doi.org/10.18520/CS/V108/I5/833-841.

[34] S. Li, W. Song, L. Fang, Y. Chen, P. Ghamisi, and J. A. Benediktsson, "Deep Learning for Hyperspectral Image Classification: An Overview," IEEE Trans. Geosci. Remote Sens., vol. 57, no. 9, pp. 6690–6709, Sep. 2019, doi: 10.1109/TGRS.2019.2907932.

[35] X. Yang, Y. Ye, X. Li, R. Y. K. Lau, X. Zhang, and X. Huang, "Hyperspectral Image Classification With Deep Learning Models," IEEE Trans. Geosci. Remote Sens., vol. 56, no. 9, pp. 5408–5423, Sep. 2018, doi: 10.1109/TGRS.2018.2815613.

[36] G. E. Chanchí Golondrino, M. A. Ospina Alarcón, and M. Saba, "Vegetation Identification in Hyperspectral Images Using Distance/Correlation Metrics," Atmosphere (Basel)., vol. 14, no. 7, p. 1148, Jul. 2023, doi: 10.3390/atmos14071148.

[37] B. Dastourian, E. Dastourian, S. Dastourian, and O. Mahnaie, "Discrete Wavelet Transforms Of Haar's Wavelet," Int. J. Sci. Technol. Res., vol. 3, pp. 247–251, 2014.

[38] D. B. Percival and A. T. Walden, "The Discrete Wavelet Transform," in Wavelet Methods for Time SeriesAnalysis, Cambridge: Cambridge University Press, 2000, pp. 56–158. doi: 10.1017/CBO9780511841040.005.

[39] H. Husain and A. Amran, "Forecasting Time Series Data Using Haar Discrete Wavelet Transformation," J. Mat. Stat. dan Komputasi, vol. 19, no. 3, pp. 484–497, May 2023, doi: 10.20956/j.v19i3.24807.

[40] S. Gurumoorthy, N. Babu Muppalaneni, and G. Sandhya Kumari, "EEG Signal Denoising Using Haar Transform and Maximal Overlap Discrete Wavelet Transform (MODWT) for the Finding of Epilepsy," in Epilepsy - Update on Classification, Etiologies, Instrumental Diagnosis and Treatment, IntechOpen, 2021. doi: 10.5772/intechopen.93180.

[41] F. Salem, M. Kafatos, T. El-Ghazawi, R. Gomez, and R. Yang, "Hyperspectral image assessment of oil-contaminated wetland," Int. J. Remote Sens., vol. 26, no. 4, pp. 811–821, Feb. 2005, doi: 10.1080/01431160512331316883.

[42] D. W. y Yanbo Huang y Zhao Chunjiang y Wang Xiu, "Identificación de plántulas de col y malezas mediante imágenes hiperespectrales," Int. J. Agric. Biol. Eng., vol. 8, pp. 65–72, 2015, doi: 10.25165/IJABE.V8I5.1492.

Impact of Climate Change on Animal Diseases Based on Machine Learning

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***Abstract*—The rapid pace of climate change has altered the distribution of animal diseases, increased their frequency, and dispersed them over a larger geographic area. Rising temperatures, fluctuating humidity, and erratic rainfall patterns have increased the risk of illness in cows. These modifications have facilitated the growth of diseases and vectors. As a result, timely and accurate identification of these illnesses has become crucial for both food security and sustainable animal health management. To detect and classify animal diseases using visual data, this study proposes a diagnostic framework that utilizes machine learning approaches, with a focus on convolutional neural networks (CNNs) in conjunction with classification models, including ResNet, YOLOv5, and AltCLIP. By learning to distinguish between healthy and sick animals, the model enables prompt identification and treatment of sick animals. Merging data on disease detection with climate parameters, we make comparisons between them to get the best result and use this to generate advanced tools for detecting diseases. This informs us about potential risks. According to the results, machine learning-based diagnosis can improve disease detection's accuracy and efficiency while also providing important new information for climate adaptation strategies in cattle management. The optimal model will produce a graphical user interface (GUI) that displays environmental risk scores, diagnostic data, and recommendations for actions such as monitoring the situation, seeking immediate veterinary care, or verifying the animal's health.**

***Keywords*—Climate change; environmental health; convolutional neural network (CNN); animal diseases; graphical user interface (GUI)**

I. Introduction

To prevent epidemics and safeguard the health of animals, illness prediction is crucial. Farmers can avoid suffering and financial loss by taking preventive action as soon as possible, thanks to early detection. Additionally, it contributes to the preservation of wildlife, the food chain, and global health initiatives [1]. Predicting illnesses also encourages research and development, which results in new treatments and vaccines.

A. Significance of Disease Prediction

Anticipating potential illness in animals is essential for epidemic management and the preservation of animal health [2, 3]. Timely detection allows farmers to swiftly adopt preventive strategies, thereby reducing their distress and economic losses. Furthermore, it protects animals, supports global health security efforts, and guarantees the integrity of the food supply chain.

B. The Essence of Disease Prediction in Animals

A proactive approach to ensure animal health is to anticipate potential diseases. It functions as a sentinel, identifying potential health concerns prior to their emergence [4]. Prompt intervention can mitigate distress and financial expenditure due to this prior awareness [5]. It strengthens the foundations of our food supply chain to guarantee its safety and reliability, akin to a sentinel. Furthermore, it maintains the complex network that illustrates the interdependence of all life by linking the well-being of humans, animals, and the environment. This proactive strategy fortifies against developing health challenges, enhances compliance with regulations, and elevates awareness of ethical pet ownership [6]. Disease prediction serves as a beacon, guiding humans and animals towards more harmonious and healthier coexistence. Forecasting animal diseases is an essential aspect of a robust ecosystem in its own distinct manner [7].

Preserving the equilibrium between nature and human endeavors contributes to the safeguarding of endangered species and the vitality of animal populations [8]. It functions as a vigilant sentinel, identifying and mitigating zoonotic threats to safeguard global health security and avert possible pandemics. This proactive strategy also cultivates innovation, leading to the development of novel vaccinations, medicines, and diagnostic tools [9]. Disease prediction underscores the need for early identification and treatment by cultivating a culture of readiness and accountability through continuous vigilance. Ultimately, it illustrates our collective commitment to enhancing the quality of life for all and fostering global peace.

C. Machine Learning's Role in Disease Prediction

The Principles of Predicting Animal Diseases: By predicting animal diseases, we can protect their health before they happen. Machine learning is poised to become an integral part of clinical diagnosis, enhancing the accuracy and efficiency of medical evaluations and treatments. [10]. It looks out for your health problems before they happen, like a guardian angel. This knowledge lets you respond quickly, which reduces pain and financial loss [11]. It guards the pillars of our food supply chain like a sentinel to make sure it is secure and reliable [12]. It also protects the complex network that connects the health of people, animals, and the environment, showing how all living things are connected. This progressive approach also makes people more likely to follow the rules, learn more about how to care for pets, and protect us all from new health problems. Essentially, predicting disease is like a beacon that shows people the road to

a calm and healthy life [13]. For disease prediction, machine learning is very important since it uses data to find patterns and make accurate predictions. It lets you look at a lot of data, from genetic markers to environmental factors, to find early signs of illness [14]. Machine learning models can find little connections that people would miss by using advanced algorithms [15]. This makes it possible to create predictive models that can figure out how likely it is that a person or group of people will get sick. Also, these models can change and get better over time as more data is collected, making them more reliable and accurate. Machine learning changes how people understand and process information. It is also a powerful tool for keeping an eye on and stopping diseases before they happen. This leads to better results for both people and animals. The effects of climate change on diseases affecting cattle and other animals, along with the introduction of novel infectious organisms, remain inadequately researched.

II. Literature Review

A. Applications of Machine Learning in Animal and Veterinary Public Health Surveillance

Machine learning (ML) is a type of artificial intelligence that employs algorithms to improve its ability to reach a certain goal (such as categorization or prediction) directly from the data itself, without needing explicit and detailed instructions on how to do so [17]. Monitoring systems for zoonotic and animal diseases depend on a range of tasks being done well, and some of these tasks can be done by machine learning algorithms. Machine learning has become a lot more common in veterinary and animal public health surveillance in the past few years, just like it has in other fields. ML algorithms are being used to solve tasks that were unfeasible before big datasets, new ways to look at them, and more computing power were available.

B. Disease Prediction Using Machine Learning Algorithms: KNN and CNN

People today suffer from a variety of diseases because of their lifestyle choices and the environment. Therefore, it becomes crucial to predict the disease early on. However, the doctor finds it too challenging to provide an accurate diagnosis based just on symptoms. Making accurate disease predictions is one of the most challenging tasks [18]. To solve this issue, data mining plays a crucial role in disease prediction. The amount of data in medical science is growing significantly every year. The increasing amount of data in the medical and healthcare domains has made accurate medical data analysis beneficial for early patient care. To find concealed information in massive amounts of medical data, data mining employs sickness data. The patient's symptoms led us to provide a general illness prediction. Accurate disease prediction is achieved using machine learning techniques such as K-Nearest Neighbor (KNN) and convolutional neural networks (CNN). For prediction, a dataset of disease symptoms was required [16]. A person's daily routine and medical history are considered to make an accurate general illness diagnosis. With an accuracy of 84.5% in 2025, the role of machine learning in infectious disease early detection and prediction in the MENA region, CNN performs better than the KNN method in the general disease prediction task. Furthermore, compared to CNN, KNN uses more memory and time.

C. Comparative Study of IoT- and AI-Based Computing Disease Detection Approaches

The growth of several computing methods, such as cloud-, fog-, and edge-based Internet of Things (IoT) systems, has enabled the creation of intelligent sickness detection systems. Because models using deep learning have outperformed shallow learning when handling large volumes of data, the research community has focused more on them than on other machine learning models [19]. However, there hasn't been a comprehensive examination of computer-based and Internet of Things-related systems that employ deep learning techniques for disease diagnosis. To assess different machine learning and deep learning algorithms, as well as their hybrid and optimized algorithms for IoT-based disease detection, this study used the most recent publications on IoT-based disease detection systems that utilize computing technologies, such as cloud, edge, and fog. Their work focused on an IoT architecture for deep learning that may be used to detect diseases. It also recognizes that to develop more efficient IoT sickness detection systems, researchers must concentrate on several factors. This work may be helpful to researchers who want to enhance hybrid IoT-based illness detection and prediction systems that rely on deep learning.

D. "Cattle Disease Identification Using Prediction Techniques"

In developing nations like India, Bangladesh, Nepal, and many others, dairy farming was one of the first forms of occupation. One of the main factors contributing to the increase in productivity in dairy production is dairy farm automation. Numerous illnesses can affect cattle, some of which can reduce output and the quality of dairy products [20]. If not detected early, these illnesses can also lead to livestock mortality, which is significantly hampered by the country's economy's steady growth [21]. Cattle are present in considerable numbers in dairy products. Taking care of them and monitoring the dairy cow's health is simply too difficult. Additionally, the dairy owner and the local government are crucial to this endeavor. The primary characteristic of a health management approach is the ongoing monitoring of each cow's health, prompt diagnosis, and early handling of ill animals. We track the fundamental elements of animal activity, such as temperature, heart rate, etc., using sensor technology. To determine whether an impending disease episode is anticipated, this data is combined and fed into a data mining algorithm. It increases the possible expenses of animal health care as well as the lowest level of veterinarian examination. This study offers a method that describes how IOT and data mining can be used to identify uncommon cow illnesses in farm animal hospitals with affordable treatment options. Animal Disease Prediction using Machine Learning Techniques. In recent years, there has been a significant increase in the variety of animal diseases. Many of these illnesses have a propensity to become zoonotic diseases, which can affect both humans and animals and prove to be highly contagious [22]. The study of having machines or computers learn on their own so that additional predictions can be made is known as machine learning, produced for a variety of uses [23]. Machine learning techniques for human disease identification have been around for a while, but there haven't been many developments for animal diseases. By using machine learning approaches to

categorize certain animal diseases and forecast their spread, we bring a novel contribution to the subject with this research study [24]. When animal sickness develops into zoonosis, it can significantly affect both human and animal populations. Therefore, as part of this investigation, we also employed specific methods to determine whether the illness is zoonotic. Keywords: classification, regression, machine learning, zoonosis, and research.

E. Artificial Intelligence and its Application in Animal Disease Diagnosis

The current study looks at the rules, history, subfields, and real-world applications of artificial intelligence in animal disease detection. There are two subfields of artificial intelligence (AI), or intelligence displayed by machines: machine learning and deep learning. In machine learning (ML), algorithms are used to find patterns in data and build a model for future forecasting [25]. Among the most popular algorithms are support vector machines, K-nearest, decision trees, random forests, and linear regression. The four categories of deep learning methods are sparse coding, restricted state machines, convolutional neural networks, and autoencoders [26]. One of the most widely used methods, Convolutional Neural Networks (CNN), automatically recognizes important elements without the need for human supervision. AlexNet, ZFNet, GoogLeNet, VGG-16, and other impressive CNN architectures were on display during the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). The National Animal Disease Referral Expert System (NADRES) of ICARE-NIVEDI, the identification of left atrial enlargement on canine thoracic radiology, the prediction of survivability and the necessity of horses with colic, and the machine learning-based detection of subclinical mastitis in cows by Ebrahimi et al. are a few examples of the documented evidence of AI's application in veterinary sciences [27].

There are many methods used for detecting animal diseases. In this study, different types are chosen to get the highest result for the problem and make a comparison for building a hybrid model to collect data from animals, such as pictures, and climate change parameters. There are two phases of the first set of traditional deep learning, and then we get the advanced one to compare the results.

III. Methodology

The methodology employed in this research aimed to create and assess a resilient machine learning framework for identifying animal diseases, considering the effects of climate change. Because illness dynamics are so complicated and interact with environmental conditions, the method merged image-based deep learning with climate-related data to make predictions more accurate and generalize better. The research utilized a phased development methodology, initiating with a basic Convolutional Neural Network (CNN) exclusively trained on image data, and later integrating additional components such as climatic variables, transfer learning frameworks, and regularization techniques. This study employs a multimodal data fusion approach to accurately assess the influence of climate change on animal disease diagnosis by integrating visual data with climatic textual data. The visual modality comprises animal images used for the identification of disease related symptoms, whereas the climatic modality encompasses numerical and textual representations of environmental data, including temperature and humidity. The image data undergoes processing via deep learning feature extraction networks, including convolutional neural networks (CNNs) and models such as ResNet and YOLOv5. These models acquire advanced visual traits that signify illness patterns, lesions, or atypical physical characteristics. This stage produces a concise feature vector that represents the visual health status of the animal. Simultaneously, the meteorological data, depicted as organized numerical values (e.g., temperature and humidity), are standardized and converted into a feature representation appropriate for machine learning analysis. These climatic characteristics encapsulate environmental stressors that affect illness vulnerability and advancement. The two feature sets are subsequently integrated at the feature level, wherein visual features and climatic features are amalgamated into a cohesive representation. The integrated feature vector is then transmitted to a classification layer or fully connected network that acquires knowledge of the interrelations between visual symptoms and environmental factors. By concurrently learning from multiple modalities, the model can more effectively evaluate illness risk and severity compared to utilizing image data in isolation. The integrated output is utilized to produce diagnostic forecasts, environmental risk assessments, and decision-support suggestions. This multimodal integration enables the system to correlate illness symptoms with climatic conditions, facilitating more precise, climate-informed disease diagnosis and aiding early intervention techniques in livestock.

IV. Results

The results encompass the preparation of both image and climate data, the construction and training of multi-input deep learning models, and the implementation of advanced architectures, including EfficientNetB0. We used training and validation accuracy metrics to evaluate the model, paying close attention to overfitting, model stability, and generalization performance. The suggested method combines traditional CNN-based image classification with environmental data integration and cutting-edge transfer learning. This makes it a complete way to deal with both the problems of finding animal diseases and the growing effects of climate change, as shown in Table I.

TABLE I. The CNN and Deep Learning Models Result

Model Phase	Training Accuracy (%)	Validation Accuracy (%)
Phase 1: CNN (Images Only)	88	65
Phase 2: CNN + Climate Data	88	75
Phase3: EfficientNet0 +Climate Data	92	87
Phase 4: EfficientNet + Regularization	90	91

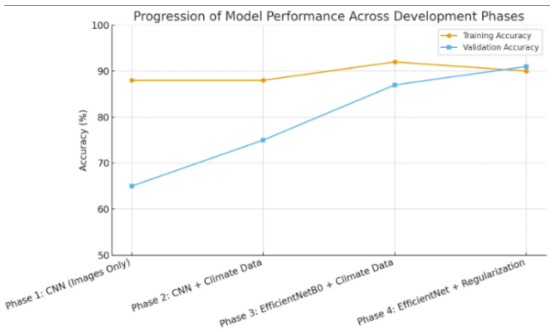


Fig. 1. The progression of accuracy across four phases.

In Fig. 1, the starting point of the CNN that was exclusively trained on image data (Phase 1) was a clear case of overfitting because the training accuracy was about 88%, but the validation accuracy was only about 65%. This revealed that the model couldn't use what it learnt on data that wasn't in the training set. We added climate elements, including temperature and humidity, in Phase 2, which raised the validation accuracy to 75%. The performance of the training remained unchanged. This shows that adding environmental data narrows the gap between training and validation and makes generalization better. We employed EfficientNetB0 for transfer learning in Phase 3, which made both training and validation much more accurate (92% and 87%, respectively). The pre-trained feature extraction layers gave us a strong base, which helped us reach our goal faster and improved the overall prediction performance. Finally, in Phase 4, freezing the pre-trained layers and employing stronger regularization approaches like dropout and L2 regularization made the training and validation performance stay the same. The accuracy of the training data dropped to 90%, but the accuracy of the validation data rose to roughly 91%. This shows that the model is more generic and stable. The final optimized model has a CNN accuracy of more than 90%. Adding climatic data was helpful for making things better. Generalization, transfer learning, and regularization procedures made sure that the model stayed stable and didn't overfit. The link between climate change and animal health shows how important it is to use new diagnostic methods. New vectors and infections appear in areas that were not affected before as temperatures rise, rainfall patterns change, and humidity levels increase. This tendency not only raises the likelihood of outbreaks, but it also makes it harder to manage diseases. Machine learning–based diagnostic tools offer a proactive strategy by facilitating real-time monitoring and early diagnosis, which are crucial for alleviating the impacts of these climate-induced changes. Additionally, connecting illness surveillance systems with climate data can improve early warning systems and help policymakers create targeted policies. The results show that the model's performance has steadily improved from a baseline accuracy of 65% to a higher level by following the previous diagram in the last research, as shown in Fig. 2.

Our second step is a comparative analysis of ResNet, YOLOv5, and AltCLIP methods to get results from different methodologies that we used on the same dataset to check the results compared to the previous one in the training and validation phases.

We start to show the results for three models that were used to make the comparison, starting with the YOLOv5 model.

The training loss for YOLOv5 started at 0.494 and went down to 0.203 by the end of the last epoch. The loss for validation started at 0.528 and went down to 0.426 (Fig. 4). The Top1 Accuracy went up consistently from 78.7% in the first epoch to 85.6% in the last epoch, which shows that the model was learning and performing well on the dataset (Fig. 3).

Then we showed the result, and it's impressive that the algorithm can distinguish between sick and healthy cows. For cows that are lumpy, it gets it right 61% to 83% of the time, and for healthy cows, it gets it right 61% to 99% of the time. The expected probabilities show this difference even more clearly: the confidence ratings for healthy cows are between 0.17 and 0.99, whereas those for lumpy cows are between 0.13 and 0.83. But since the chances are about 0.5 for both (Fig. 6).

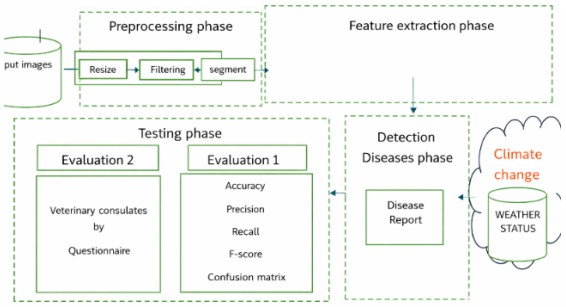


Fig. 2. Block diagram for the prediction of disease in animals [1].

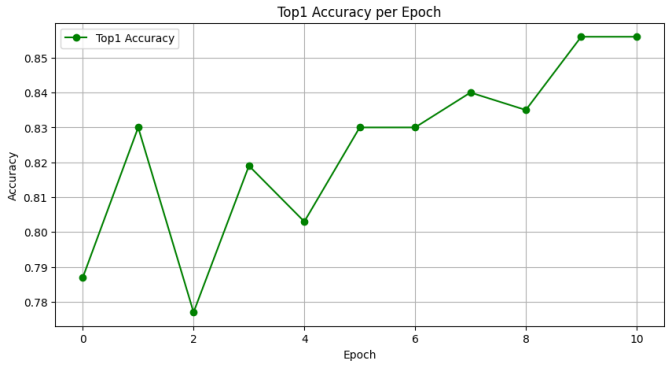


Fig. 3. The accuracy per epoch for YOLOv5.

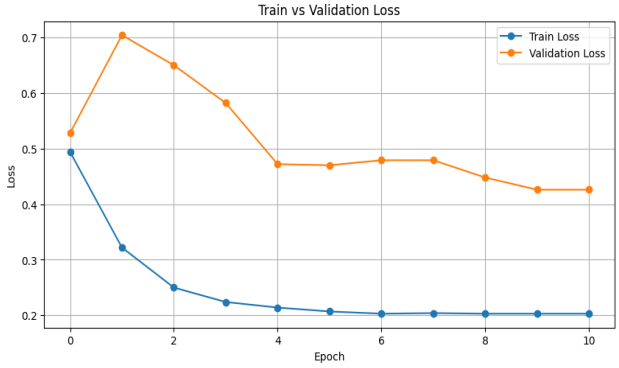


Fig. 4. The train and validation loss results for YOLOv5.

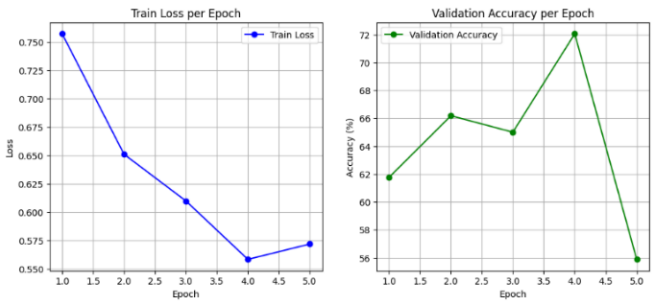


Fig. 5. The train and validation results for ResNet.

The training loss for ResNet went from 0.7572 to 0.5586 during five epochs, which shows that it was learning well. The validation accuracy began at 61.76%, increased to 96.18% in the second epoch, and thereafter decreased to 55.88%. This suggests that ResNet can be quite precise at some stages during training (Fig. 5).

The dataset was carefully prepared using an 80/20 train-validation split, ensuring proper shuffling and organization for balanced learning. Over the course of 10 training epochs, the model achieved a final Top 1 accuracy of 85%, with the training loss reduced to 0.2 and validation loss to 0.3. The small loss gap of 0.1 indicates strong generalization and minimal signs of overfitting. Analysis suggests that the optimal stopping point was around Epoch 8, where performance stabilized. Overall, the model trained successfully, demonstrating reliable accuracy and robustness, making it well-suited for final testing and deployment.

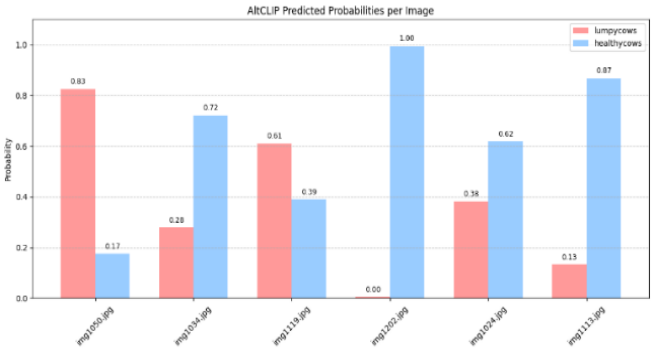


Fig. 6. The training and validation for ResNet results.

Groups, the model doesn't know what to do with more unclear photographs. Even with these issues, the model has gotten better at generalizing across different samples because of data augmentation techniques, including rotation, random flipping, and scaling. Future improvements could include adding more data to the dataset and employing fine-tuning methods to make class separation better and reduce confusion. This would make the performance better and more stable. Table II shows all the outcomes of the comparisons.

Interventions. While promising, this approach requires continued investment in data collection, model refinement, and interdisciplinary collaboration between veterinarians, climate scientists, and computer engineers to maximize its impact. At the end, we show the total result in Fig. 7.

TABLE II. THE COMPARISON OF THE MODELS' RESULTS

Model	Training Loss Trend	Validation Loss / Accuracy	Key Results	Strengths
YOLOv 5	Decreased from 0.494 → 0.203	Validation loss 0.528 → 0.426; Top-1 Accuracy improved from 78.7% → 85.6%	Stable and consistent improvement	Reliable performance across epochs; best for general classification & detection
ResNet	Decreased from 0.7572 → 0.5586 (5 epochs)	Validation accuracy started 61.76%, peaked at 96.18%, fluctuated between 65–72%, ended at 55.88%	Can reach very high accuracy at certain stages	Strong peak accuracy, but unstable validation results
AltCLIP	N/A (probability -based output)	Provides per-class probabilities (e.g., 0.825 lumpycows, 0.996 healthycows, 0.721–0.868 for other images)	High confidence and precise predictions	Best for detailed per-image classification and semantic discrimination

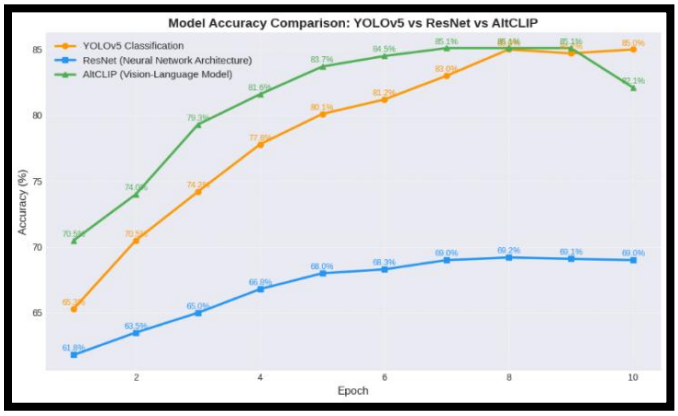


Fig. 7. The accuracy comparison between the models.

In the last step, we use the best result of models to the GUI, which was also built to merge visual and environmental data so that diseases might be found on their own. The trained models in the system use weather data and pictures of animals to make an environmental interpretation, a combined stress index, a quantitative risk score (0–100), and suggestions for what to do next, like getting immediate veterinary care, keeping an eye on the animal often, or making sure it is healthy. This combination approach shows that using climate-sensitive analysis with deep learning architectures may make diagnoses far more accurate, let doctors make proactive choices, and allow for ecological.

V. Graphical User Interface (GUI) for Climate-Aware Animal Disease Diagnosis

To turn the complex parts of the proposed machine learning architecture into an app that is easy to use and accessible, it is important to make a graphical user interface (GUI). Its main purpose is to make it easier to enter, process, and understand data, which will make the system more useful and applicable in real-life weather data that is important, such as temperature and humidity. After the inputs are sent in, the interface automatically runs them through the learnt classification models, which gives very detailed diagnostic results. These include a combined stress index, descriptions of the environment, graphs showing how likely an illness is to happen, and a risk score that can be measured and goes from zero to one hundred. GUI also gives simple suggestions depending on the diagnostic results, including getting immediate veterinary attention, keeping an eye on the situation regularly, or confirming that the animal is healthy. We take a photo and send it to the system. The pic shown below is an example of upload in the system, using two climate change temperature and humidity, and the shape of the GUI for the system, as shown in Fig. 8.

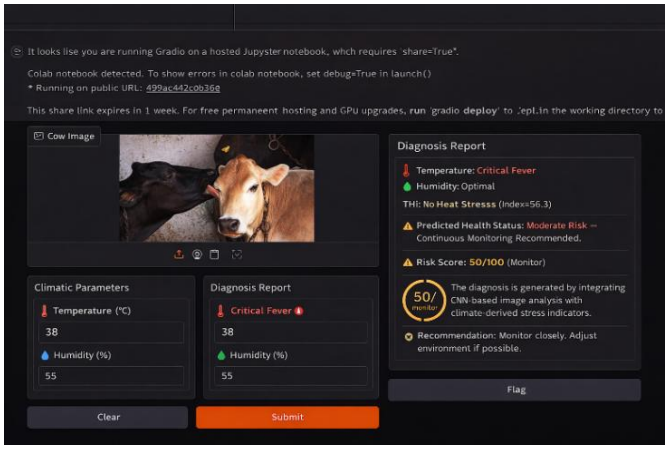


Fig. 8. The GUI and the result after uploading the picture.

The GUI that was built uses animal picture processing and environmental data (temperature = 33 °C, humidity = 60%) to automatically discover diseases. The system used the model YOLOv5 to find hypothermia at the right humidity and a THI of 28.9, which suggests there was no heat stress. The diagnosis assigned the case a risk score of 50 out of 100 and indicated it "Needs Monitoring". This suggested that the person should be followed attentively, and the environment should be modified. This shows how the system could keep an eye on animal health by using AI-based detection and climate evaluation together.

VI. Discussion

This study's findings illustrate the efficacy of combining machine learning methods with climatic data to improve the diagnosis of animal diseases amid shifting environmental conditions. The noted enhancement in diagnostic precision corroborates the concept that climate variability, especially variations in temperature and humidity, significantly influences the onset and development of bovine illnesses. By integrating these environmental aspects into the diagnostic framework, the proposed model offers a more thorough comprehension of disease dynamics than image-based analysis alone. The utilization of convolutional neural networks, in conjunction with sophisticated classification models like ResNet, YOLOv5, and AltCLIP, facilitated effective feature extraction and dependable disease classification. These models proficiently differentiated between healthy and unhealthy animals, even in visually intricate situations, illustrating their appropriateness for veterinary diagnostic applications. The findings demonstrate that transfer learning and multimodal designs enhance generalization and decrease misclassification, especially in instances where disease symptoms are mild or overlapping. The incorporation of climate factors with ocular illness detection markedly improved the system's prediction performance. The integrated analysis enabled the model to evaluate environmental stressors and correlate them with disease risk, providing significant insights into the impact of climate change on livestock health. This method enhances early disease identification and facilitates proactive risk assessment and climate adaptation measures in cattle management. The creation of a graphical user interface (GUI) enhances the practical utility of the proposed technology. GUI facilitates the connection between intricate machine learning models and end users, including farmers and veterinarians, by displaying diagnostic results, environmental risk assessments, and practical advice in an easily understandable style. This promotes informed decision-making, allowing for prompt actions that can mitigate disease transmission, lessen economic losses, and enhance animal welfare. Notwithstanding these encouraging outcomes, specific limits must be recognized. The model's effectiveness is contingent upon the quality and diversity of the training data, whereas discrepancies in picture quality or insufficient climatic records may influence diagnostic precision. Subsequent research may rectify these limitations by integrating larger, multi-regional datasets, supplementary environmental factors, and real-time sensor data to augment robustness and scalability. This study underscores the capacity of climate-conscious machine learning frameworks to revolutionize animal disease detection. The suggested method integrates visual analysis with environmental context, enhancing sustainable livestock management and providing a crucial tool for alleviating the increasing health concerns linked to climate change.

VII. Conclusion

Climate change is making animal diseases spread faster, and outbreaks happen more often, are worse, and are affecting more animals. These changes pose a major threat to the stability of agricultural economies around the world, food safety, and animal health. Standard diagnostic methods are useful, but they might not be useful in all cases because they cost a lot, take a long time, and aren't very scalable. This makes them less useful for keeping an eye on diseases in real-time over a wide area in a world that is changing quickly. This study presents a sophisticated diagnostic system that utilizes image-based data to rapidly and accurately identify animal diseases through cutting-edge machine learning and deep learning techniques. The suggested method combines convolutional neural networks (CNNs) with several strong classification architectures, such as ResNet, YOLOv5, and AltCLIP, to make feature extraction, localization, and visual-semantic comprehension better. The method enhances early diagnosis by integrating diagnostic

predictions with environmental factors such as temperature and humidity.

VIII. Future Directions

There are several interesting avenues for this field's research. First, the robustness and generalizability of CNN-based diagnostic models will be enhanced by enlarging datasets to encompass a greater variety of animal species, illnesses, and climates. Second, the accuracy of disease prediction and outbreak forecasting can be improved by combining multi-modal data, including sensor data (e.g., temperature, humidity, and movement tracking), farm management techniques, and satellite-based climate information. Farmers in rural or resource-poor areas might also benefit from real-time diagnostic tools that don't need expensive infrastructure. They could do this by making lightweight AI models that work well on mobile or edge devices. Future research may also examine explainable AI (XAI) methodologies to enhance the transparency and dependability of model decisions, hence facilitating informed decision-making by policymakers and veterinarians. Finally, creating worldwide data-sharing platforms that connect animal health records and weather trends will make it easier to keep an eye on huge areas, help create early warning systems, and help design agricultural systems that can handle climate change.

References

[1] Gehad K. Hussien, Mohamed H. Khafagy and Hossam M. Elbehiery, "The Effect of Climate Change on Animal Diseases by Using Image Processing and Deep Learning Techniques" International Journal of Advanced Computer Science and Applications(ijacsa), 16(3), 2025.

[2] Borham, A., Abdel Motaal, K., ElSersawy, N., Ahmed, Y. F., Mahmoud, S., Musaibah, A. S., & Abdelnaser, A. (2025). Climate Change and Zoonotic Disease Outbreaks: Emerging Evidence from Epidemiology and Toxicology. International Journal of Environmental Research and Public Health, 22(6), 883.

[3] Vardhan, B. A., Phanindra, K. R., Sumith, K., Sirisha, T., & Kakulapati, V. (2025). Explainable AI for Livestock Disease Detection: An Integrated ML/DL Framework. Asian Journal of Research in Computer Science, 18(6), 147-153.

[4] Guo, R., Dai, Y., & Hu, J. (2025). Research on the prediction model of mastitis in dairy cows based on time series characteristics. Frontiers in Veterinary Science, 12, 1575525.

[5] Girmaw, D. W. (2025). Livestock animal skin disease detection and classification using deep learning approaches. Biomedical Signal Processing and Control, 102, 107334.

[6] SERRADJ, Z. (2025). Animal Skin Disease Identification Using Machine Learning Methods (Doctoral dissertation, University of Echahid Cheikh Larbi Tébessi-Tébessa).

[7] Ali, M. Z., Carlile, G., & Giasuddin, M. (2020). Impact of global climate change on livestock health: Bangladesh perspective. Open veterinary journal, 10(2), 178-188.

[8] Munir, K., Ghafoor, M., Khafagy, M., & Ihshaish, H. (2022). AgroSupportAnalytics: a cloud-based complaints management and decision support system for sustainable farming in Egypt. Egyptian Informatics Journal, 23(1), 73-82.

[9] Cheng, M., McCarl, B., & Fei, C. (2022). Climate change and livestock production: a literature review. Atmosphere, 13(1), 140.

[10] Shivahare, B. D., Singh, J., Ravi, V., Chandan, R. R., Alahmadi, T. J., Singh, P., & Diwakar, M. (2024). Delving into machine learning's influence on disease diagnosis and prediction. The Open Public Health Journal, 17(1).

[11] Forster, P. M., Smith, C. J., Walsh, T., Lamb, W. F., Lamboll, R., Hauser, M., ... & Zhai, P. (2023). Indicators of Global Climate Change 2022: annual update of large-scale indicators of the state of the climate system and human influence. Earth System Science Data, 15(6), 2295-2327.

[12] Noto, L.V.; Cipolla, G.; Francipane, A.; Pumo, D. Climate change in the mediterranean basin (part I): Induced alterations on climate forcings and hydrological processes. Water Resour. Manag. 2023, 37, 2287–2305.

[13] Piekarski, M., Jaworek-Korjakowska, J., Wawrzyniak, A. I., & Gorgon, M. (2020). Convolutional neural network architecture for beam instabilities identification in Synchrotron Radiation Systems as an anomaly detection problem. Measurement, 165, 108116.

[14] Gwaka, J.K.; Demafo, M.A.; N'konzi, J.-P.N.; Pak, A.; Olumoh, J.; Elfaki, F.; Adegboye, O.A. Machine Learning Approach for Risk Estimation and Risk Prediction of the Effect of Climate on Bovine Respiratory Disease. Mathematics 2023, 11, 1354.

[15] Ceia-Hasse, A., Sousa, C. A., Gouveia, B. R., & Capinha, C. (2023). Forecasting the abundance of disease vectors with deep learning. Ecological Informatics, 78, 102272.

[16] Genemo, M. D. (2022). Suspicious activity recognition for monitoring cheating in exams. Proceedings of the Indian National Science Academy, 88(1), 1-10.

[17] Guitian, J., Arnold, M., Chang, Y., & Snary, E. L. (2023). Applications of machine learning in animal and veterinary public health surveillance. Rev. Sci. Tech, 42, 230-241.

[18] Kumar, K. P., Pravalika, A., Sheela, R. P., & Vishwam, Y. (2022). Disease prediction using machine learning algorithms KNN and CNN. International Journal for Research in Applied Science and Engineering Technology, 10(5), 446-450.

[19] .Rhmann, W., Khan, J., Khan, G. A., Ashraf, Z., Pandey, B., Khan, M. A.,& Shaik, M. K. (2025). Comparative study of IoT-and AI-based computing disease detection approaches. Data Science and Management, 8(1), 94-106.

[20] Kishan, N. V., Trinath, Y. S., Kavalur, S., Sangamesha, V., & Reddy, S. (2021). Cattle disease identification using Prediction Techniques. IJARIIE-ISSN (O), 2395-4396.

[21] Wei, Z., Song, H., Chen, L., Li, Q., & Han, G. (2019). Attention-based DenseUnet network with adversarial training for skin lesion segmentation. IEEE Access, 7, 136616-136629.

[22] Werkheiser, I. (2020). Technology and responsibility: a discussion of underexamined risks and concerns in precision livestock farming. Animal Frontiers, 10(1), 51-57.

[23] Rekha, G. S., & Rani, T. P. (2022). K, Sai Prasanna, P. Rathnamala, Gulshan Kumar Jha, P. Srinivas Rao. COVID-19: Deep Learning Approach for Diagnosis.

[24] Mohamed, M. H., Khafagy, M. H., & Ibrahim, M. H. (2020). Two recommendation system algorithms used SVD and association rule on implicit and explicit data sets. Int. J. Sci. Technol. Res, 9(11), 508-515.

[25] Kour, S., Agrawal, R., Sharma, N., Tikoo, A., Pande, N., & Sawhney, A. (2022). Artificial intelligence and its application in animal disease diagnosis. Journal of Animal Research, 12(1), 1-10.

[26] Boyce, R. M., Hollingsworth, B. D., Baguma, E., Xu, E., Goel, V., Brown-Marusiak, A., ... & Mulogo, E. M. (2022). Dihydroartemisinin-piperaquine chemoprevention and malaria incidence after severe flooding: evaluation of a pragmatic intervention in rural Uganda. Clinical Infectious Diseases, 74(12), 2191-2199.

[27] Bozzo, G.; Corrente, M.; Testa, G.; Casalino, G.; Dimuccio, M.M.; Circella, E.; Brescia, N.; Barrasso, R.; Celentano, F.E. Animal Welfare, Health and the Fight against Climate Change: One Solution for Global Objectives. Agriculture 2021, 11, 1248.

Linking Leadership Styles to Corporate ESG Performance: A Novel Sierpinski Triangle Fuzzy Decision-Making Modelling

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***Abstract*—Existing research generally addresses the factors affecting ESG performance at a general level, but fails to examine the relative impact of leadership approaches on this performance with a holistic decision-making model. This deficiency makes it difficult for businesses to align their sustainability strategies with the right leadership styles and creates uncertainty in achieving their ESG goals. In this context, the aim of this study is to determine the most appropriate leadership style for improving ESG performance and to prioritize the criteria influencing this selection with an integrated approach. To address this gap in the literature, the study proposes a new multi-criteria decision-making model. The model utilizes a combination of the Z-score-based normalized ideal distance method (z-NIDM), CIMAS, RAM, and the innovative Sierpinski triangle fuzzy sets. According to the analysis results, the most important criterion for improving ESG performance is promoting green innovation, with a weight of 0.108, followed by resource efficiency, with a weight of 0.105. The most appropriate leadership style was determined to be ethical leadership, with a weight of 1.4841. These findings suggest that, to achieve their sustainability goals, businesses must adopt ethical management approaches, increase investments in green innovation, and make resource efficiency a strategic priority. This study offers a unique contribution by introducing a new fuzzy set approach to the literature, analyzing the relationship between ESG and leadership with an integrated decision-making model, and proposing a methodologically robust framework.**

***Keywords*—Leadership approaches; ESG performance; z-NIDM; CIMAS; RAM**

I. Introduction

The concept of ESG (environmental, social, and governance) is a sustainability approach that considers not only the financial performance of businesses but also their responsibilities to the environment, society, and corporate governance. ESG performance is a key indicator of companies' long-term success and stakeholder trust, as elements such as environmentally responsible production processes, respect for employee rights, ethical management, and transparency create both reputation and competitive advantage. Therefore, strong ESG performance increases investor interest, mitigates risks, and supports sustainable growth. However, achieving this performance depends largely on leadership [1]. Transformational Leadership motivates employees with its visionary approach, creates an organizational culture open to change, and inspires the achievement of sustainability goals. Servant leadership strengthens the social dimension by focusing on the needs of employees and society and emphasizes ethical values. Ethical leadership establishes a strong foundation in governance by integrating the principles of justice, honesty, and responsibility into corporate governance processes. Adaptive leadership, on the other hand, enhances the capacity to cope with environmental and social challenges by making flexible and innovative decisions in response to changing environmental conditions. Therefore, the conscious and balanced application of different leadership styles strengthens businesses' ESG performance, creates sustainable competitive advantage, and contributes to the formation of a credible corporate identity in the eyes of stakeholders.

Determining which leadership model is most effective in improving companies' ESG performance is critical to achieving sustainable performance, as each leadership model impacts the environmental, social, and governance dimensions differently. Environmentally, resource efficiency, optimizing energy, water, and raw material use, reducing carbon emissions, and encouraging green innovation enable businesses to develop environmentally responsible strategies [2]. In this process, visionary and innovative leadership approaches facilitate the adoption of environmentally friendly products and processes. Socially, employee engagement and motivation, effective implementation of diversity and inclusion policies, trust-based relationships with society, and stakeholder satisfaction contribute to the development of a strong corporate culture. In these areas, servant and transformational leadership styles strengthen social sustainability by centering the expectations of employees and society. In governance, ethical decision-making, transparency, risk management, accountability, and a long-term sustainability vision form the foundation of corporate trust. In this context, ethical and adaptive leadership support a flexible, reliable, and auditable organizational structure. In terms of overall performance, the integration of ESG strategies into corporate objectives, openness to change, and contribution to long-term financial sustainability enhance a company's competitiveness. Therefore, the choice of leadership model is shaped by the interaction of these multidimensional variables,

and the right leadership approach strengthens businesses' capacity to achieve sustainable success and create social value by ensuring holistic development of ESG performance.

Identifying the leadership styles that should be considered most when improving companies' ESG performance is crucial, as leadership approaches directly impact all dynamics, from a company's strategic decision-making processes to its corporate culture. If the most appropriate leadership style is not determined, business policies cannot align with ESG objectives, leading to weakened environmental, social, and governance performance. Therefore, determining which leadership model most strongly supports ESG performance is critical for sustainable corporate success. However, this determination process depends not only on the general characteristics of leadership styles but also on the criteria that most influence this choice [3]. Factors such as environmental sensitivity, ethical decision-making capacity, ability to manage stakeholder expectations, level of employee engagement, and openness to innovation can all be decisive in choosing a leadership style. If these critical factors are not properly identified and prioritized, businesses may direct their resources in the wrong areas, struggle to achieve their sustainability goals, and lose stakeholder trust. However, the literature is quite limited in analyzing the criteria by which leadership styles that influence ESG performance should be prioritized. This deficiency creates a significant gap in the ESG and leadership literature. This gap creates both theoretical and practical misconceptions, measurement difficulties, and strategic uncertainties. Therefore, developing a new and comprehensive materiality analysis on this topic would make an original contribution to the literature and help businesses more effectively align their leadership strategies with their ESG objectives.

The aim of this study is to identify the leadership types that should be most considered when improving the ESG performance of businesses. To this end, the study aims to fill the existing gap in the sustainability and leadership literature and provide decision-makers with a scientifically based assessment model. The motivation for this research stems from the limited literature on how leadership approaches that influence ESG performance can be prioritized under different criteria. In this context, an extensive literature review was conducted, and twelve different assessment criteria affecting ESG performance were identified. Furthermore, five different leadership types that can be effective in ESG-focused management processes were selected as alternatives. In the study, evaluations of these criteria and alternatives were obtained from 10 different subject-matter experts. To account for demographic differences and evaluation consistency among the experts, importance weights were calculated using the Z-score-based normalized ideal distance method (z-NIDM). Additionally, the CIMAS technique was applied to determine the importance of the criteria. Furthermore, alternative leadership types were ranked using the RAM method. The newly developed Sierpinski triangle fuzzy settler approach was used in the analysis process to more precisely assess uncertainties. This comprehensive model enables the holistic evaluation of both quantitative and qualitative data in a multi-criteria decision-making process. The study addresses the following research questions: 1) Which leadership style has the most critical impact on improving ESG performance? 2) What are the most important criteria for determining leadership selection for ESG performance? 3) How do the weights of these criteria change under uncertainty? and 4) What innovation does the developed integrated model offer to existing analysis methods in the field of ESG and leadership? By addressing these questions, the study aims to make an original contribution to the ESG and leadership literature at both theoretical and applied levels.

This study provides a unique methodological and conceptual contribution to the literature by analyzing the most effective leadership type for improving ESG performance and the most critical criteria determining this choice using a new integrated multi-criteria decision-making model. The model proposed in this study offers significant advantages in several aspects compared to previously developed decision-making models in the literature: 1) First and foremost, the development of Sierpinski triangle fuzzy sets stands out as a unique innovation. This approach offers higher discrimination power and uncertainty sensitivity compared to existing uncertainty representation methods such as classical fuzzy sets, intuitionistic fuzzy sets, or type-2 fuzzy sets. The Sierpinski triangle structure can more accurately capture small differences in decision-makers' assessments, thus minimizing information loss. Thus, this study not only proposes a new decision model but also makes a methodological contribution by introducing a new type of fuzzy set to the literature. 2) The use of the z-NIDM technique in determining experts' importance weights is another significant advantage of the model. This method applies weighting by objectively considering the experts' demographic characteristics, knowledge levels, and evaluation consistency. In most studies in the literature, the assumption of equal weighting of experts increases the subjectivity and reduces the reliability of decision results. In contrast, the z-NIDM technique integrates expert opinions into the model in a more equitable, balanced, and statistically based manner. 3) Furthermore, the use of the CIMAS technique in calculating the importance weights of the criteria also increases the effectiveness of the model. Although many weighting methods, such as AHP, Entropy, CRITIC, and SWARA, are used in the literature, the CIMAS technique produces a more balanced result by integrating both objective and subjective information components. The CIMAS method is particularly suitable for multidimensional and uncertain issues such as ESG and leadership relationships, as it considers inter-criteria dependencies and adds flexibility to the decision process, compared to other techniques. Thanks to these three key innovations, the proposed model is superior to existing decision-making approaches in terms of both methodological robustness and practical applicability.

The following Section II explains the missing part in the literature. The proposed model is defined in Section III. The analysis results are demonstrated in Section IV. Moreover, Section V includes a discussion, and Section VI identifies the main concluding remarks.

II. Literature Review

In today's rapidly changing and transforming business environment, companies strive to maintain their operations and achieve a competitive advantage. In this process, focusing exclusively on financial operations is not sufficient to respond to varying stakeholder demands in a balanced manner. It is also necessary to demonstrate sensibility to environmental factors, social factors, and stakeholder expectations. The limited availability of resources in view of increasing consumption and demand makes environmental sustainability an ethical concern. In addition to environmental factors, being transparent and fulfilling responsibilities toward society, individuals and shareholders are becoming critical factors that determine the future of the business. Hence, companies share information about sustainability or corporate social responsibility activities in addition to financial reporting. Nevertheless, unstable conditions and diverse stakeholder demands necessitate more endeavors. As companies are accountable to all stakeholders, they need to share transparent information regarding environmental, social and governance activities for the sustainability of their operations. In this context, stakeholder theory proposes promoting innovation and sustainable development through actively communicating with all stakeholders [4]. Stakeholder orientation can significantly influence all aspects of an organization, from corporate governance to ethical practices and sustainability initiatives, from employee relations to customer and community engagement [5].

Environmental performance indicates the influence of a company on the natural environment. This ecological impact comprises resource protection, waste management, emissions reduction, energy efficiency and biodiversity conservation [6]. Growing environmental and ecological concerns, particularly climate change, impact corporate operations in different aspects. These rising concerns lead international communities and global leaders to initiate various reforms and agreements to protect the natural environment. In this context, companies incline to place greater emphasis on environmental sustainability practices such as recycling, resource reduction, product and service redesign to establish a trustworthy image, enhance their reputation and protect the planet [7]. Dohrmann et al. [8] found that environmental performance has a positive influence on firm performance and board independence strengthens this relationship. According to Tong et al. [9], reducing emissions, within the scope of environmental performance, is one of the crucial ways to engage the attention of stakeholders. Companies can effectively address their stakeholders' needs by creating, implementing and publicly disclosing the strategies of carbon emission reduction. These effective strategies enable companies to improve their reputation and attract more investors. In this process, companies can convey new business processes and their benefits to relevant stakeholders by establishing open and transparent communication. Innovation, one of the important business processes, plays a central role in company growth. Wang and Ahmad [10] conducted a study on green process, green product innovation and financial performance. In this study, green innovation impacts financial performance positively. Companies that invest in green process and product innovation may provide advantages in terms of mitigating environmental concerns and potential penalties, creating new market niches, developing nature-friendly products, having a green image and enhancing financial performance. By integrating a strong ethical approach and environmental awareness, companies may adopt sustainable practices, reduce ecological effects and advance environmental performance [11].

Another notable aspect for companies is social factors. Social performance involves corporate endeavors to improve and manage relationships with stakeholders such as employees, community, customers and suppliers [12]. According to Covington et al. [13], diversity and inclusion, one of the social factors, refers to an environment that values differences among employees and encourages both individuality and a sense of belonging. Hence, this social factor may have a significant impact on corporate performance. As a matter of fact, in the study conducted by the same authors, it was observed that companies with higher diversity and inclusion ratings exhibited stronger innovation performance in terms of parameters such as number of patents, number of citations and the economic value of patents. Within the scope of social factors, product responsibility may influence consumer behavior and corporate image. According to Mensah et al. [14], companies that focus on product responsibility can strengthen brand image and achieve greater consumer loyalty. To lower transaction costs, reduce waste and minimize customer complaints and returns, companies can use environmentally sustainable materials and prioritize product robustness.

Sustainable development requires the protection of resources and the minimization of transaction costs. Hence, companies need to meticulously consider factors such as board diversity and board size to achieve sustainable development goals [15]. At this point, governance is another critical factor in terms of sustainable operations and corporate reputation. Companies can create a mutual trust in the relations with stakeholders and enhance company value through effective governance practices. Companies need to center upon ameliorating governance practices such as transparency and accountability and align their governance-related activities with strategic objectives [16]. As key stakeholders of a company, senior management personnel have critical roles in the governance practices and decision-making process. Moreover, their attitudes and behaviors toward sustainable development goals impact the efficiency of corporate social responsibility activities. The purposeful development of corporate social responsibility strategies can yield positive results for the company. In fact, it has been observed in the literature that corporate social responsibility practices have significant and positive effects on financial performance, innovation, reputation and firm sustainability [17]. Herewith, corporate governance becomes a strategic obligation for organizations aiming to lead change, create sustainable value and enhance performance. In a dynamic and complex business environment, companies can provide a basis for long-term achievement and resilience by balancing interests, encouraging innovation, managing risks and involving stakeholders in the processes [18].

Environmental, social and governance-related activities encompass aspects that companies need to prioritize. The concept of ESG, which considers these factors together, becomes a focal point of research since it has significant effects on corporate reputation and investor preferences. ESG encompasses a company's environmental influence, social responsibilities and governance implementations at the heart of its actions [19]. ESG criteria become the main indicators of risk management, management competence and non-financial performance. ESG consists of a wide range of environmental concerns such as carbon emissions, climate change and energy use; social issues such as employee well-being, product safety and human rights; and governance-related issues such as corruption, board independence and protection of shareholder rights. Bai et al. [20] stated that ethical constraints and public pressure can encourage companies to prioritize environmental and social factors and adopt more active ESG practices, thereby improving their ESG performance. Increasing ESG performance enables companies to enhance their corporate reputation and reduce certain risks by minimizing environmental penalties and financial restrictions. According to Chen et al. [21], companies that operate their activities ethically and responsibly to advance the society's welfare can contribute to increased company value. ESG disclosure enables a company to gain competitive advantages, strengthen its reputation from the perspective of stakeholders and enhance long-term performance.

The literature review reveals that environmental, social and governance activities have significant effects on financial performance, sustainability and corporate reputation of companies. Transparently sharing information regarding these activities enables companies to attract strategic investors, gain stakeholder trust and increase financial performance. ESG practices, which consider environmental, social and governance activities together, have become a prominent concept in the literature and the business world in recent years. The presence of effective leaders may be crucial for the adoption and successful implementation of ESG practices by employees at all levels within a company. In this regard, it has been observed that studies examining the effect of leadership types on ESG performance are limited. However, no comparative study has been found that examines which leadership type has the greatest impact on ESG performance on a sectoral basis. Hence, this study may fill a research gap in the relevant literature and provide guidance to practitioners to improve ESG performance in business.

III. METHODOLOGY

This section includes the definitions and formulations of z-NIDM, STFSs, CIMAS and RAM, respectively. In expert-based solutions, assuming the same importance of evaluations is criticized. To address this criticism objectively, the z-NIDM approach is integrated into the model. This approach generates expert-weighted values, aiming to yield more realistic results. In the optimal analysis process, the CIMAS method is used to prioritize decision-making criteria. RAM finds the optimal solution by considering the importance of these criteria. The process of methodology is presented in Fig. 1.

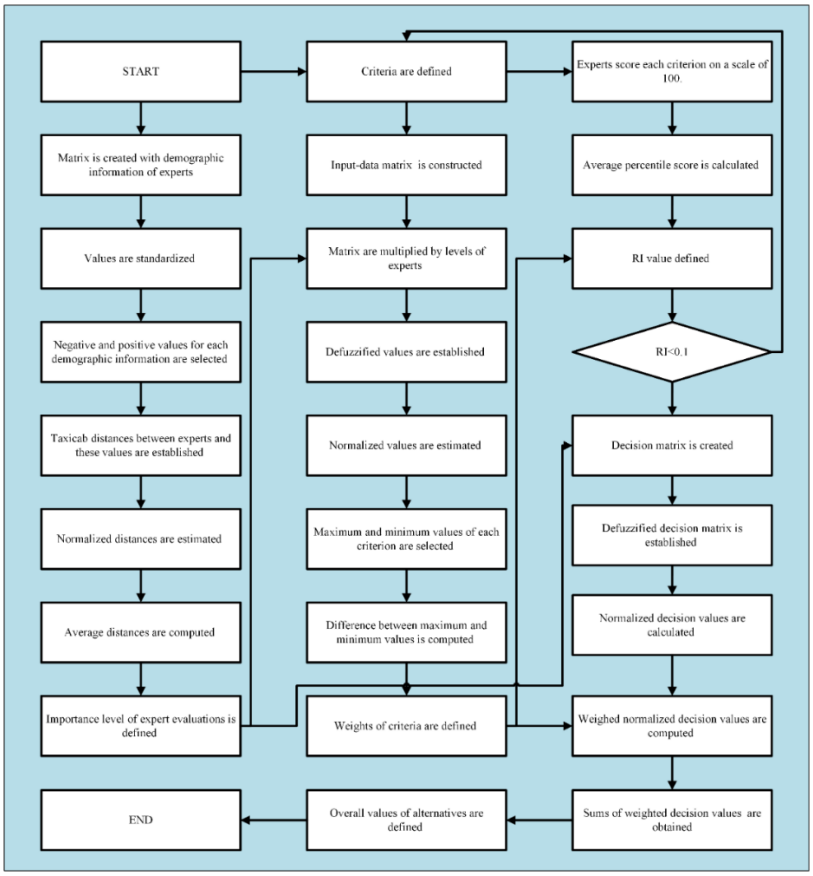


Fig. 1. Process of methodology.

A. z-NIDM

This approach allows the importance value of expert evaluations to be calculated objectively using demographic information. This approach is based on the average distance normalized to negative and positive values [22]. The calculation steps are as follows.

Firstly, the matrix formed in Eq. (1) is created with demographic information of experts.

$$Y = \left[y_{ij}\right]_{e\times d} \tag{1}$$

where, e and d are the numbers of experts and demographic information. Thus, y_{ij} means the value of ith demographic information of jth expert. Since the value ranges of the information are different from each other, the values need to be standardized with the help of Eq. (2) to Eq. (4).

$$\bar{y}_j = \frac{1}{e}\sum_{i=1}^{e} y_{ij} \tag{2}$$

$$\sigma_j = \sqrt{\frac{1}{e}\sum_{i=1}^{e}(y_{ij}-\bar{y}_j)^2} \tag{3}$$

$$z_{ij} = \frac{y_{ij}-\bar{y}_j}{\sigma_j} \tag{4}$$

Afterwards, the negative and positive values for each demographic information are selected via Eq. (5) and Eq. (6), respectively.

$$neg_j = \min_i z_{ij} \tag{5}$$

$$pos_j = \max_i z_{ij} \tag{6}$$

After determining the negative and positive values, the Taxicab distances between experts and these values are established by Eq. (7) and Eq. (8), respectively.

$$negD_i = \sum_{j=1}^{d}\left|z_{ij} - neg_j\right| \tag{7}$$

$$posD_i = \sum_{j=1}^{d}\left|z_{ij} - pos_j\right| \tag{8}$$

Next, the normalized distances are estimated with the help of Eq. (9) and Eq. (10).

$$negN_i = \frac{negD_i}{\max negD_i} \tag{9}$$

$$posN_i = \frac{\min posD_i}{posD_i} \tag{10}$$

Then, the average distances are computed using Eq. (11).

$$A_i = \frac{1}{2}(negN_i + posN_i) \tag{11}$$

Finally, the importance level of expert evaluations is defined as Eq. (12):

$$E_i = \frac{A_i}{\sum_{i=1}^{e} A_i} \tag{12}$$

B. STFSs

Fuzzy sets are a theory used in uncertainty measurement and are defined by degrees of membership and non-membership of an object. STFSs are a set inspired by the Sierpinski Triangle fractal shapes. This fractal shape has a structure with an infinitely sided main field that converges to zero [23]. This feature makes it useful for studying chaotic systems. It is recommended to use this fractal dimension $\left(\frac{\log 3}{\log 2} \approx 1.585\right)$, for optimal modelling of chaotic structure in linguistic structures. A STFS $\left(\tilde{F}\right)$ is described with Eq. (13).

$$\tilde{F} = \{x, (\alpha_{\tilde{F}}(x), \beta_{\tilde{F}}(x)) : x \in D\} \tag{13}$$

wherein, α and β are between zero and one and named as membership and non-membership degrees. These degrees satisfy the condition in Eq. (14).

$$0 \le \alpha_{\tilde{F}}^{1.585}(x) + \beta_{\tilde{F}}^{1.585}(x) \le 1 \tag{14}$$

The indeterminacy degree is computed with Eq. (15).

$$\pi_{\tilde{F}}(x) = \sqrt[1.585]{1 - \alpha_{\tilde{F}}^{1.585}(x) - \beta_{\tilde{F}}^{1.585}(x)} \tag{15}$$

Consider that $\tilde{X}$ and $\tilde{Y}$ are two fuzzy numbers. Then general operations are calculated by Eq. (16) to Eq. (21). $(s, \lambda > 0)$

$$\tilde{X} \cup \tilde{Y} = (\max\{\alpha_{\tilde{X}}, \alpha_{\tilde{Y}}\}, \min\{\beta_{\tilde{X}}, \beta_{\tilde{Y}}\}) \tag{16}$$

$$\tilde{X} \cap \tilde{Y} = (\min\{\alpha_{\tilde{X}}, \alpha_{\tilde{Y}}\}, \max\{\beta_{\tilde{X}}, \beta_{\tilde{Y}}\}) \tag{17}$$

$$\tilde{X}\oplus\tilde{Y} = \begin{pmatrix} \sqrt[1.585]{\dfrac{\alpha_{\tilde{X}}^{1.585}+\alpha_{\tilde{Y}}^{1.585}-\alpha_{\tilde{X}}^{1.585}\alpha_{\tilde{Y}}^{1.585}-(1-s)\alpha_{\tilde{X}}^{1.585}\alpha_{\tilde{Y}}^{1.585}}{1-(1-s)\alpha_{\tilde{X}}^{1.585}\alpha_{\tilde{Y}}^{1.585}}}, \\ \dfrac{\beta_{\tilde{X}}\beta_{\tilde{Y}}}{\sqrt[1.585]{s+(1-s)\left(\beta_{\tilde{X}}^{1.585}+\beta_{\tilde{Y}}^{1.585}-\beta_{\tilde{X}}^{1.585}\beta_{\tilde{Y}}^{1.585}\right)}} \end{pmatrix} \tag{18}$$

$$\tilde{X}\otimes\tilde{Y} = \begin{pmatrix} \sqrt[1.585]{\dfrac{\alpha_{\tilde{X}}\alpha_{\tilde{Y}}}{\sqrt[1.585]{s+(1-s)\left(\alpha_{\tilde{X}}^{1.585}+\alpha_{\tilde{Y}}^{1.585}-\alpha_{\tilde{X}}^{1.585}\alpha_{\tilde{Y}}^{1.585}\right)}}}, \\ \sqrt[1.585]{\dfrac{\beta_{\tilde{X}}^{1.585}+\beta_{\tilde{Y}}^{1.585}-\beta_{\tilde{X}}^{1.585}\beta_{\tilde{Y}}^{1.585}-(1-s)\beta_{\tilde{X}}^{1.585}\beta_{\tilde{Y}}^{1.585}}{1-(1-s)\beta_{\tilde{X}}^{1.585}\beta_{\tilde{Y}}^{1.585}}} \end{pmatrix} \tag{19}$$

$$\lambda\odot\tilde{X} = \begin{pmatrix} \sqrt[1.585]{\dfrac{\left[1+(s-1)\alpha_{\tilde{X}}^{1.585}\right]^{\lambda}-\left(1-\alpha_{\tilde{X}}^{1.585}\right)^{\lambda}}{\left[1+(s-1)\alpha_{\tilde{X}}^{1.585}\right]^{\lambda}-(s-1)\left(1-\alpha_{\tilde{X}}^{1.585}\right)^{\lambda}}}, \\ \dfrac{\sqrt[1.585]{s}\beta_{\tilde{X}}^{\lambda}}{\sqrt[1.585]{\left[1+(s-1)\left(1-\beta_{\tilde{X}}^{1.585}\right)\right]^{\lambda}+(s-1)\beta_{\tilde{X}}^{1.585\lambda}}} \end{pmatrix} \tag{20}$$

$$\tilde{X}^{\lambda} = \begin{pmatrix} \dfrac{\sqrt[1.585]{s}\alpha_{\tilde{X}}^{\lambda}}{\sqrt[1.585]{\left[1+(s-1)\left(1-\alpha_{\tilde{X}}^{1.585}\right)\right]^{\lambda}+(s-1)\alpha_{\tilde{X}}^{1.585\lambda}}}, \\ \sqrt[1.585]{\dfrac{\left[1+(s-1)\beta_{\tilde{X}}^{1.585}\right]^{\lambda}-\left(1-\beta_{\tilde{X}}^{1.585}\right)^{\lambda}}{\left[1+(s-1)\beta_{\tilde{X}}^{1.585}\right]^{\lambda}-(s-1)\left(1-\beta_{\tilde{X}}^{1.585}\right)^{\lambda}}} \end{pmatrix} \tag{21}$$

Suppose that $\tilde{F}$ is ST fuzzy number. Score and accuracy function are established using Eq. (22) and Eq. (23), respectively.

$$SF\left(\tilde{F}\right) = \frac{\alpha_{\tilde{F}}^{1.585}(x) - \beta_{\tilde{F}}^{1.585}(x) + 1}{2} \tag{22}$$

$$AF\left(\tilde{F}\right) = \alpha_{\tilde{F}}^{1.585}(x) + \beta_{\tilde{F}}^{1.585}(x) \tag{23}$$

C. STF-CIMAS

The CIMAS approach, which integrates the level of experts in the process of determining the criterion importance, has the advantage over other methods in terms of calculating the RI value for the reliability of the results. The steps in which ST fuzzy numbers are integrated into CIMAS are as follows [24]:

In the traditional CIMAS method, the expert level is obtained by normalizing the years of experience. However, since this approach is too soft, in this manuscript, the expert-level values obtained from z-NIDM are used. After determining the level of experts, experts express the importance of n criteria with linguistic scale. These linguistic scales of the experts are converted into ST fuzzy numbers and the input-data matrix in Eq. (24) is constructed.

$$\tilde{H} = \begin{bmatrix} \tilde{h}_{11} & \cdots & \tilde{h}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{h}_{e1} & \cdots & \tilde{h}_{en} \end{bmatrix} \tag{24}$$

where, $\tilde{h}_{ij} = \left(\alpha_{\tilde{h}_{ij}}, \beta_{\tilde{h}_{ij}}\right)$ represents the value of jth criterion of ith expert. Next, the values of this matrix are multiplied by the levels of experts using Eq. (25).

$$\tilde{K} = E_i \odot \tilde{H} = \begin{bmatrix} \tilde{k}_{11} & \cdots & \tilde{k}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{k}_{e1} & \cdots & \tilde{k}_{en} \end{bmatrix} = \begin{bmatrix} E_1 \odot \tilde{h}_{11} & \cdots & E_1 \odot \tilde{h}_{1n} \\ \vdots & \ddots & \vdots \\ E_e \odot \tilde{h}_{e1} & \cdots & E_e \odot \tilde{h}_{en} \end{bmatrix} \tag{25}$$

Afterwards, the defuzzified values are established with the help of Eq. (26).

$$F = SF\left(\tilde{K}\right) = \begin{bmatrix} f_{11} & \cdots & f_{1n} \\ \vdots & \ddots & \vdots \\ f_{e1} & \cdots & f_{en} \end{bmatrix} = \begin{bmatrix} SF(\tilde{k}_{11}) & \cdots & SF\left(\tilde{k}_{1n}\right) \\ \vdots & \ddots & \vdots \\ SF\left(\tilde{k}_{e1}\right) & \cdots & SF(\tilde{k}_{en}) \end{bmatrix} \tag{26}$$

After creating the defuzzified matrix, the normalized values are estimated via Eq. (27).

$$\mathfrak{y}_{ij} = \frac{f_{ij}}{\sum_{i=1}^{e} f_{ij}} \tag{27}$$

Next, the maximum and minimum values of each criterion for normalized matrix are selected by Eq. (28) and Eq. (29), respectively.

$$mx_j = \max_i \mathfrak{y}_{ij} \tag{28}$$

$$mn_j = \min_i \mathfrak{y}_{ij} \tag{29}$$

Then, difference between maximum and minimum values for each criterion is computed with Eq. (30).

$$diff_j = mx_j - mn_j \tag{30}$$

The weights of criteria are defined as Eq. (31):

$$w_j = \frac{diff_j}{\sum_{j=1}^{n} diff_j} \tag{31}$$

Finally, the reliability index is estimated. This time, experts score each criterion on a scale of 100. The sum of the scales assigned by each expert to the criteria should be 100. Then, the average percentile score is calculated using Eq. (32), where g_{ij} is the percentile score given by the ith expert for the jth criterion.

$$APS_j = \frac{1}{e}\sum_{i=1}^{e} g_{ij} \tag{32}$$

Afterwards, the RI value defined in Eq. (33) is obtained between the criteria weights obtained from CIMAS and the average percentage scores.

$$RI = \frac{\sum_{j=1}^{n} |100 w_j - APS_j|}{100} \tag{33}$$

If the RI value is less than 0.1, the results are reliable. Otherwise, the analysis process is repeated.

D. STF-RAM

The RAM method ranks alternatives by using the differences in compensation levels across benefit and utility criteria. Like other methods, this method ranks alternatives without converting cost criteria into benefit criteria. The steps in which ST fuzzy numbers are integrated into RAM are as follows [25]:

Firstly, m alternatives are evaluated by experts with linguistic scales. These linguistic scales are transformed into ST fuzzy numbers. Thus, the matrix in Eq. (34) is created for the tth expert.

$$\tilde{R}^{(t)} = \begin{bmatrix} \tilde{r}_{11}^{(t)} & \cdots & \tilde{r}_{1n}^{(t)} \\ \vdots & \ddots & \vdots \\ \tilde{r}_{m1}^{(t)} & \cdots & \tilde{r}_{mn}^{(t)} \end{bmatrix} \tag{34}$$

where, $\tilde{r}_{ij}^{(t)} = \left(\alpha_{\tilde{r}_{ij}^{(t)}}, \beta_{\tilde{r}_{ij}^{(t)}}\right)$. Next, these values are multiplied by levels of experts with the help of Eq. (35).

$$\tilde{U}^{(t)} = E_{(t)} \odot \tilde{R}^{(t)} = \begin{bmatrix} E_{(t)} \odot \tilde{r}_{11}^{(t)} & \cdots & E_{(t)} \odot \tilde{r}_{1n}^{(t)} \\ \vdots & \ddots & \vdots \\ E_{(t)} \odot \tilde{r}_{m1}^{(t)} & \cdots & E_{(t)} \odot \tilde{r}_{mn}^{(t)} \end{bmatrix} = \begin{bmatrix} \tilde{u}_{11}^{(t)} & \cdots & \tilde{u}_{1n}^{(t)} \\ \vdots & \ddots & \vdots \\ \tilde{u}_{m1}^{(t)} & \cdots & \tilde{u}_{mn}^{(t)} \end{bmatrix} \tag{35}$$

Then, matrices are summed by Eq. (36).

$$\tilde{A} = \sum_{t=1}^{e} \tilde{U}^{(t)} = \begin{bmatrix} \sum_{t=1}^{e} \tilde{u}_{11}^{(t)} & \cdots & \sum_{t=1}^{e} \tilde{u}_{1n}^{(t)} \\ \vdots & \ddots & \vdots \\ \sum_{t=1}^{e} \tilde{u}_{m1}^{(t)} & \cdots & \sum_{t=1}^{e} \tilde{u}_{mn}^{(t)} \end{bmatrix} = \begin{bmatrix} \tilde{a}_{11} & \cdots & \tilde{a}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{a}_{m1} & \cdots & \tilde{a}_{mn} \end{bmatrix} \tag{36}$$

Afterwards, the defuzzified decision matrix is established using Eq. (37).

$$A = SF\left(\tilde{A}\right) = \begin{bmatrix} SF(\tilde{a}_{11}) & \cdots & SF(\tilde{a}_{1n}) \\ \vdots & \ddots & \vdots \\ SF(\tilde{a}_{m1}) & \cdots & SF(\tilde{a}_{mn}) \end{bmatrix} = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix} \tag{37}$$

After constructing the defuzzified decision matrix, the normalized decision values are calculated with Eq. (38).

$$\xi_{ij} = \frac{a_{ij}}{\sum_{i=1}^{m} a_{ij}} \quad (38)$$

The weighed normalized decision values are computed using Eq. (39).

$$b_{ij} = \xi_{ij} w_j \quad (39)$$

Finally, the sums of weighted decision values of benefit and cost criteria of alternatives are obtained by Eq. (40) and Eq. (41). Then, overall values of alternatives are defined as Eq. (42).

$$S_{+i} = \sum_{j=1}^{n} b_{+ij} \quad (40)$$

$$S_{-i} = \sum_{j=1}^{n} b_{-ij} \quad (41)$$

$$\theta_i = \sqrt[2+S_{-i}]{2 + S_{+i}} \quad (42)$$

IV. Analysis

This section includes the results of methodology. All tables are given in the Appendix section (Table I to Table XXI).

A. Establishing the Levels of Experts

Within the z-NIDM framework, demographic information about experts is needed for analysis. Experts' age, total experience, industry experience, management experience, teaching experience, and number of projects are collected regarding expertise. This information is shown in Table I. The values' statistics are estimated with Eq. (2) and Eq. (3). The arithmetic mean and standard deviation of each information are given in Table II. Using these statistics, the values are standardized with the help of Eq. (4). The standardized information matrix is shared in Table III. Afterwards, the negative and positive values for each demographic information are selected via Eq. (5) and Eq. (6), respectively. The negative and positive values for each standardized information are summarized in Table IV. After determining the negative and positive values, the Taxicab distances between experts and these values are established by Eq. (7) and Eq. (8), respectively. Next, the normalized distances are estimated with the help of Eq. (9) and Eq. (10). The results are summarized in Table V. Then, the average distances are computed using Eq. (11). Finally, the importance value of expert evaluations is defined as Eq. (12). The results are illustrated in Fig. 2.

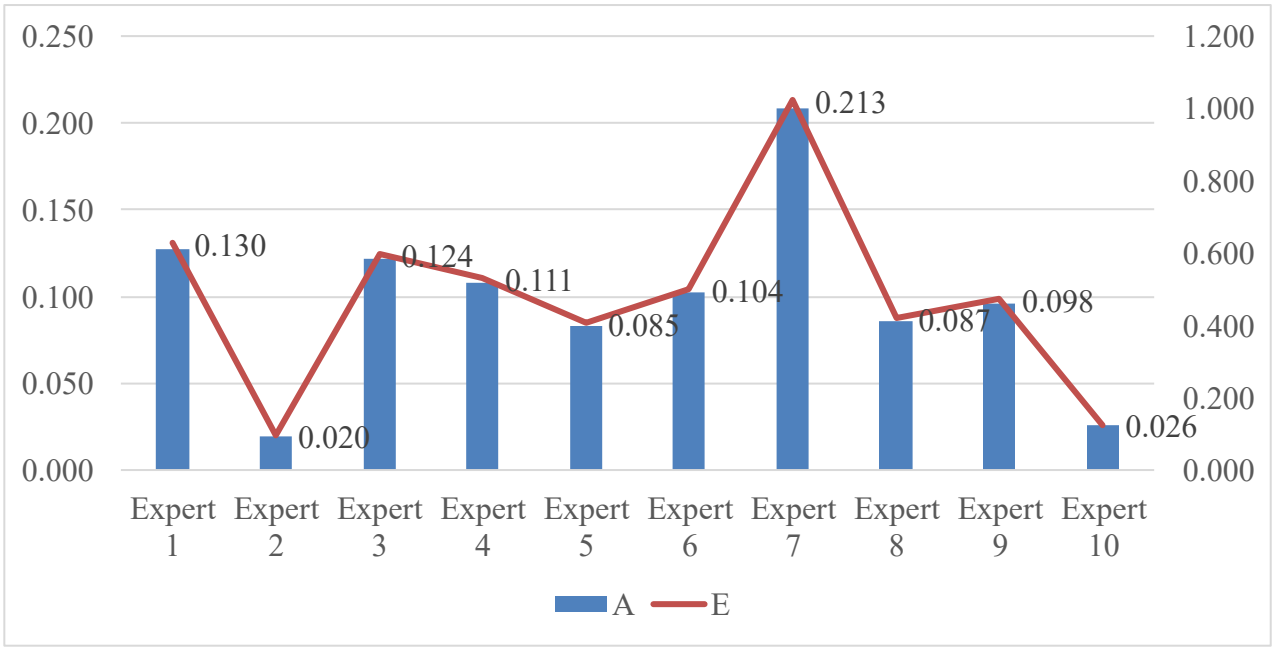


Fig. 2. Levels of experts.

As can be seen, E values in Fig. 2, the highest level is Expert 7 with .213. Expert 7 has the maximum age, total experience, industry experience, manager experience, and teaching experience. The second level is Expert 1 with .130.

B. Weighting of the Criteria

Twelve criteria across four dimensions are determined to improve the ESG performance of companies. This list of criteria and the short codes created for use in the analysis are presented in Table VI. Two of these criteria, ethical problems and difficulty of integrating ESG strategies into corporate objectives, are of the cost type, while the other ten criteria are constructed as benefit type and introduced to the experts as such. Ten experts express the importance of 12 criteria with linguistic scale. The results are displayed in Table VII. These linguistic scales of the experts are converted into ST fuzzy numbers and the input-data matrix in Eq. (24) is constructed. The input-data matrix is exhibited in Table VIII. Next, the values of this matrix are multiplied by the levels of experts using Eq. (25). The levels of experts are defined in Fig. 2. The expert-weighted values are expressed in Table IX. Afterwards, the defuzzified values are established with the help of Eq. (26). In other words, the score functions of fuzzy numbers in Table IX are estimated. The defuzzified matrix is shown in

Table X. After creating the defuzzified matrix, the normalized values are estimated via Eq. (27). That is, the columns are summed, and the values are divided by this total. The normalized matrix is illustrated in Table XI. Next, the maximum and minimum values of each criterion for normalized matrix are selected by Eq. (28) and Eq. (29), respectively. Then, the difference between maximum and minimum values for each criterion is computed with Eq. (30). The results are summarized in Table XII. The weights of the criteria are defined as Eq. (31). The weights of criteria are visualized in Fig. 3.

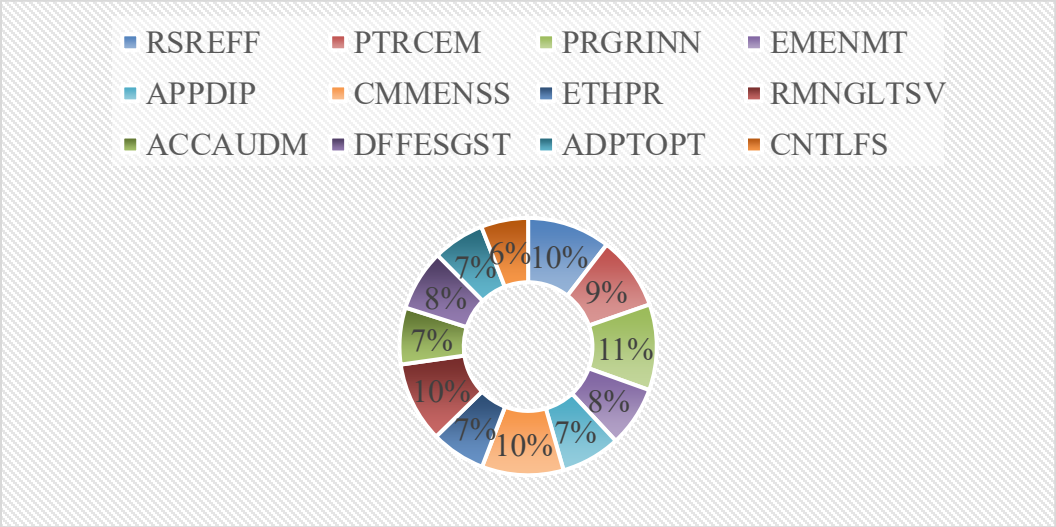


Fig. 3. Weights of the criteria

When Fig. 3 is examined, the most important criterion to improve the ESG performance of companies is promoting green innovation with .108. The second important criterion is resource efficiency with .105. Finally, the reliability index is estimated. This time, experts score each criterion on a scale of 100. The percentile scores are shown in Table XIII. Then, the average percentile score is calculated using Eq. (32). The average percentile scores are shared in Table XIV. Afterwards, the RI value defined in Eq. (33) is obtained between the criteria weights obtained from CIMAS in Fig. 3 and the average percentage scores in Table XIV. RI equals to .078. This value is smaller than 0.1. That is, the results are reliable.

C. Ranking Leadership Styles

The general leadership styles are transformational leadership (TR), servant leadership (SR), ethical leadership (ET), adaptive leadership (AD), and authentic leadership (AU). These 5 leadership styles are evaluated by experts with linguistic scales. The results are displayed in Table XV. These linguistic scales are transformed into ST fuzzy numbers. Thus, the matrix in Eq. (34) is created. Next, these values are multiplied by the levels of experts with the help of Eq. (35). Then, matrices are summed by Eq. (36). The decision matrix is shared in Table XVI. Afterwards, the defuzzified decision matrix is established using Eq. (37). The defuzzified decision matrix is illustrated in Table XVII. After constructing the defuzzified decision matrix, the normalized decision values are calculated with Eq. (38). The normalized decision matrix is summarized in Table XVIII. The weighted normalized decision values are computed using Eq. (39). The values in Fig. 3 are used as weight of the criteria. The weighted normalized decision matrix is displayed in Table XIX. Finally, the sums of weighted decision values of benefit and cost criteria of alternatives are obtained by Eq. (40) and Eq. (41). Then, overall values of alternatives are defined as Eq. (42). The results are shared in Table XX. As can be understood from the overall values in Table XX, the most suitable leadership style to improve the ESG performance of companies is the ethical leadership style, with 1.4841.

A sensitivity analysis is conducted to test the sensitivity and robustness of the results. For this purpose, scenarios are created and the analyses are rerun. In this context, different scenarios are constructed by increasing the weight of each criterion by 10%. The value of the first criterion in Fig. 3 for the first scenario is increased by 10%, and then criteria weights are normalized. The RAM analysis is repeated with the new weights. In other words, twelve scenarios are created for twelve criteria, and twelve RAM analyses are run. The results are summarized in Table XXI. As can be seen from the ranks in Table XXI, the results are the same across scenarios. This shows that the methodology is robust.

V. Discussion

The results of the study indicate that the most important criterion for improving companies' ESG performance is encouraging green innovation, with a weighting of 0.108, followed by resource efficiency, with a weighting of 0.105. This finding demonstrates the critical importance of investing in innovative and environmentally friendly technologies to enhance their sustainability performance [26]. The importance of green innovation is frequently emphasized in the literature. The primary reason for this is that developing environmentally friendly products and processes not only reduces environmental impacts but also significantly contributes to businesses' competitive advantage, brand reputation, and long-term financial sustainability. Resource efficiency, in turn, reduces costs and environmental burden by optimizing the use

of energy, water, and raw materials. In light of these findings, policymakers should create tax incentives, sustainable production funds, and environmentally responsible investment programs to support businesses' green R&D activities [27]. At the corporate level, companies should establish sustainable innovation units, adopt circular economy principles in their supply chains, and train their employees in an organizational culture with a high environmental awareness. Furthermore, green innovation and resource efficiency indicators should be clearly defined in performance measurement systems and integrated into management decision-making processes. This will ensure both institutional sustainability at the micro level and create a development model that supports environmental and economic balance at the macro level.

According to the study results, ethical leadership, with a weighting of 1.4841, is the most suitable leadership style for improving companies' ESG performance. This finding demonstrates that a management approach based on ethical values plays a decisive role in companies achieving their sustainability goals. By centering the principles of fairness, honesty, responsibility, and transparency in decision-making processes, ethical leadership both improves the quality of corporate governance and strengthens stakeholder trust. The literature frequently emphasizes that ethical leadership is one of the most critical factors supporting ESG performance [28]. Ethics-based management approaches increase employee motivation and a sense of corporate belonging, while also embedding social responsibility and environmental awareness in the corporate culture. In this context, it is recommended that ethical leadership training be expanded at the policy level for business managers, corporate codes of ethics are established, and independent units are established to monitor their implementation [29]. Furthermore, public authorities and regulatory bodies should develop reward mechanisms and sustainable management standards that encourage ethical leadership practices in businesses. From a corporate strategy perspective, it's crucial to prioritize executives with a high sensitivity to ethical values in leadership selection and promotion processes, to assess stakeholder expectations from an ethical perspective in decision-making, and to strengthen accountability mechanisms [30]. Thus, an ethical leadership approach will not only enhance the quality of governance but also lay the foundation for sustainable corporate transformation in environmental and social dimensions.

VI. Conclusion

This study aims to determine the most effective leadership style in improving the ESG performance of businesses and to identify the most important criteria influencing this choice. In this context, an extensive literature review is conducted, 12 criteria affecting ESG performance are identified, and five different leadership styles are evaluated as alternatives. Expert opinions are utilized throughout the analysis process, and their importance weights are objectively calculated using the z-NIDM. Criteria importance levels are determined using the CIMAS method, and alternative leadership styles are ranked using the RAM technique. Furthermore, to more accurately model uncertainties, the Sierpinski triangle fuzzy sets developed in this study are used, thus introducing a new fuzzy set approach to the literature. The analysis results indicate that ethical and transformational leadership styles are the most effective approaches in improving ESG performance, while criteria related to environmental and governance dimensions most strongly shape leadership impact. These findings demonstrate that leadership style is a determinant not only of organizational success but also of sustainability performance. The study provides original and significant contributions to the literature by proposing a new integrated multi-criteria decision-making model from a methodological perspective, introducing Sierpinski triangle fuzzy sets to the literature, and presenting an empirical analysis of the ESG-leadership relationship.

This study has some theoretical and methodological limitations. First, the scope of the research is based on a general assessment across sectors, and no sector-specific analysis is conducted. However, different sectors may exhibit differences in ESG dynamics, environmental sensitivity levels, and leadership structures. Therefore, future studies applying the model to specific sectors such as energy, finance, healthcare, or manufacturing could provide a more in-depth understanding of the impact of leadership types on ESG performance within the context of sectoral differences. Furthermore, while the integrated decision-making model proposed in this study, the z-NIDM–CIMAS–RAM–Sierpinski fuzzy approach, offers a robust methodological framework, it does have certain limitations. Because the applicability of the model relies heavily on expert opinion, the results obtained may vary depending on the participant profile. Furthermore, because Sierpinski triangle fuzzy sets are a novel structure, they need to be tested on different problem types and samples. Comparing this method with other fuzzy logic approaches in future research will increase the generalizability and reliability of the model. However, evaluating the adaptability of the model in different decision environments, especially dynamic and uncertain data structures, is also suggested as an important research area for future studies.

References

[1] Alahdal, W. M., Pandey, D. K., Sahu, M., Nguyen, T., & Hashim, H. A. (2025). Environmental, social and governance and earnings management research: current trends and future research. *Accounting Research Journal*, *38*(3-4), 527-550.

[2] Wang, S., & Zhang, H. (2025). Enhancing environmental, social, and governance performance through artificial intelligence supply chains in the energy industry: Roles of innovation, collaboration, and proactive sustainability strategy. *Renewable Energy*, *245*, 122855.

[3] Liu, E. X., & Song, Y. (2025). ESG performance, environmental uncertainty, and firm risk. *Journal of International Financial Management & Accounting*, *36*(2), 292-322.

[4] Zhao, X., Zhu, R., Li, Q., & Hu, J. (2024). Unleashing the impact of environmental information disclosure on corporate green innovation: The role of audit quality and media attention. *Environmental Development*, *52*, 101078.

[5] Park, E., Lange, D., & Jeon, C. (2025). How shareholder litigation risk influences firm orientation toward stakeholders. *Strategic Management Journal*, *46*(5), 1149-1182.

[6] Sun, L., Bai, C., & Sarkis, J. (2024). Environmental and social performance relationships to firm efficiency: Evidence from the semiconductor industry. *International Journal of Production Economics*, *278*, 109410.

[7] Bhuiyan, F., Adu, D. A., Ullah, H., & Islam, N. (2025). Employee organisational commitment and corporate environmental sustainability

practices: mediating role of organisation innovation culture. *Business Strategy and the Environment*, *34*(4), 4485-4506.

[8] Dohrmann, M., Martinez-Blasco, M., Moring, A., & Margarit, J. C. (2024). Environmental performance and firm performance in Europe: The moderating role of board governance. *Corporate Social Responsibility and Environmental Management*, *31*(6), 5863-5880.

[9] Tong, Z., Li, B., & Yang, L. (2025). Digital transformation, carbon performance and financial performance: Empirical evidence from the Chinese stock market. *Environment, Development and Sustainability*, *27*(7), 17129-17146.

[10] Wang, Y. Z., & Ahmad, S. (2024). Green process innovation, green product innovation, leverage, and corporate financial performance; evidence from system GMM. *Heliyon*, *10*(4).

[11] Xie, J., Abbass, K., & Li, D. (2024). Advancing eco-excellence: Integrating stakeholders' pressures, environmental awareness, and ethics for green innovation and performance. *Journal of environmental management*, *352*, 120027.

[12] Sun, Y., Liao, C., Chen, Y., & Xu, X. L. (2025). The impacts of ESG policy on clean technology innovation: a gateway to promote renewable energy transition. *Clean Technologies and Environmental Policy*, *27*(6), 2305-2319.

[13] Covington, T., Le, T. D., & Ngo, J. (2025). Diversity and inclusion in the workplace and corporate innovation. *Finance Research Letters*, *76*, 106938.

[14] Mensah, L., Arhinful, R., Obeng, H. A., & Gyamfi, B. A. (2025). The impact of capital structure on product responsibility and corporate reputation: Evidence from non-financial institutions listed on the London stock exchange. *European Research on Management and Business Economics*, *31*(3), 100287.

[15] Yang, Z., Na, J., & Dong, X. (2024). Corporate governance for sustainable development: A study on mechanism configuration. *Journal of Cleaner Production*, *458*, 142509.

[16] Bagh, T., Hunjra, A. I., & Corbet, S. (2025). The impact of corporate governance on firm value: Understanding the role of strategic change. *International Review of Economics & Finance*, 104472.

[17] Oduro, S., Umar, R. M., De Massis, A., & Haylemariam, L. G. (2025). Corporate social responsibility and family firm performance: A meta-analytic review. *Corporate Social Responsibility and Environmental Management*, *32*(2), 1412-1443.

[18] Bagh, T., Fuwei, J., & Khan, M. A. (2024). From risk to resilience: climate change risk, ESG investments engagement and Firm's value. *Heliyon*, *10*(5).

[19] Khaw, T. Y., Amran, A., & Teoh, A. P. (2024). Factors influencing ESG performance: A bibliometric analysis, systematic literature review, and future research directions. *Journal of Cleaner Production*, *448*, 141430.

[20] Bai, F., Shang, M., & Huang, Y. (2024). Corporate culture and ESG performance: Empirical evidence from China. *Journal of Cleaner Production*, *437*, 140732.

[21] Chen, S., Song, Y., & Gao, P. (2023). Environmental, social, and governance (ESG) performance and financial outcomes: Analyzing the impact of ESG on financial performance. *Journal of environmental management*, *345*, 118829.

[22] Dinçer, H., Yüksel, S., & Pedrycz, W. (2025). Assessment of renewable energy alternatives for sustainable resource policies with knowledge-based expert prioritized quantum picture fuzzy rough modelling. *Expert Systems with Applications*, *273*, 126826.

[23] Kou, G., Eti, S., Yüksel, S., Dinçer, H., Sağır, S., & Köklü, K. (2025). Next-gen fractal fuzzy sets with Koch Snowflake, Cantor Dust, and Sierpinski Triangle structures for space-based solar energy storage investments. *International Journal of Electrical Power & Energy Systems*, *171*, 111052.

[24] Yüksel, S., Eti, S., Dinçer, H., Pamucar, D., Saldı, M. H., Ergün, E., & Simic, V. (2025). Driving sustainable hydroelectric investments: Leveraging two-step logarithmic normalization for sustainable investment prioritization. *Energy Reports*, *14*, 2110-2122.

[25] Durán, O., Orellana, F., Lobos, G., & Ibacache, A. (2024). Integrating Fuzzy FMEA and RAM Analysis for Evaluating Modernization Strategies in an LNG Plant Pumping and Vaporization Facility. *Applied Sciences*, *14*(22), 10729.

[26] Hao, P., Alharbi, S. S., Hunjra, A. I., & Zhao, S. (2025). How do ESG ratings promote digital technology innovation?. *International Review of Financial Analysis*, *97*, 103886.

[27] Zhao, C., Wang, Z., Tang, Y., & Yang, F. (2025). ESG performance, green technology innovation, and corporate value: Evidence from industrial listed companies. *Alexandria Engineering Journal*, *123*, 369-380.

[28] Anastasiou, S. (2025). Counteracting Toxic Leadership in Education: Transforming Schools Through Emotional Intelligence and Ethical Leadership. *Administrative Sciences*, *15*(8), 312.

[29] Kyambade, M., & Namatovu, A. (2025). Exploring the role of ethical leadership and personality traits in shaping ethical behavior among Ugandan security officers. *International Journal of Public Leadership*, *21*(1), 18-36.

[30] Iqbal, J., & Parray, Z. A. (2025). Leading with integrity: illuminating the pathway to positive job outcomes through ethical leadership and CSR. *Social Responsibility Journal*, *21*(2), 320-336.

APPENDIX

TABLE I. INFORMATION ABOUT EXPERTS

	Age	Total Experience	Industry Experience	Manager Experience	Teaching Experience	Number of Projects
Expert 1	51	30	28	11	3	3
Expert 2	35	13	11	4	2	2
Expert 3	54	32	28	11	3	2
Expert 4	52	31	26	10	3	2
Expert 5	46	27	25	10	2	2
Expert 6	51	28	23	9	4	2
Expert 7	54	35	33	13	5	2
Expert 8	45	24	20	8	2	4
Expert 9	47	25	22	9	2	4
Expert 10	37	18	13	5	1	2

TABLE II. ARITHMETIC MEAN AND STANDARD DEVIATION OF INFORMATION

	Age	Total Experience	Industry Experience	Manager Experience	Teaching Experience	Number of Projects
Arithmetic	47.2	26.3	22.9	9.0	2.7	2.5
Stand. Dev.	6.353	6.325	6.457	2.608	1.100	.806

TABLE III. STANDARDIZED INFORMATION MATRIX

	Age	Total Experience	Industry Experience	Manager Experience	Teaching Experience	Number of Projects
Expert 1	.598	.585	.790	.767	.273	.620
Expert 2	-1.920	-2.103	-1.843	-1.917	-.636	-.620
Expert 3	1.070	.901	.790	.767	.273	-.620
Expert 4	.756	.743	.480	.383	.273	-.620
Expert 5	-.189	.111	.325	.383	-.636	-.620
Expert 6	.598	.269	.015	.000	1.182	-.620
Expert 7	1.070	1.375	1.564	1.534	2.091	-.620
Expert 8	-.346	-.364	-.449	-.383	-.636	1.861
Expert 9	-.031	-.206	-.139	.000	-.636	1.861
Expert 10	-1.606	-1.312	-1.533	-1.534	-1.545	-.620

TABLE IV. NEGATIVE AND POSITIVE VALUES OF EACH STANDARDIZED INFORMATION

	Age	Total Experience	Industry Experience	Manager Experience	Teaching Experience	Number of Projects
Neg	-1.920	-2.103	-1.843	-1.917	-1.545	-.620
Pos	1.070	1.375	1.564	1.534	2.091	1.861

TABLE V. DISTANCES AND NORMALIZED DISTANCES

	negD	posD	negN	posN
Expert 1	13.582	5.863	.801	.423
Expert 2	.909	18.535	.054	.134
Expert 3	13.130	6.315	.774	.393
Expert 4	11.964	7.481	.705	.332
Expert 5	9.323	10.121	.550	.245
Expert 6	11.393	8.051	.672	.308
Expert 7	16.964	2.481	1.000	1.000
Expert 8	9.631	9.814	.568	.253
Expert 9	10.797	8.648	.636	.287
Expert 10	1.799	17.646	.106	.141

TABLE VI. LIST OF CRITERIA

Dimensions	Criteria	Short Codes
Environmental Dimension	Resource efficiency	RSREFF
	Potential for reducing carbon emissions	PTRCEM
	Promoting green innovation	PRGRINN
Social Dimension	Employee engagement and motivation	EMENMT
	Applicability of diversity and inclusion policies	APPDIP
	Community engagement and stakeholder satisfaction	CMMENSS
Governance Dimension	Ethical problems	ETHPR
	Risk management and long-term sustainability vision	RMNGLTSV
	Accountability and audit mechanisms	ACCAUDM
General / Performance Dimension	The difficulty of integrating ESG strategies into corporate objectives	DFFESGST
	Adaptation and openness to change	ADPTOPT
	Contribution to long-term financial sustainability	CNTLFS

TABLE VII. LINGUISTICS OF CRITERIA

	RSREFF	PTRCEM	PRGRINN	EMENMT	APPDIP	CMMENSS	ETHPR	RMNGLTSV	ACCAUDM	DFFESGST	ADPTOPT	CNTLFS
Expert 1	ML	MH	L	L	MH	ML	M	L	M	ML	M	M
Expert 2	Vl	M	L	ML	L	L	MH	Vl	Vl	Vl	Vl	ML
Expert 3	MH	L	Vl	MH	MH	L	ML	Vl	ML	L	M	MH
Expert 4	M	Vl	MH	M	Vl	MH	M	ML	L	MH	ML	MH
Expert 5	M	Vl	ML	M	M	ML	ML	MH	L	L	Vl	L
Expert 6	ML	M	L	MH	L	ML	L	M	L	M	MH	MH
Expert 7	MH	L	Vl	Vl	M	MH	ML	MH	ML	Vl	L	ML
Expert 8	Vl	MH	Vl	ML	M	ML	Vl	MH	MH	ML	MH	M
Expert 9	L	L	Vl	Vl	MH	ML	Vl	MH	MH	M	M	Vl
Expert 10	M	Vl	L	L	L	L	M	ML	Vl	MH	Vl	ML

TABLE VIII. INPUT-DATA MATRIX

	RSREFF	PTRCEM	PRGRINN	EMENMT	APPDIP	CMMENSS	ETHPR	RMNGLTSV	ACCAUDM	DFFESGST	ADPTOPT	CNTLFS
Expert 1	(.4,.5)	(.6,.3)	(.25,.6)	(.25,.6)	(.6,.3)	(.4,.5)	(.5,.4)	(.25,.6)	(.5,.4)	(.4,.5)	(.5,.4)	(.5,.4)
Expert 2	(.1,.75)	(.5,.4)	(.25,.6)	(.4,.5)	(.25,.6)	(.25,.6)	(.6,.3)	(.1,.75)	(.1,.75)	(.1,.75)	(.1,.75)	(.4,.5)
Expert 3	(.6,.3)	(.25,.6)	(.1,.75)	(.6,.3)	(.6,.3)	(.25,.6)	(.4,.5)	(.1,.75)	(.4,.5)	(.25,.6)	(.5,.4)	(.6,.3)
Expert 4	(.5,.4)	(.1,.75)	(.6,.3)	(.5,.4)	(.1,.75)	(.6,.3)	(.5,.4)	(.4,.5)	(.25,.6)	(.6,.3)	(.4,.5)	(.6,.3)
Expert 5	(.5,.4)	(.1,.75)	(.4,.5)	(.5,.4)	(.5,.4)	(.4,.5)	(.4,.5)	(.6,.3)	(.25,.6)	(.25,.6)	(.1,.75)	(.25,.6)
Expert 6	(.4,.5)	(.5,.4)	(.25,.6)	(.6,.3)	(.25,.6)	(.4,.5)	(.25,.6)	(.5,.4)	(.25,.6)	(.5,.4)	(.6,.3)	(.6,.3)
Expert 7	(.6,.3)	(.25,.6)	(.1,.75)	(.1,.75)	(.5,.4)	(.6,.3)	(.4,.5)	(.6,.3)	(.4,.5)	(.1,.75)	(.25,.6)	(.4,.5)
Expert 8	(.1,.75)	(.6,.3)	(.1,.75)	(.4,.5)	(.5,.4)	(.4,.5)	(.1,.75)	(.6,.3)	(.6,.3)	(.4,.5)	(.6,.3)	(.5,.4)
Expert 9	(.25,.6)	(.25,.6)	(.1,.75)	(.1,.75)	(.6,.3)	(.4,.5)	(.1,.75)	(.6,.3)	(.6,.3)	(.5,.4)	(.5,.4)	(.1,.75)
Expert 10	(.5,.4)	(.1,.75)	(.25,.6)	(.25,.6)	(.25,.6)	(.25,.6)	(.5,.4)	(.4,.5)	(.1,.75)	(.6,.3)	(.1,.75)	(.4,.5)

TABLE IX. EXPERT-WEIGHTED VALUES

	RSREFF	PTRCEM	PRGRINN	EMENMT	APPDIP	CMMENSS	ETHPR	RMNGLTSV	ACCAUDM	DFFESGST	ADPTOPT	CNTLFS
Expert 1	(.12,.91)	(.19,.85)	(.07,.94)	(.07,.94)	(.19,.85)	(.12,.91)	(.15,.89)	(.07,.94)	(.15,.89)	(.12,.91)	(.15,.89)	(.15,.89)
Expert 2	(.01,.99)	(.05,.98)	(.02,.99)	(.04,.99)	(.02,.99)	(.02,.99)	(.06,.98)	(.01,.99)	(.01,.99)	(.01,.99)	(.01,.99)	(.04,.99)
Expert 3	(.19,.86)	(.07,.94)	(.03,.96)	(.19,.86)	(.19,.86)	(.07,.94)	(.12,.92)	(.03,.96)	(.12,.92)	(.07,.94)	(.15,.89)	(.19,.86)
Expert 4	(.14,.9)	(.03,.97)	(.17,.88)	(.14,.9)	(.03,.97)	(.17,.88)	(.14,.9)	(.11,.93)	(.06,.95)	(.17,.88)	(.11,.93)	(.17,.88)
Expert 5	(.12,.93)	(.02,.98)	(.09,.94)	(.12,.93)	(.12,.93)	(.09,.94)	(.09,.94)	(.15,.9)	(.05,.96)	(.05,.96)	(.02,.98)	(.05,.96)
Expert 6	(.1,.93)	(.13,.91)	(.06,.95)	(.17,.88)	(.06,.95)	(.1,.93)	(.06,.95)	(.13,.91)	(.06,.95)	(.13,.91)	(.17,.88)	(.17,.88)
Expert 7	(.26,.77)	(.1,.9)	(.04,.94)	(.04,.94)	(.21,.82)	(.26,.77)	(.16,.86)	(.26,.77)	(.16,.86)	(.04,.94)	(.1,.9)	(.16,.86)
Expert 8	(.02,.98)	(.15,.9)	(.02,.98)	(.09,.94)	(.12,.92)	(.09,.94)	(.02,.98)	(.15,.9)	(.15,.9)	(.09,.94)	(.15,.9)	(.12,.92)
Expert 9	(.06,.95)	(.06,.95)	(.02,.97)	(.02,.97)	(.16,.89)	(.1,.93)	(.02,.97)	(.16,.89)	(.16,.89)	(.13,.91)	(.13,.91)	(.02,.97)
Expert 10	(.06,.98)	(.01,.99)	(.03,.99)	(.03,.99)	(.03,.99)	(.03,.99)	(.06,.98)	(.04,.98)	(.01,.99)	(.07,.97)	(.01,.99)	(.04,.98)

TABLE X. DEFUZZIFIED MATRIX

	RSREFF	PTRCEM	PRGRINN	EMENMT	APPDIP	CMMENSS	ETHPR	RMNGLTSV	ACCAUDM	DFFESGST	ADPTOPT	CNTLFS
Expert 1	.103	.169	.068	.068	.169	.103	.133	.068	.133	.103	.133	.133
Expert 2	.007	.033	.016	.025	.016	.016	.042	.007	.007	.007	.007	.025
Expert 3	.163	.065	.031	.163	.163	.065	.099	.031	.099	.065	.129	.163
Expert 4	.118	.028	.150	.118	.028	.150	.118	.090	.060	.150	.090	.150
Expert 5	.096	.023	.074	.096	.096	.074	.074	.123	.048	.048	.023	.048
Expert 6	.087	.113	.057	.144	.057	.087	.057	.113	.057	.113	.144	.144
Expert 7	.243	.100	.049	.049	.193	.243	.149	.243	.149	.049	.100	.149
Expert 8	.023	.126	.023	.076	.099	.076	.023	.126	.126	.076	.126	.099
Expert 9	.054	.054	.026	.026	.137	.083	.026	.137	.137	.108	.108	.026
Expert 10	.040	.009	.020	.020	.020	.020	.040	.031	.009	.051	.009	.031

TABLE XI. NORMALIZED MATRIX

Experts	RSREFF	PTRCEM	PRGRINN	EMENMT	APPDIP	CMMENSS
Expert 1	.110	.235	.132	.087	.173	.112
Expert 2	.008	.046	.031	.032	.016	.018
Expert 3	.175	.091	.061	.209	.167	.071
Expert 4	.126	.039	.292	.150	.029	.163
Expert 5	.103	.031	.144	.123	.098	.081
Expert 6	.093	.156	.111	.183	.058	.095
Expert 7	.260	.139	.095	.062	.197	.265
Expert 8	.025	.174	.045	.097	.101	.083
Expert 9	.058	.076	.050	.033	.140	.090
Expert 10	.043	.012	.038	.025	.020	.022

Experts	ETHPR	RMNGLTSV	ACCAUDM	DFFESGST	ADPTOPT	CNTLFS
Expert 1	.175	.070	.161	.133	.154	.138
Expert 2	.055	.007	.009	.009	.008	.026
Expert 3	.130	.032	.120	.085	.148	.169
Expert 4	.155	.093	.072	.194	.104	.155
Expert 5	.097	.127	.059	.063	.026	.050
Expert 6	.075	.116	.069	.146	.165	.148
Expert 7	.196	.251	.181	.063	.115	.154
Expert 8	.031	.130	.152	.098	.145	.102
Expert 9	.034	.142	.166	.140	.124	.026
Expert 10	.053	.032	.011	.067	.010	.032

TABLE XII. MAXIMUM, MINIMUM, AND DIFFERENCE

	RSREFF	PTRCEM	PRGRINN	EMENMT	APPDIP	CMMENSS	ETHPR	RMNGLTSV	ACCAUDM	DFFESGST	ADPTOPT	CNTLFS
Max	.260	.235	.292	.209	.197	.265	.196	.251	.181	.194	.165	.169
Min	.008	.012	.031	.025	.016	.018	.031	.007	.009	.009	.008	.026
Diff	.252	.223	.260	.183	.180	.248	.165	.243	.172	.185	.157	.143

TABLE XIII. PERCENTILE SCORES

	RSREFF	PTRCEM	PRGRINN	EMENMT	APPDIP	CMMENSS
Expert 1	10	9	10	5	10	10
Expert 2	11	10	10	5	10	10
Expert 3	15	10	10	5	5	15
Expert 4	5	10	15	10	5	15
Expert 5	10	9	5	10	10	5
Expert 6	10	11	5	5	15	10
Expert 7	10	15	5	5	5	15
Expert 8	15	10	15	15	5	5
Expert 9	10	7	10	10	9	10
Expert 10	10	5	10	10	4	5
	ETHPR	**RMNGLTSV**	**ACCAUDM**	**DFFESGST**	**ADPTOPT**	**CNTLFS**
Expert 1	5	10	5	6	10	10
Expert 2	5	10	5	6	9	9
Expert 3	5	5	5	6	9	10
Expert 4	5	5	5	6	9	10
Expert 5	10	5	7	15	6	8
Expert 6	5	7	7	5	9	11
Expert 7	10	7	7	5	7	9
Expert 8	10	8	10	3	2	2
Expert 9	5	15	10	4	5	5
Expert 10	5	20	10	10	6	5

TABLE XIV. AVERAGE PERCENTILE SCORES

	RSREFF	PTRCEM	PRGRINN	EMENMT	APPDIP	CMMENSS	ETHPR	RMNGLTSV	ACCAUDM	DFFESGST	ADPTOPT	CNTLFS
APS	10.6	9.6	9.5	8	7.8	10	6.5	9.2	7.1	6.6	7.2	7.9

TABLE XV. LINGUISTICS OF LEADERSHIP STYLES

	RSREFF	PTRCEM	PRGRINN	EMENMT	APPDIP	CMMENSS	ETHPR	RMNGLTSV	ACCAUDM	DFFESGST	ADPTOPT	CNTLFS
TR	M	M	H	MH	M	M	ML	M	MH	L	M	M
SR	M	H	M	M	MH	MH	L	H	MH	ML	MH	MH
ET	VVH	H	VVH	VH	VH	VH	VVL	H	VH	Vl	VH	VVH
AD	H	MH	M	M	H	H	L	MH	M	M	H	MH
AU	MH	M	MH	H	MH	H	M	H	H	L	M	MH
	RSREFF	PTRCEM	PRGRINN	EMENMT	APPDIP	CMMENSS	ETHPR	RMNGLTSV	ACCAUDM	DFFESGST	ADPTOPT	CNTLFS
TR	MH	M	MH	MH	H	M	L	H	H	L	MH	MH
SR	H	H	H	M	H	M	L	H	H	M	H	H
ET	VVH	VVH	VVH	VVH	VVH	VVH	VVL	VH	VVH	Vl	VH	H
AD	M	H	MH	MH	MH	M	ML	MH	H	ML	MH	H
AU	M	H	MH	H	M	M	ML	MH	MH	ML	MH	H
	RSREFF	PTRCEM	PRGRINN	EMENMT	APPDIP	CMMENSS	ETHPR	RMNGLTSV	ACCAUDM	DFFESGST	ADPTOPT	CNTLFS
TR	M	MH	H	MH	M	MH	M	M	H	ML	MH	MH
SR	MH	M	H	H	M	MH	ML	MH	MH	ML	MH	M
ET	VVH	VH	VH	H	VH	VH	VVL	VVH	VVH	Vl	H	VH
AD	M	MH	MH	MH	H	M	ML	MH	MH	M	M	H
AU	M	M	MH	MH	M	M	M	H	MH	ML	M	M
	RSREFF	PTRCEM	PRGRINN	EMENMT	APPDIP	CMMENSS	ETHPR	RMNGLTSV	ACCAUDM	DFFESGST	ADPTOPT	CNTLFS
TR	MH	MH	H	H	MH	H	M	MH	MH	L	H	M
SR	H	MH	M	MH	M	M	ML	M	M	M	M	H
ET	VH	VH	VH	VH	VVH	VVH	Vl	VH	H	Vl	H	VVH
AD	MH	H	M	MH	M	M	M	H	H	M	M	H
AU	MH	M	MH	H	MH	H	L	MH	MH	L	MH	M
	RSREFF	PTRCEM	PRGRINN	EMENMT	APPDIP	CMMENSS	ETHPR	RMNGLTSV	ACCAUDM	DFFESGST	ADPTOPT	CNTLFS
TR	H	M	H	MH	MH	M	M	MH	MH	M	M	H
SR	H	M	H	H	M	MH	M	H	MH	ML	M	MH
ET	H	H	VVH	VVH	H	VVH	Vl	H	VVH	VVL	VVH	VVH
AD	MH	H	MH	MH	MH	MH	ML	H	M	ML	M	H
AU	M	MH	MH	H	M	MH	ML	H	H	L	M	MH
	RSREFF	PTRCEM	PRGRINN	EMENMT	APPDIP	CMMENSS	ETHPR	RMNGLTSV	ACCAUDM	DFFESGST	ADPTOPT	CNTLFS
TR	M	M	H	H	H	H	L	M	MH	L	MH	M
SR	H	H	MH	MH	MH	M	ML	H	MH	L	H	M

ET	VVH	VH	VVH	VH	VH	VH	VVL	H	VH	VVL	VVH	VVH
AD	H	H	H	M	M	H	ML	M	M	ML	M	H
AU	M	H	MH	M	MH	M	M	H	M	L	H	M
	RSREFF	**PTRCEM**	**PRGRINN**	**EMENMT**	**APPDIP**	**CMMENSS**	**ETHPR**	**RMNGLTSV**	**ACCAUDM**	**DFFESGST**	**ADPTOPT**	**CNTLFS**
TR	H	MH	H	MH	H	MH	M	M	MH	ML	M	MH
SR	MH	MH	H	M	M	H	L	H	M	ML	M	MH
ET	VVH	VVH	VVH	VVH	H	VVH	VVL	VH	H	VVL	VH	VH
AD	MH	MH	MH	MH	M	MH	L	M	MH	ML	MH	M
AU	H	M	MH	H	MH	MH	ML	H	H	M	MH	MH
	RSREFF	**PTRCEM**	**PRGRINN**	**EMENMT**	**APPDIP**	**CMMENSS**	**ETHPR**	**RMNGLTSV**	**ACCAUDM**	**DFFESGST**	**ADPTOPT**	**CNTLFS**
TR	MH	M	M	M	MH	H	ML	MH	H	ML	MH	M
SR	MH	MH	MH	M	M	MH	L	H	H	ML	MH	M
ET	VH	H	VH	VVH	VH	VVH	Vl	VVH	VH	VVL	VH	H
AD	M	MH	M	M	H	H	L	MH	H	L	MH	H
AU	M	M	MH	H	H	H	L	M	MH	ML	M	H
	RSREFF	**PTRCEM**	**PRGRINN**	**EMENMT**	**APPDIP**	**CMMENSS**	**ETHPR**	**RMNGLTSV**	**ACCAUDM**	**DFFESGST**	**ADPTOPT**	**CNTLFS**
TR	M	H	H	H	MH	M	ML	MH	M	ML	H	H
SR	H	MH	H	M	MH	H	L	H	M	L	H	M
ET	VH	VVH	H	H	VH	VVH	Vl	VVH	H	Vl	VVH	VVH
AD	M	M	M	MH	MH	MH	L	MH	M	ML	M	H
AU	MH	H	H	MH	M	M	L	M	M	M	MH	MH
	RSREFF	**PTRCEM**	**PRGRINN**	**EMENMT**	**APPDIP**	**CMMENSS**	**ETHPR**	**RMNGLTSV**	**ACCAUDM**	**DFFESGST**	**ADPTOPT**	**CNTLFS**
TR	MH	M	M	M	MH	MH	ML	MH	H	M	H	MH
SR	MH	MH	M	H	H	H	M	M	MH	M	H	M
ET	VVH	VVH	VVH	VVH	VVH	VVH	Vl	VVH	VVH	VVL	H	VH
AD	H	M	M	MH	H	MH	M	MH	M	L	M	M
AU	H	M	H	H	H	MH	L	M	MH	L	M	MH

TABLE XVI. DECISION MATRIX

	RSREFF	**PTRCEM**	**PRGRINN**	**EMENMT**	**APPDIP**	**CMMENSS**	**ETHPR**	**RMNGLTSV**	**ACCAUDM**	**DFFESGST**	**ADPTOPT**	**CNTLFS**
TR	(.6,.3)	(.57,.33)	(.68,.22)	(.63,.27)	(.62,.28)	(.61,.29)	(.44,.45)	(.55,.35)	(.62,.28)	(.37,.52)	(.59,.31)	(.58,.32)
SR	(.64,.26)	(.61,.29)	(.64,.26)	(.58,.32)	(.55,.35)	(.62,.28)	(.34,.54)	(.67,.23)	(.58,.32)	(.39,.5)	(.59,.3)	(.58,.32)
ET	(.87,.11)	(.82,.12)	(.86,.11)	(.84,.12)	(.8,.12)	(.87,.1)	(.1,.84)	(.82,.12)	(.8,.13)	(.1,.82)	(.82,.12)	(.86,.11)
AD	(.6,.3)	(.63,.27)	(.57,.33)	(.57,.33)	(.61,.29)	(.62,.28)	(.35,.53)	(.6,.3)	(.59,.31)	(.43,.47)	(.57,.33)	(.65,.25)
AU	(.59,.31)	(.56,.33)	(.61,.29)	(.66,.24)	(.58,.31)	(.61,.29)	(.4,.49)	(.65,.24)	(.63,.27)	(.38,.51)	(.57,.33)	(.58,.32)

TABLE XVII. DEFUZZIFIED DECISION MATRIX

	RSREFF	PTRCEM	PRGRINN	EMENMT	APPDIP	CMMENSS	ETHPR	RMNGLTSV	ACCAUDM	DFFESGST	ADPTOPT	CNTLFS
TR	.644	.620	.727	.674	.666	.655	.495	.598	.669	.424	.640	.633
SR	.684	.660	.686	.629	.597	.667	.403	.714	.624	.447	.643	.625
ET	.884	.850	.880	.862	.832	.889	.137	.847	.832	.145	.847	.876
AD	.651	.674	.621	.620	.655	.664	.408	.644	.636	.478	.615	.697
AU	.641	.614	.663	.711	.634	.657	.457	.702	.680	.437	.621	.632

TABLE XVIII. NORMALIZED DECISION MATRIX

	RSREFF	PTRCEM	PRGRINN	EMENMT	APPDIP	CMMENSS	ETHPR	RMNGLTSV	ACCAUDM	DFFESGST	ADPTOPT	CNTLFS
TR	.184	.181	.203	.193	.197	.185	.260	.171	.195	.219	.190	.183
SR	.195	.193	.192	.180	.176	.189	.212	.204	.181	.231	.191	.181
ET	.252	.249	.246	.247	.246	.252	.072	.242	.242	.075	.252	.253
AD	.186	.197	.174	.177	.194	.188	.215	.184	.185	.248	.183	.201
AU	.183	.180	.185	.203	.187	.186	.240	.200	.197	.226	.184	.182

TABLE XIX. WEIGHTED DECISION MATRIX

	RSREFF	PTRCEM	PRGRINN	EMENMT	APPDIP	CMMENSS	ETHPR	RMNGLTSV	ACCAUDM	DFFESGST	ADPTOPT	CNTLFS
TR	.019	.017	.022	.015	.015	.019	.018	.017	.014	.017	.012	.011
SR	.020	.018	.021	.014	.013	.019	.015	.021	.013	.018	.012	.011
ET	.026	.023	.027	.019	.018	.026	.005	.024	.017	.006	.016	.015
AD	.019	.018	.019	.013	.014	.019	.015	.019	.013	.019	.012	.012
AU	.019	.017	.020	.015	.014	.019	.016	.020	.014	.017	.012	.011

TABLE XX. SUMS AND OVERALL VALUES

	S+	S-	Overall
TR	.161	.035	1.4603
SR	.162	.032	1.4613
ET	.212	.011	1.4841
AD	.159	.034	1.4601
AU	.161	.034	1.4607

TABLE XXI. SENSITIVITY ANALYSIS

	TR	SR	ET	AD	AU
Senario_1	4	2	1	5	3
Senario_2	4	2	1	5	3
Senario_3	4	2	1	5	3
Senario_4	4	2	1	5	3
Senario_5	4	2	1	5	3
Senario_6	4	2	1	5	3
Senario_7	4	2	1	5	3
Senario_8	4	2	1	5	3
Senario_9	4	2	1	5	3
Senario_10	4	2	1	5	3
Senario_11	4	2	1	5	3
Senario_12	4	2	1	5	3

Temporal-Cross-Modal Intelligence for Detecting Fraudulent Crowdfunding Campaigns

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***Abstract*—Reward-based crowdfunding platform fraud has now become a multimodal and temporally dynamic threat, with conventional text-only or snapshot-based detection methods ineffective at detecting more complex deceptive campaigns. In this study, a Temporal Dynamics Aware Multi-Model Fraud Detection Framework (TDMM-FDF) that simultaneously models linguistic indicators, visual discrepancies, and time behavioral changes is proposed. The framework introduces three key innovations: 1) HM4, a Hidden Method-of-Moments Markov model for modeling long-range latent transitions across campaign updates, 2) Polynomial Expansion Canonical Correlation Analysis (PECCA) for quantifying nonlinear semantic discrepancies between textual narratives and associated images, and 3) Frequency-Gated GRU (FG-GRU) which separates recurrent activations into low frequency (trend) and high frequency (anomaly) components in order to achieve higher sensitivity to abrupt fraudulent behaviors. Massive simulations on an actual Kickstarter data set prove that the given architecture outperforms classical machine learning models, sequence encoders, and transformer baselines significantly [96.4% accuracy and good calibration (ECE = 0.06) and high ROC-AUC]. The supplementary role of all modules is confirmed in ablation studies, and their qualitative analyses provide precise semantic-visual discrepancies and semantic time anomalies of fraudulent campaigns.**

Keywords*—Crowdfunding fraud detection; multimodal learning; temporal behavior modeling; cross-modal consistency analysis; blockchain-based verification

I. Introduction

Over the past years, online crowdfunding sites have transformed the world of entrepreneurship and innovation funding through a system that helps individuals and startups to raise funds through the help of a large group of supporters and cuts off the middlemen. In fact, the reward-based crowdfunding model has gained popularity; specifically, the Kickstarter platform has already assisted in the launch of hundreds of thousands of campaigns, with the billions of dollars pledged [1], [2]. This liberalization of capital has opened new possibilities to both project creators and those who support the projects. However, it has also brought great new risks.

Fraud is one of the gravest threats to crowdfunding ecosystems: creators who lie about themselves, who cannot deliver on their promises, or otherwise abuse the trust of backers. The trend of misleading campaigns based on the use of linguistic indicators, insignificant responsibility of creators, and the absence of effective control over platforms is increasing. Crowdfunding fraud is a betrayal of trust, a risk to the reputation of the platform, and compromises the future sustainability of the crowdfunding business model [3]. Nevertheless, even being significant, the analysis of fraud in this field of crowdfunding is at a comparatively young age, particularly in comparison with fraud prevention in the banking or credit-card sectors.

One of the difficulties of identifying crowdfunding fraud is time-related factors. Although much of the literature is devoted to the fixed characteristics of campaigns (e.g., funding goal, number of backers, presence of video), the movement of a campaign, how updates are displayed, how the activity of backers varies with time, and how communications by creators vary with time can provide dense information about legitimacy or dishonesty. To give an example, Bernardino et al. in their exploratory analyses of crowdfunding dynamics observed that backer and updates temporal dynamics may differentiate between successful and non-successful campaigns [4]. Nevertheless, these time indicators are still mostly unexploited in the field of fraud detection studies. According to one of the recent systematic reviews [5], the detection of fraud within the context of crowdfunding tends to ignore the time and multi-modality of behavior, concentrating on static snapshot characteristics. Multi-modal information is also another important dimension. Contemporary crowdfunding efforts usually contain text (project description, updates, and comments), images and video (media of the product or prototype), and time (frequency of updates, funding pattern, reactions of backers). Fraudsters can exploit a single modality and conceal inconsistencies in another (or both) or may conceal discrepancies between modalities or in the timing of interactions. Such cross-modal incongruity as a shiny image of the product, but slow updates or missing comments by true backers can be powerful red flags, but there is little incorporation of multiple modalities and time.

This study introduces a temporal dynamics-aware multi-modal fraud detection framework, which is explicitly implemented in a reward-based crowdfunding platform. It can be driven by the fact that there is a growing sophistication in terms of deceiving potential followers using multimedia content and time behavior by fraudulent campaigns. To overcome these difficulties, we design our framework, incorporating time modelling, multi-modal feature fusion, and cross-modal

consistency validation to have a holistic mechanism of fraud detection. Our system is based on the Hidden Method-of-Moments Markov Model (HM4), the first great component that represents sequential dependencies in campaign updates and interactions between supporters. HM4 is useful in learning such latent behavioral patterns, which differentiate legitimate campaigns and those with suspicious or erratic updating behavior patterns. This time sensitivity enables the model to sense any abnormality in the frequency of postings, development of contents and the support of posts over time.

This study was inspired by the fact that the nature of deception on crowdfunding sites has been evolving at a high rate since the phishers on the crowdfunding sites have outgrown the textual lies into the so-called temporal-multimodal deception. Although the current body of literature has devoted much attention to the so-called snapshot-characteristics these approaches are getting more and more oblivious to the high-tech rhythm of the modern fraud. A dishonest designer might be able to provide a professional impression, but have a suspicious update rate or textual content that does not match visual prototype clues. It is in dire need of a framework that not only views multiple data types but also comprehends their correlation and time dynamics. The optimization of verifying temporal behaviors should be coupled with cross-distribution checks, whereby platforms can transition to the state of proactive fraud resistance and high precision.

For fusing heterogeneous data modalities, we propose a Frequency-Gated Gated Recurrent Unit (FG-GRU) architecture. This new form of GRU inserts multi-scale frequency gating to primarily highlight meaningful temporal variations. The FG-GRU takes in three streams of inputs: 1) textual features, which have been extracted based on a Hierarchical Pattern Distillation-based approach on BERT representations to identify semantic inconsistencies, 2) visual features, which have been extracted based on ICI-based CLAHE and HOG/SIFT to take in image manipulation or reuse, and 3) temporal states by the HM4 model. The combination of those modalities allows the classifier to make resilient campaign honesty forecasts. We also use Polynomial Expansion Canonical Correlation Analysis (PECCA) in cross-modal consistency checking between textual and visual modalities. This will guarantee the semantics adherence, where the potential discrepancies will be indicated, including the presence of overly professional imagery and the incoherent or misleading textual explanations. This will make PECCA more interpretable and will increase the trust in the decision-making process of the model.

The rest of the study is structured in the following way: Section II is the review of the related literature about crowdfunding fraud, temporal modelling, and multi-modal detection. Section III will provide our methodology, such as data preprocessing, feature extraction, model configuration, and training strategy. Section IV presents our results, comparison with baselines, ablation studies and qualitative case studies. Lastly, Section V concludes and identifies the future research directions.

II. Related Work

Crowdfunding has grown into a mainstream tool of financing in its early stages, but the transparency that empowers creativity can also prove flaws on the platforms in its ease of cheating. Initial studies of crowdfunding-related fraud focused their analysis more on fixed characteristics of campaigns, such as creator profile features, language indicators, and top-level engagement mechanisms, and used classical classifiers. Lee et al. have built a labelled Kickstarter corpus and have shown that forward stepwise logistic regression using engineered campaign/creator/content features can distinguish between fraudulent and legitimate campaigns with an accuracy of 87.3%; noteworthy, they also observed the vulnerability of snapshot features that disregard the dynamics of behaviors over time [1]. As previously explained, Perez et al. expanded the field to include platforms, modalities, and reported good AUC when using text-image features and traditional ML baselines, but not with temporal signals in model selection [3]. Qu and Hou wrote a corresponding thread about textual self-contradiction in a campaign and suggested a dual BERT-mT5 pipeline with sentence designs and sentiment classification to achieve 85.26% accuracy-text only, but ignoring visual/temporal cues [6]. A PRISMA bibliometric study has enhanced the fragmentation in the field and identified precisely such gaps as a deficient temporal modelling and a deficient multi-modal integration as the key obstacles to effective fraud detection in the sites of a crowdfunding business [7].

Temporal signals are significant candidates of project success and, by implication, plausibly informative of fraud detection in the event of the patterns being out of place. In each of the 2852 projects, the analysis by Solodoha revealed non-linear effects of frequency of updates: both neglect and over-updating imply different implications on the results, hence the importance of fixed snapshots being blind to important context [8]. Though neighboring entrepreneurship literature explores uncertainty, hype, and incompleteness of decisions in crowdfunding and similar environments, it usually does not go beyond this; however, these articles encourage behavioral and time-sensitive phenomena (e.g., cadence of updates, latency between commitments and posts, dynamics of backer counts) that a fraud detector should learn [9]. Together with the preceding stream, this stream justifies the requirement of sequence-sensitive models as opposed to fixed classifiers.

Because most of these deceptive campaigns appear through professional-looking media so as to conceal suspicious text, cross-modal reasoning is paramount. Lin introduced a text-image fusion image-to-text misinformation model, which is an improvement over unimodal baselines and demonstrates that joint representations can detect subtle inconsistencies that individual modalities would be blind to [10]. This concept is refined in a few deep multimodal fake-news experiments that have contrastive objectives and optimal transportation to align and compare modalities (Shen et al.), or that have contrastive learning based on data-augmentation to harden models to distribution changes (Hua et al.) [11], [12]. Segura-Bedmar and Martinez showed that CNN-based fusion achieved competitive accuracy in Fakeddit, which proves the worth of acquired cross-modal features in comparison with concatenation alone [9]. In this area (Nasser et al.; Shen et al.), architectural forms, including late versus early fusion, attention-based alignment, and consistency scoring, are synthesized and can be directly translated to crowdfunding, although benchmarks may vary

[13], [14]. The literature confirms that explicit text-image correspondence plays a critical role in determining that there is a semantic discrepancy in digital content. Mohan et al. suggested a synergistic detection model based on TextGCN, Vision Transformers to learn intricate inter-modal association [15]. Hangloo and Arora proposed a feature fusion model that is specifically created to identify multimodal fake news through matching between divergent streams of data [16]. Huang et al. revealed that the diffusion model could be used to reveal text-image inconsistencies through visual data reconstruction based on textual prompts [17]. In addition, Kumari and Singh proposed a multimodal deep learning framework that combines different techniques of feature extraction to enhance the accuracy of the classification [18]. Fraud cannot easily take a single and fixed signature, and much more frequently is manifested in local anomalies in more or less plausible regions of behavior. The Local Outlier Factor (LOF) has been appealing to high-throughput systems since it models density-based deviations without any heavy parametric restrictions. Adesh et al. explain LOF and improved-LOF in the context of HPCC environments and focus on additional considerations of scalability and practical deployment that are relevant in the context of real-time platform defense [19].

Hybrid pipelines are being more often applied in further financial and enterprise terms to stabilize predictions. Cherif et al. provided a systematic review of credit card fraud detection with disruptive technologies and stressed on the transition to integrated deep learning models [20]. Khalid et al. suggested an ensemble machine learning methodology which involves using a combination of several classifiers to improve the screening of fraudulent transactions [21]. Ismail and Haq showed how enterprise financial fraud detection can be enhanced by addressing the features of engineering and hybrid model architecture to process unstructured information [22]. These experiments validate the application of unsupervised locality scores, e.g., LOF, to scale-down pronounced supervised classification confidence.

In modern fraud detection, signals occur in a sequence, or updates, comments, promises, but models must be able to retain long-range and short-range dependencies. Other than LSTM/GRU surveys, there are two strands that are of particular interest. First, GRU, based on architecture or training innovations offer more robust sequence encoders at restricted data. To learn spatial-temporal dependencies, Liu et al. use GRUs in a graph neural network to form GR-GNN and obtain reduced error in time-series prediction and how graphical inductive bias can stabilize recurrent learning [23]. Another article by Liu et al. is devoted to evolutionary optimization of GRU hyperparameters, where the authors report steady improvement as compared to vanilla GRUs in sequential prediction [24]. Second, there are spatial-temporal models of GAST (graph attention + temporal forecasting) which show that the attention toward changing relational structure enhances predictive fidelity when encountering the problem of distributional shift [25]. These advances provide information that leads us to augment GRU with (and for an NAR) frequency gating for separating low-frequency (slow-varying, strategic behavior) and high-frequency (abrupt, tactical actions) components to better pad both the drift and sudden anomalies at the campaign level.

Irrespective of the improvement, there are several loopholes. Multimodal datasets with temporal granularity unique to the phenomena of crowdfunding are still rare; much of the existing literature brings in the experiences of fake-news or financial transactions with alternative labels. Measures that are reported are usually based on average accuracy or AUC but do not include calibration and early-warning performance, which is also fundamental to intervention on the platform. Finally, multimodal, temporality explainability is underdeveloped; besides the attention maps, techniques that assign cross-modal discrepancies to tangible objects would be more helpful in moderating workflows.

III. Methodology

The proposed Temporal Dynamics Aware Multi-Modal Fraud Detection Framework (TDMM-FDF) combines the text, visual, and temporal features to detect fraudulent crowdfunding campaigns. The architecture consists of nine steps, namely, data collection and preprocessing, feature extraction, temporal modelling, cross-modal consistency validation, feature selection, classification with FG-GRU, and blockchain verification. Fig. 1 depicts the block diagram of a sequential workflow in which a preprocessing stage is carried out on the text and images obtained in the form of crowdfunding campaigns and the features are extracted and aligned, and HM4 is used to model the temporal patterns. Such multimodal representations are merged with each other and maximized and then given into the FG-GRU classifier. The final legitimate results are recorded in a ledger infrastructure based on blockchain to provide integrity and security.

A. Data Collection and Preprocessing

The data used in this research was obtained from the Kickstarter crowdfunding platform and was heterogeneous in multimodal form, that are needed to conduct effective fraud analysis. The dataset used is summarized in Table I. In each campaign example, there were organized and unstructured items, such as the project title, entire narrative descriptions, creator profiles, visual media, logs of updates and backer comments in a timely manner. The time-sensitive aspect of these fields allowed the modelling of both the static correlations, as well as dynamic behavioral routes that are usually characteristic of a fraudulent campaign.

Considering the noisiness and informality of user-generated Kickstarter contents, an elaborate pretext text processing pipeline was used so as to make sure semantic integrated before feature extraction. First of all, the extraneous HTML tags, links, emojis, and non-standard punctuation were eliminated, and lexical distortion was avoided. Any textual information was then normalized in two steps: 1) lowercasing all texts to token uniformity, and 2) stop word elimination to bury high-frequency and low-information words. This normalization can be formulated as in Eq. (1):

$$T' = Normalize(T) = Lowercase\,(RemoveStopwords(T)) \quad (1)$$

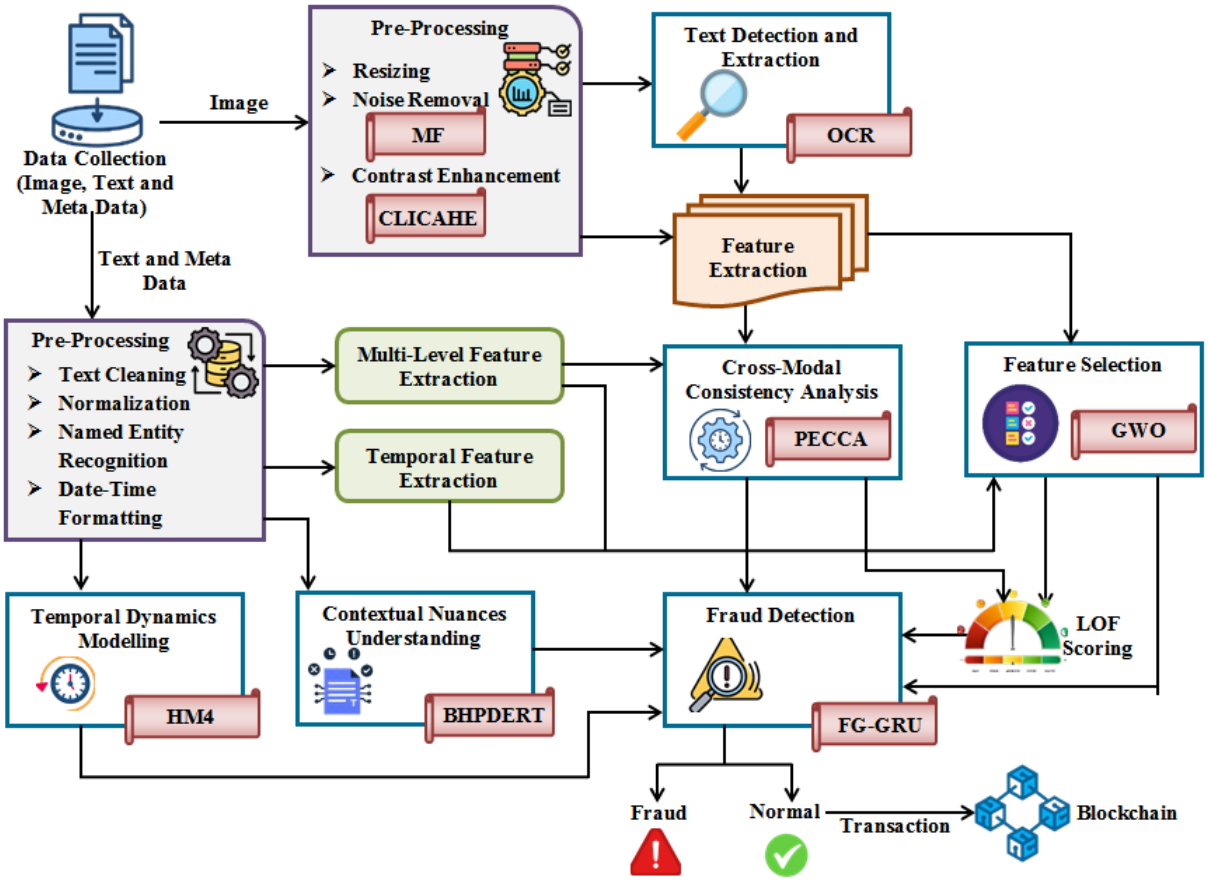


Fig. 1. Block diagram of the proposed framework.

TABLE I. DATASET AND PREPROCESSING SUMMARY

Attribute	Description
Number of campaigns	28,500 campaigns after preprocessing
Temporal coverage	2014–2024 Kickstarter data
Textual components	Titles, long descriptions, FAQs, updates, comments, creator metadata
Visual components	Poster images, prototype photos (1–8 per campaign)
Temporal sequences	Update timelines, backer activity logs, milestone timestamps
OCR-derived features	Extracted embedded poster text
Text preprocessing	HTML/emoji removal, normalization, stemming, NER
Image preprocessing	Median filtering, CLICAHE, OCR
Output modalities	Text vectors, image descriptors, temporal latent states

In addition, stemming was used to decrease inflexion forms, which minimized the inflexibility of token distribution. NER was later used to recognize semantically important entities which included organization names, product identifiers, time phrases, monetary values, and geopolitical positions. These entity-level annotations facilitated the verification of cross-image-based and time-based signals later on in the framework.

The image processing pipeline of the campaign was a combination of noise removal, texture-textuality-sensitive contrast segmentation, and inscribed text recovery to ensure the visual data quality brought across the actions of different campaigns matched adequately. Firstly, the images were morphologically enhanced with the Median Filtering (MF), which is a non-linear denoising operator that is efficient in noise reduction, especially salt-and-pepper noise, and the edges of the images are maintained. The process of filtering is given in the form of an equation, as shown in Eq. (2):

$$I'(x,y) = median\{I(i,j) \mid (i,j) \in N(x,y)\} \quad (2)$$

Subsequently, image contrast was improved using Contrast-Limited Image Complexity Adaptive Histogram Equalization (CLICAHE), an advanced extension of CLAHE. Unlike standard CLAHE, which applies a fixed clip limit, CLICAHE dynamically adjusts the clip threshold based on the Image Complexity Index (ICI) of each local region. Let H_k denote the histogram of a contextual region k, and let α_k [Eq. (3)] be the adaptive clip limit:

$$\alpha_k = \alpha_0(1 + \lambda \cdot ICI_k) \quad (3)$$

where, α_0 is the baseline clip limit, λ controls sensitivity to complexity, and ICI_k is defined as in Eq. (4):

$$ICI_k = \frac{1}{|R_k|}\sum_{(x,y)\in R_k}|\nabla I(x,y)| \quad (4)$$

Lastly, Optical Character Recognition (OCR) was used to extract textual clues that were within the poster-type images like product specifications, promotional statements, or disclaimers.

The OCR text was subsequently cross tabulated with the cleaned narrative descriptions to determine the presence of any textual variation or exaggerations that were suggestive of some form of fraud.

B. Textual Feature Extraction

The textual modality was enhanced by the extraction of lexical, semantic, and pragmatic cues, which make it possible to model linguistic behaviors of deceptive or misleading narratives in a comprehensive manner. The lexical indicators consisted of part-of-speech (POS) distributions, type-token ratios, and vocabulary richness measures, which all measure structural characteristics of campaign narratives. The pragmatic features have been calculated in order to distinguish between professionally written descriptions and suspiciously twisted or over-simplified text. Also, sentiment polarity and subjectivity scores were calculated to measure the tone of emotion, as fraudulent campaigns tend to be based on overstated optimism or framing of sentiment.

To have a deep semantic representation, the study utilized the Bidirectional Hierarchical Pattern Distillation Transformer (BERT-HPD), an improved transformer architecture, which aims to maintain the contextual depth and, at the same time, minimize computational costs. The underlying BERT encoder uses a contextualizing representation of all the tokens in the text by learning bi-directional dependencies between the text. Mathematically, given a sequence of input tokens ($w_1, w_2, \dots, w_n$), BERT will compute a contextual representation vector h_i [Eq. (5)] at every token position:

$$h_i = BERT(w_1, w_2, \dots, w_n) \tag{5}$$

As much as standard BERT offers high-quality semantic features, when operational on a large scale, its implementation can be expensive in terms of computation requirement to large multimodal pipelines. To solve this, a masked generation architecture (HPD) mechanism was incorporated that enabled the transfer of hierarchical linguistic knowledge of a high-capacity teacher BERT to a smaller student model. This distillation has a guarantee that significant syntactic/semantic/discourse-level structure is still present in the reduced representation. $h_l^{(teacher)}$ and $h_l^{(student)}$ will represent the hidden states of layer l of the teacher and student models, respectively. The objective of the HPD is to reduce the difference between representations on a layer basis and to be able to faithfully recreate linguistic hierarchical patterns. The loss during the distillation is determined as in the Eq. (6):

$$\mathcal{L}_{HPD} = \sum_{l=1}^{L} \left\| h_l^{(teacher)} - h_l^{(student)} \right\|_2^2 \tag{6}$$

The student model implements multi levels of linguistic abstraction, including local syntactic interactions as well as global semantic dependencies, without initially having the computational costs of the entire BERT architecture, by applying this constraint. The process does not only minimize the overfitting potential that would have occurred when, in the text training, it is important to train on text that has strong stylistic variations like crowdfunding campaigns but also retains fine-grained deception signals such as semantic inconsistencies, over-general content, and unnatural emphasis patterns. Consequently, BERT-HPD offers a high-capacity and effective basis of downstream multimodal fraud detection.

C. Temporal Dynamics Modelling

To model the temporal evolution of campaign behavior, this work employs the HM4, an advanced variant of the traditional HMM. HM4 is designed to capture long-range dependencies and structural dynamics in sequential update patterns that often characterize legitimate and fraudulent crowdfunding projects. Let the hidden state space be defined as, $S = \{s_1, s_2, \dots, s_k\}$, where each latent state corresponds to an underlying behavioural regime such as consistent updates, erratic communication, sudden activity surges, or prolonged inactivity. Similarly, the observable sequence is represented as, $O = \{o_1, o_2, \dots, o_T\}$, derived from timestamped campaign updates, linguistic tone shifts, and engagement metrics.

The classical HMMs have the transition matrix A, emission matrix B, and initial state distribution π, which are estimated by the Baum-Welch algorithm, which is an Expectation-Maximization (EM) implementation. Despite its popularity, Baum-Welch is iterative in nature and tends to become trapped in bad local minima especially when dealing with noisy or high-variability behavioral data like crowdfunding updates. This is the restriction that renders standard HMMs inadequate in detecting fraud cases when the underlying behavioral patterns are not close to stationary or smooth tracks.

To overcome these issues, HM4 is introduced to replace EM-based optimization with a global statistical moment-matching model, which allows analytical recovery of model parameters. The point is that when properly designed, low-order observable moments capture enough information concerning the dynamics of latent states. The first-order moment of observations meets the Eq. (7). Similarly, second-order cross-moments between adjacent observations capture transition structure:

$$E|O_t| = \sum_{i=1}^{k} \pi_i \mu_i, \qquad E|O_t O_{t+1}| = \pi_i A_{ij} \mu_i \mu_j^T \tag{7}$$

These moment equations constitute a web of algebraic equations. HM4 computes transmission and emission parameters without the need to find the transition matrix A or q in an iterative improvement HM4 computes the initial state distribution p, the emission parameters B and the overall transition matrix A by means of spectral decomposition or by means of the tensor's factorization directly. This does away with local minima vulnerability and offers a globally compatible forecast of the temporal dynamics.

D. Image Feature Extraction

After contrast enhancement and denoising, each processed image was then run through a detailed feature extraction pipeline that aimed to extract a set of complementary image features with respect to fraud detection. Images used in crowdfunding campaigns frequently include minor anomalies, including recycled or stock images, artificially-enhanced prototypes, or artificial visuals of products, that cannot be readily found by raw pixel inspection. To resolve this, a collection of well-defined handcrafted descriptors was used and each of them provided a different approach to texture, structure, and information in the key point level.

Local Binary Patterns (LBP) were first calculated to describe the patterns of micro-textures of the surface of the image. LBP represents local spatial difference by thresholding intensity of neighborhoods around each pixel thus producing rotation-invariant descriptors, which are very sensitive to material textures and surface consistency. This is especially concerning when trying to determine the inconsistencies on the surfaces of products or when trying to detect image patches which are artificial and are very common in fake campaigns. Then, Gray Level Co-occurrence Matrix (GLCM) characteristics were computed to measure the existence of higher-order spatial relations. GLCM is the intensity correlation of pairs of values at a set of offsets, and it can measure the contrast, homogeneity, entropy, and correlation. These characteristics give an understanding of structural coherence and can identify abnormalities like inappropriate lighting patterns, inappropriate shading, or a background that has been made up, which would suggest tampered or non-original images.

Histogram of Oriented Gradients (HOG) descriptors were applied to obtain geometric information. The distribution of gradient orientations is coded in HOG and the edges and contours and object boundaries can be represented in detail. This assists in revealing unnatural formation of edges or silhouettes that are overly smooth that can indicate image manipulation or utilization of unrealistic prototype images. The Scale-Invariant Feature Transform (SIFT) algorithm was also used to find strong key points and calculate local descriptions that are feature scale, rotation and illumination independent. SIFT is specifically good at recognizing recurring regions in images or recognizing the presence of an image borrowed by external, publicly accessible stock libraries. The resulting image-feature representation is an ensemble of all the descriptors obtained [Eq. (8)]:

$$F_{img} = [LBP, GLCM, HOG, SIFT] \quad (8)$$

E. Cross-Modal Consistency Check

The suggested framework includes the cross-modal consistency analysis mechanism, as PECCA, to be sure that textual and visual modalities are mutually consistent in terms of evidence. This module assesses the semantic consistency between campaign images and textual descriptions, which are essential in fraud detection since misleading campaigns tend to exhibit images that do not match with the textual description to give the illusion of being credible. Canonical Correlation Analysis (CCA) provides the classical foundation for Multiview alignment by learning linear projections of text features X and image features Y such that the correlation between their projected representations is maximized.

The architecture uses PECCA, which is a nonlinear extension of CCA that develops each modality by feature expansion via polynomials. These extended representations enable PECCA to represent the higher-order dependencies among modalities, which in effect capture subtle nonlinear dependencies, e.g., stylistic inconsistencies or unrealistic image-text co-occurrence or semantic discrepancies between the claimed product functionality and the visual representation. After its expansion, PECCA uses standard CCA on transformed feature spaces $\emptyset(X)$ and $\emptyset(Y)$, therefore integrating the analysis of nonlinear correlations and omitting deep learning-based fusion networks.

F. Feature Selection

After extracting text-based, image-based, and temporal features, the three modalities were concatenated [Eq. (9)] to form a unified multimodal representation. Whereby each element holds complementary data: the semantics of language and cues of deception in the text, structural and surface-level data in the images, and behavior patterns in the dynamics of time. This fused representation, despite being very expressive, generally falls into a high-dimensional feature space. This dimensionality may bring about redundancy, higher computational cost, and even diminished model generalization because of irrelevant or noisy attributes. Metaheuristic strategy of feature selection, which relies on the optimization of the grey wolf (GWO), was used to solve these problems.

$$F = [F_{text}, F_{img}, F_{temp}] \quad (9)$$

GWO is a bio-inspired optimization method which imitates the hierarchical leadership and hunter-cooperative behavior of the grey wolves. This hierarchy places the three most fit wolves in the form of α, β, and δ. They are the candidate solutions that are most fit in the feature space, and direct the search means the feature space. The rest of the wolves, the ω wolves, refresh their locations in accordance with such three leaders, and in this way, we have a balance in exploration and exploitation in the optimization. A fitness function based on classification accuracy was used to assess the quality of an individual candidate feature subset. In particular, a lightweight classifier was trained on a validation split based on the selected subset of features only, and the accuracy obtained was used as the fitness score.

G. Fraud Detection Model (FG-GRU)

The last prediction step performed by the proposed framework uses a Frequency-Gated Gated Recurrent Unit (FG-GRU), a recurrent network architecture specific to both gradual and rapid behavioral change, as well as sudden, high-intensity change that often indicates a fraudulent campaign. Compared to the classical GRU, which interacts dependency with time using its update and reset gates, the FG-GRU proves this operation, dividing the dynamics of the hidden state into low-frequency and high-frequency components and is able to significantly differentiate two long-term behavioral patterns and discrete upsurges. The base GRU computes its hidden state h_t at time step t using the gated recurrence formulation [Eq. (10)].

$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot \tanh(Wx_t + r_t \odot Uh_{t-1}) \quad (10)$$

To better distinguish between smooth behavioral progressions and sharp deviations, the FG-GRU introduces a frequency decomposition stage. The hidden state h_t is passed through two filtering operators $F_{\text{low}}(\cdot)$, which extracts low-frequency (slow-varying) temporal components, and $F_{\text{high}}(\cdot)$, which extracts high-frequency (rapid-change) components. To integrate both frequency bands, FG-GRU introduces two learnable gating functions, g_{LF} and g_{HF}, which determine how much each component contributes to the final blended representation [Eq. (11)].

$$h_t^{FG} = g_{LF} \odot h_t^{LF} + g_{HF} \odot h_t^{HF} \quad (11)$$

To increase the reliability of the decisions, the FG-GRU output is assessed based on Local Outlier Factor (LOF). LOF

measures the isolation of a particular instance against the local neighborhood of such an instance in the latent representation space. Campaigns with multimodal temporal signatures that are significantly different than normal behavioral clusters are assigned lower density scores, and thus the prediction ambiguity is minimized, and more effectively distinguish between legitimate and fraudulent activities.

H. Blockchain Execution Layer

The framework uses a blockchain-based execution layer to make sure that the results of detecting the fraud are stored in a way that is tamper-resistant and auditable. This section reserves the results of the classification engine, namely, the campaign name, fraud rating, and final decision tag, into a decentralized registry. Using blockchain to anchor these findings will create an unalterable and transparent history of all the fraud evaluations conducted, which will instill greater confidence in the administrators of these platforms, campaign creators and sponsors.

A blockchain transaction Tx_i is created with each campaign C_i that has been taken through the multimodal evaluation pipeline. This is a transaction that includes key metadata, such as campaign ID, an output of the metadata, the fraud score S_i, or classification, and the time of evaluation t_i. The content of the transaction is encrypted with the help of a cryptographic hash, $H(\cdot)$, the implementation of which makes it impossible to make any changes to the stored information.

After it has been created, every transaction is added to the shared blockchain list stored by numerous nodes. The decentralization of the ledger makes it so that no one can manipulate or overwrite the outcome of a fraud assessment, and in the highly stakes setting of a crowdfunding site, where a challenge to the legitimacy of a campaign can emerge, it is of utmost importance. Additionally, the append-only cryptographically secured ledger does offer a verifiable audit trace that can be consumed either to conduct compliance audits, to resolve disputes, or to provide a long-term audit of campaign behavior.

IV. Results and Analysis

A. Simulation Setup

The study was performed on a real-life dataset that was gathered on Kickstarter, which is one of the biggest reward-based crowdfunding platforms. The structure of the dataset consists of campaign descriptions, project titles, visual media, creator metadata, update logs, timestamps, and funding progress indicators. Fraud labels have been generated using cases of scams reported publicly, campaigns identified as suspicious by the platform, and those reported by the community as fraudulent. To avoid the effect of temporal leakage, an inherent problem in sequential or time-dependent data where information in a future sample somehow affects the model's knowledge of historical behavior, the data has been stratified on a chronological basis. This guarantees that the time sequence of the campaign events is maintained during training and assessment. Namely, the first 70 per cent of campaigns were designated to the training set, which enabled the model to learn the patterns based on the historical data exclusively. The mid-period time frame entailed the subsequent 15% of campaigns, which made up the validation set and was utilized to tune hyperparameters and refine models. The last 15 percent of campaigns were used as the test set, which allowed the fair assessment of the model to generalize to new, unobservable campaigns that emerge in the future. Table II lists the most important hyperparameters for each component: HM4, PECCA, feature extractor modules, and the FG-GRU classifier.

TABLE II. Model Hyperparameters

Module	Parameter	Value / Description
HM4 (Temporal Model)	Hidden States (K)	6
	Moment Order Used	Up to 3rd-order cross-moments
	Transition Estimation	Algebraic MoM solver
	Emission Model	Gaussian Mixture (3 components)
Textual Encoder (BERT-HPD)	Max Seq Length	256 tokens
	Teacher Model	BERT-base (110M parameters)
	Student Model	8-layer distilled variant
	Distillation Loss	Layer-wise MSE + KL divergence
Image Processing	MF Kernel Size	5×5
	CLICAHE Tiles	8×8 blocks
	Clip-Limit	Adaptive (0.5–3.0)
Image Feature Extraction	LBP Radius	1
	GLCM Angles	{0°, 45°, 90°, 135°}
	HOG Cells	8×8
	SIFT Keypoints	Up to 500 per image
PECCA (Cross-Modal)	Polynomial Order	3
	Latent Dim (CCA Space)	120
	Correlation Threshold	0.55
FG-GRU Classifier	GRU Units	256
	Frequency Filters	Low (0–2 Hz), High (2–20 Hz)
	Batch Size	32
	Optimizer	AdamW
	Learning Rate	1.00E-04
	Epochs	50

B. Performance Comparison

To rigorously assess the efficiency of the developed multimodal fraud detector, the performance of the framework was compared to a collection of more popular baseline models, including classical ML methods, such as SVM and RF, and DL models, such as LSTM, GRU, and fine-tuned BERT. There were the same baselines train on the same experimental conditions, with the same chronologically stratified splits, and with the same normalized feature representations, in order to have an unbiased and fair comparison.

The outcomes of the performance, which are provided in Table III, indicate a steady and significant percentage of

improvement provided by the proposed model in all significant evaluation indicators. Conventional baselines like SVM and RF are also somewhat effective, but they fail to deal with the high temporal, visual, linguistic, and disparate nature of fraudulent crowdfunding activities. The sequential models, including LSTM and GRU, exhibit significant improvements since they can learn temporal dependencies; nevertheless, they cannot work well in the situation when cross-modal contradictions or irregularities in the behavioral pattern are present. The performance of Fine-tuned BERT is as good as it should be, especially regarding its contextual semantic knowledge, but it is restricted by its lack of inter-modal footing and explicitly modelled time view.

TABLE III. PERFORMANCE COMPARISON WITH BASELINE METHODS

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC	ECE
SVM	82.40%	79.50%	74.20%	76.70%	0.84	0.19
Random Forest	86.10%	83.80%	81.20%	82.50%	0.88	0.15
LSTM	88.70%	86.50%	84.10%	85.30%	0.9	0.13
GRU	90.30%	88.10%	85.60%	86.80%	0.92	0.12
BERT (Fine-tuned)	92.80%	91.20%	89.60%	90.40%	0.95	0.11
Proposed HM⁴ + PECCA + FG-GRU	96.40%	95.10%	94.20%	94.60%	0.982	0.06

The developed HM4 + PECCA + FG-GRU fusion architecture is obviously more superior. The system learns a much more diverse range of behavioral and semantic cues by combining HM4 with its strong ability to estimate temporal states, PECCA with its ability to model nonlinearly across cross-modal features, and frequency-aware sequential modelling, which is provided by FG-GRU. This leads to particularly high increases in Recall, a vital measure on fraud detection, and missing a fraudulent campaign is risky. The fact that the ROC-AUC score is very close to 0.98 is also a testimony to the high discriminatory power of the model in ranking suspicious campaigns over legitimate ones, suggesting that there is reliable discriminatory power even in difficult borderline cases. The other important benefit is the fact that the Expected Calibration Error (ECE) is reduced drastically between 0.11 with fine-tuned BERT and 0.06 in the offered system. This enhancement also indicates more credible confidence estimates, so that forecasts of fraud are closer to the likely outcomes, a necessary quality of real-world decision-making systems employed by crowdfunding platforms.

The proposed system has an ROC curve (Fig. 2) that shows a steep and very steep climb up to the upper-left corner, indicating that it has a high capacity to differentiate between fraudulent and legitimate campaigns at different decision thresholds. The model with a ROC-AUC of 0.982 has a significantly high discrimination capacity in comparison to all the baseline methods. This implies that, with the combination of time, text, and visual cues, the classifier is able to make accurate and correct ranking decisions even in borderline cases.

The Precision-Recall (PR) curve (Fig. 3) also proves the strength of the model to deal with the inherent class imbalance in fraud detection tasks. The suggested framework ensures that its precision exceeds 0.90 throughout a broad range of recall, which proves that the framework is capable of detecting fraudulent campaigns in an effective manner without the use of many false positives. This is especially crucial in real-life environments where a high rate of false alarms would destroy credibility and augment the operational load of investigation teams. The model proposed is highly precise at above 0.90 recall level, which can be explained by the fact that PECCA and FG-GRU complement each other with nonlinear multimodal alignment and frequency-conscious temporal modeling, respectively. These mechanisms taken jointly can provide a more detailed insight into campaign behavior and the system would hold true even in challenging conditions.

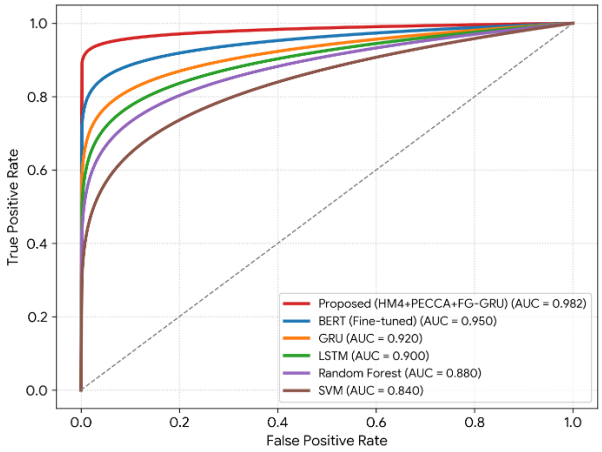


Fig. 2. ROC curve of the proposed fraud detection model.

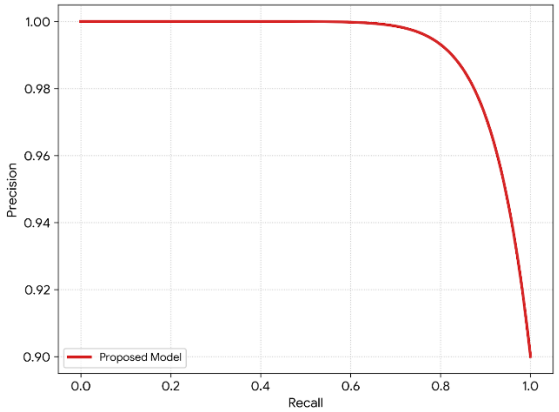


Fig. 3. Precision–Recall (PR) curve of the proposed fraud detection model.

As in Table IV, the confusion matrix obtained after testing the set shows that the proposed model possesses significantly low misclassification rates. Among all valid campaigns, 41 were falsely reported as fraudulent and the number of false negatives was only 23, which is significantly less than the baseline models. This enhancement underscores the usefulness of incorporating temporal state transitions of HM4 and multimodal contradiction detection of PECCA, which helps the system to identify subtle behavioural abnormalities that most simple models fail to detect.

Moreover, in the calibration curve (Fig. 4), it can be seen that there is a strong agreement between the predicted probability of fraud and the actual outcome frequency. It means that the model is effective in classification, as well as yielding credible confidence estimates. These predictability-aware predictions prove important at work with fraud-monitors, where the tolerance to operational risk or policy-specific to platform alert thresholds can be changed dynamically.

TABLE IV. CONFUSION MATRIX

	Predicted Legitimate	**Predicted Fraudulent**
Actual Legitimate	1035	41
Actual Fraudulent	23	412

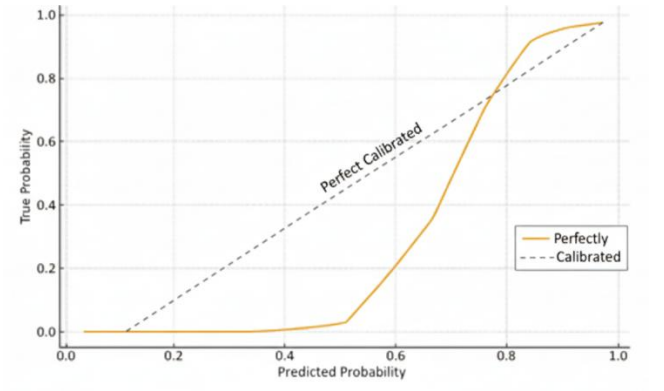


Fig. 4. Calibration curve of the proposed fraud detection

C. Computational Cost Analysis

To analyze three important aspects of computation, the runtime benchmarked three main aspects of computation, including training time per epoch, inference latency per sample, and memory usage on the GPU. The suggested model has greater computational overhead than the baseline GRU and fine-tuned BERT models, as illustrated in Table V. It has a 13.8 seconds per epoch training time and a 16.7ms per sample inference latency that indicates the extra processing added by multimodal feature integration, temporal moment modelling and frequency-gated recurrence. There is also the increment in GPU memory requirement to 7.9 GB due to the extended architecture and poly expansion modules.

A standard penciling of the blockchain integration in real-time detection systems is possible prohibitive latency, resource overhead. But in the TDMM-FDF architecture, the blockchain layer does not work as a processing module, but as an integrity-assurance layer, which is asynchronously running with the FG-GRU classifier. The system deters fraud scores (S_i) and metadata of campaigns by embedding them in a decentralized register, avoiding the so-called log-tampering that is a recognized vulnerability in a centralized platform management. We did a comparison of our blockchain-powered ledger and a regular centralized SQL-based logging system to determine that the integration is feasible. The findings, which are summarized in Table V, show that although the blockchain layer does add a slight increase in latency (22.4ms), the security advantages, namely, immutability and auditability by multiple parties, are essential to high-stakes governance of crowdfunding.

TABLE V. COMPUTATION COST ANALYSIS

Model	Training Time (per epoch)	Inference Latency (per sample)	GPU/System Memory
BERT (Fine-tuned)	11.2 s	14.3ms	6.5 GB
GRU (Vanilla)	4.3 s	5.1ms	2.1 GB
Proposed TDMM-FDF	13.8 s	16.7ms	7.9 GB
Blockchain Module	N/A (Asynchronous)	+22.4ms (Latency)	Negligible (CPU-bound)
Total Integrated System	13.8 s	39.1ms	7.9 GB + Storage

The computational trade-off would be fair even in the light of the extra costs because the gains in detection accuracy, recall, calibration reliability and ranking performance are significant. The enhanced predictive robustness and cross-modal interpretability of the suggested system offset the resource consumption increase in safety-critical settings, like fraud detection, where the outcomes of the failure to notice a fraudulent campaign can vary greatly in terms of financial and reputational implications.

D. Comparative Analysis of Feature Selection Methods

The choice to use the Grey Wolf Optimization (GWO) in the feature selection stage was due to the fact that it has a better balance of exploration and exploitation over the traditional metaheuristics. In high-dimensional multimodal spaces, such as that created by concatenating text, image and time features, approaches such as Genetic Algorithms (GA) are usually susceptible to premature convergence, whereas Particle Swarm Optimization (PSO) might get lost in local optima when optimizing non-convex fitness landscapes, as is the case with fraud detection data. In order to empirically defend this selection, a comparison was carried out with the use of a Kickstarter validation set. We compared GWO to GA, PSO and a standard L1-based (Lasso) selection. As the results, summarized in Table VI, indicate, GWO was able to find a smaller feature subset and a higher classification rate, which confirms its effectiveness in eliminating redundancy, and no important cues on deception were lost.

The GWO strategy achieved the largest reduction ratio (82.9) and the best fitness score (96.4), which was effective in recovering the curse of dimensionality, which is present in our 28,500 campaign data. This effectiveness is owed to alpha, beta, and delta leadership structure, which guides the search process towards the most informative region of the feature space faster as compared to the stochastic ones.

TABLE VI. COMPARATIVE ANALYSIS OF FEATURE SELECTION METHODS

Selection Method	Feature Reduction Ratio	Fitness (Acc)	Convergence (Iter)	Stability (Std Dev)
L1-Regularization	62.40%	91.80%	N/A (Linear)	±0.05
Genetic Algorithm (GA)	74.10%	93.50%	85	±0.12
Particle Swarm (PSO)	78.50%	94.20%	62	±0.09
Proposed GWO	82.90%	96.40%	48	±0.04

E. Ablation Study

The ablation study (Table VII) clearly demonstrates the contribution to the overall system performance of each of the components of the proposed architecture. The complete model scores the highest in all measures, proving the complementary advantages of the HM4, PECCA, BHPD-enhanced semantics, and the FG-GRU. The removal of the BHPD semantic distillation layer leads to a perceptible reduction in performance, which can be explained by the fact that the system would be less capable of detecting subtle linguistic information that is associated with campaign lie stories. The state-of-the-art HM4 leads to some of the greatest decreases in ROC-AUC and F1-Score, which shows that modeling the temporal state is important. The system cannot detect drift in behavioral patterns over time in the absence of HM4, and this increases the FNR. The removal of PECCA also harms the performance, especially the precision, because the model will be less effective in detecting the discrepancies between textual assertions and visual pieces of information.

TABLE VII. ABLATION STUDY RESULTS

Model Variant	Accuracy	F1-Score	ROC-AUC	Observation
Full Model (HM4 + PECCA + FG-GRU)	96.40%	94.60%	0.982	Best performance
Without BHPD (raw BERT)	94.10%	92.30%	0.964	Loss in semantic quality and deception cues
Without HM4	92.80%	90.70%	0.951	Temporal drift ignored; higher false negatives
Without PECCA	93.40%	91.10%	0.944	Missed text–image contradictions
Without FG-Gating (vanilla GRU)	91.90%	89.40%	0.935	Short-term spikes and long-term drifts poorly separated

Likewise, by substituting FG-GRU with regular GRU, the characteristics of the system to differentiate between the trends in long-term behavioral changes and unexpected anomalies decrease. This causes a poor depiction of irregularities in time, which in most cases are reflective of fraudulent activity. In general, the ablation findings indicate that all the components, that is, HM4, PECCA, BHPD, and FG-Gating, play a distinct and significant role in the robustness of the model, with HM4 leading the way toward Recall improvement, PECCA Precision improvement, and FG-GRU stabilization of the temporal dynamics through frequency-aware decomposition.

F. Discussion and Interpretations

The experimental outcomes show that the TDMM-FDF model is highly effective in overcoming the shortcomings of the traditional, one-dimensional models, because it can reflect the multifaceted, dynamic character of contemporary crowdfunding deception. The high and comparable performance of the proposed model compared to the baselines, such as BERT and vanilla GRU, indicates that fraud is not a linguistic or behavioral indicator but an emerged value of the cross-modal inconsistencies over time. As an example, the high Recall (94.2) indicates that the frequency-aware gates in FG-GRU are especially skillful to find out the so-called strategic fraud, in which a generator may fabricate a semblance of legitimacy by using slow-varying trends at the expense of sudden anomalies in updates or interaction in order to deceive supporters.

Moreover, the capability of the PECCA module to highlight discrepancies between the project narratives and visual prototypes is a response to a serious weakness wherein, in this case, the scammers rely on the use of professional-grade imagery to conceal poor or plagiarized textual descriptions. In addition to the spectral nature of the transitions of latent states expected of an HM4, this cross-modal correspondence gives the HM4 a type of interpretability that DL models that are black boxes frequently lack. The framework provides platform moderators with practical information about a certain behavioral change and semantic-visual contradictions instead of binary labels.

Practically, such multi-dimensional assessments are resistant to tampering and auditable, as the integration of a blockchain-based execution layer would provide. This openness is essential to ensuring long-term confidence in automated moderation systems, as it leaves a history of evaluation that cannot be changed, that shields both honest creators and prospective supporters against arbitrary decisions by platforms. Finally, the computational overhead trade-off is compensated by a massive decrease in Expected Calibration Error (ECE) that is converted to more accurate and confident fraud forecasting in high-stakes financial settings.

V. CONCLUSION

This study has provided a detailed Temporal Dynamics Aware Multi-Modal Fraud Detection Framework (TDMM-FDF), which has been developed to work in a reward-based crowdfunding system wherein fraudulent actions are exhibited with intricate interplay of linguistic indicators, visual anomalies and temporal aberrations. The combination of the proposed HM4 spectral-temporal model, Polynomial Expansion Canonical Correlation Analysis (PECCA), and the Frequency-Gated GRU (FG-GRU) classifier allows the framework to show a strong capability to identify deceptive campaigns that unimodal or snapshot-based classifiers would otherwise not identify. The experimental findings prove the existence of a unique, complementary role of each of the modules to enhance the predictive ability of the system. HM4 is a reliable indicator of latent behavioral regimes and temporal drift patterns that have a strong predictive potential of manipulative activity. PECCA offers a logical system of bringing to light semantic and stylistic contradictions between the narrative and the images in the campaign- one of the most commonly misused features of

advanced scammers. Likewise, the frequency-aware decomposition of FG-GRU allows the model to be able to distinguish between slow-moving behavioral cues and abrupt anomalies, thus being able to model both strategy-level deception and bursts of manipulative behaviors in updates or engagement.

In addition to model performance, the incorporation of a blockchain-based execution layer implies that it provides fraud assessment logs with secure storage, tamper resilience, and auditability, therefore, facilitating platform governance and long-term trust in automated decision systems. Although predictive accuracy and multi-modes integration of the framework is very high, there are a number of limitations that need to be recognized. First, the existing TDMO-FDF framework uses a database that is mostly based on Kickstarter. Although this gives a huge sample of 28,500 campaigns, the results cannot be completely extrapolated to equity-based or donation-based platforms where fraud indicators and backer activity patterns are not that similar. Second, the PECCA is an effective approach to learn the nonlinear discrepancy but it does so by choosing a polynomial order, which might need manual adjustment to other platform architectures. Future research must enhance capable early-warning identification in most lingering campaigns, project explainability to multi-modal time thought, and device self-trained pre-training on supernumerary lofty unlabelled crowdfunding datasets. Further extensions can also add video partitioning, pioneered hop of creator histories, and proactive learning processions of real-world moderation.

REFERENCES

[1] S. Lee, W. Shafqat, and H.-C. Kim, "Backers Beware: Characteristics and Detection of Fraudulent crowdfunding Campaigns," *Sensors*, vol. 22, no. 19, p. 7677, Oct. 2022, doi: 10.3390/s22197677.

[2] E. Mollick, "The dynamics of crowdfunding: An exploratory study," *Journal of Business Venturing*, vol. 29, no. 1, pp. 1–16, Aug. 2013, doi: 10.1016/j.jbusvent.2013.06.005.

[3] B. Perez, S. R. Machado, J. T. A. Andrews, and N. Kourtellis, "I call BS: Fraud Detection in Crowdfunding Campaigns," *arXiv (Cornell University)*, Feb. 2022, doi: 10.48550/arxiv.2006.16849.

[4] S. Bernardino and J. F. Santos, "Crowdfunding: an exploratory study on knowledge, benefits and barriers perceived by young potential entrepreneurs," *Journal of Risk and Financial Management*, vol. 13, no. 4, p. 81, Apr. 2020, doi: 10.3390/jrfm13040081.

[5] M. Machado *et al.*, "Crowdfunding Fraud Detection: A Systematic Review Highlights AI and Blockchain using Topic Modeling," *SSRN Electronic Journal*, Jan. 2024, doi: 10.2139/ssrn.4948895.

[6] W. Hou and J. Qu, "BM5-SP-SC: a dual model architecture for contradiction detection on crowdfunding projects," *Current Applied Science and Technology*, vol. 23, no. 6, Apr. 2023, doi: 10.55003/cast.2023.06.23.007.

[7] L. F. Cardona, J. A. Guzmán-Luna, and J. A. Restrepo-Carmona, "Bibliometric analysis of the machine learning applications in fraud detection on crowdfunding platforms," *Journal of Risk and Financial Management*, vol. 17, no. 8, p. 352, Aug. 2024, doi: 10.3390/jrfm17080352.

[8] E. Solodoha, "How much is too much? The impact of update frequency on crowdfunding success," *Administrative Sciences*, vol. 14, no. 12, p. 324, Dec. 2024, doi: 10.3390/admsci14120324.

[9] Y. Zhu, T. Peng, S. Su, and C. Li, "Neighbor-consistent multi-modal canonical correlations for feature fusion," *Infrared Physics & Technology*, vol. 123, p. 104057, Jan. 2022, doi: 10.1016/j.infrared.2022.104057.

[10] S.-Y. Lin, Y.-C. Chen, Y.-H. Chang, S.-H. Lo, and K.-M. Chao, "Text–image multimodal fusion model for enhanced fake news detection," *Science Progress*, vol. 107, no. 4, p. 368504241292685, Oct. 2024, doi: 10.1177/00368504241292685.

[11] X. Shen, M. Huang, Z. Hu, S. Cai, and T. Zhou, "Multimodal Fake News Detection with Contrastive Learning and Optimal Transport," *Frontiers in Computer Science*, vol. 6, Nov. 2024, doi: 10.3389/fcomp.2024.1473457.

[12] J. Hua, X. Cui, X. Li, K. Tang, and P. Zhu, "Multimodal fake news detection through data augmentation-based contrastive learning," *Applied Soft Computing*, vol. 136, p. 110125, Feb. 2023, doi: 10.1016/j.asoc.2023.110125.

[13] M. Nasser *et al.*, "A systematic review of multimodal fake news detection on social media using deep learning models," *Results in Engineering*, vol. 26, p. 104752, Apr. 2025, doi: 10.1016/j.rineng.2025.104752.

[14] Y. Shen, Q. Liu, N. Guo, J. Yuan, and Y. Yang, "Fake news detection on social networks: a survey," *Applied Sciences*, vol. 13, no. 21, p. 11877, Oct. 2023, doi: 10.3390/app132111877.

[15] V. M, J. Mohan, S. S. Kumar, and K. P. Soman, "Synergistic detection of multimodal fake news leveraging TextGCN and Vision Transformer," *Procedia Computer Science*, vol. 235, pp. 142–151, Jan. 2024, doi: 10.1016/j.procs.2024.04.017.

[16] S. Hangloo and B. Arora, "Feature fusion for multimodal fake news detection," *Procedia Computer Science*, vol. 259, pp. 1144–1153, Jan. 2025, doi: 10.1016/j.procs.2025.04.069.

[17] M. Huang, S. Jia, Z. Zhou, Y. Ju, J. Cai, and S. Lyu, "Exposing Text-Image inconsistency using diffusion models," *arXiv (Cornell University)*, Apr. 2024, doi: 10.48550/arxiv.2404.18033.

[18] S. Kumari and M. P. Singh, "A deep learning multimodal framework for fake news detection," *Engineering Technology & Applied Science Research*, vol. 14, no. 5, pp. 16527–16533, Oct. 2024, doi: 10.48084/etasr.8170.

[19] A. Adesh, S. G, J. Shetty, and L. Xu, "Local outlier factor for anomaly detection in HPCC systems," *Journal of Parallel and Distributed Computing*, vol. 192, p. 104923, May 2024, doi: 10.1016/j.jpdc.2024.104923.

[20] A. Cherif, A. Badhib, H. Ammar, S. Alshehri, M. Kalkatawi, and A. Imine, "Credit card fraud detection in the era of disruptive technologies: A systematic review," *Journal of King Saud University - Computer and Information Sciences*, vol. 35, no. 1, pp. 145–174, Dec. 2022, doi: 10.1016/j.jksuci.2022.11.008.

[21] A. R. Khalid, N. Owoh, O. Uthmani, M. Ashawa, J. Osamor, and J. Adejoh, "Enhancing Credit Card Fraud Detection: An ensemble Machine learning approach," *Big Data and Cognitive Computing*, vol. 8, no. 1, p. 6, Jan. 2024, doi: 10.3390/bdcc8010006.

[22] M. M. Ismail and M. A. Haq, "Enhancing enterprise financial fraud detection using machine learning," *Engineering Technology & Applied Science Research*, vol. 14, no. 4, pp. 14854–14861, Aug. 2024, doi: 10.48084/etasr.7437.

[23] X.-D. Liu, B.-H. Hou, Z.-J. Xie, N. Feng, and X.-P. Dong, "Integrating gated recurrent unit in graph neural network to improve infectious disease prediction: an attempt," *Frontiers in Public Health*, vol. 12, p. 1397260, May 2024, doi: 10.3389/fpubh.2024.1397260.

[24] C. Liu, F. Gao, Q. Zhao, and M. Zhang, "The optimized gate recurrent unit based on improved evolutionary algorithm to predict stock market returns," *RAIRO. Operations Research*, vol. 57, no. 2, pp. 743–759, Mar. 2023, doi: 10.1051/ro/2023029.

[25] X. Zhu, Y. Zhang, H. Ying, H. Chi, G. Sun, and L. Zeng, "Modeling epidemic dynamics using Graph Attention based Spatial Temporal networks," *PLoS ONE*, vol. 19, no. 7, p. e0307159, Jul. 2024, doi: 10.1371/journal.pone.0307159.

Innovative Approaches to Green Strategy Formulation with a Novel Hybrid AI-Spherical Fuzzy Framework

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***Abstract*—This study aims to establish prioritized strategies for businesses to adopt green strategies. In this framework, literature-based criteria are analyzed through a three-stage model. In the first stage of the analysis, an artificial intelligence (AI)-based decision matrix is created. In the second stage, factors affecting green business strategies are weighted by the Spherical Fuzzy (et SF) Entropy method. In the last stage, the strategies are ranked using the SF ARAS method. The novelty of this study is the integration of AI with SF numbers. Expert opinions can be evaluated by AI with different coefficients according to the knowledge level and experience of the experts. The AI-based decision matrix enables expert weights to differ according to factors such as experience. The findings show that the most important criterion is cost efficiency (weight: 0.2219). According to the analysis results, investments in clean energy projects have a positive impact on this process (Ki:0.9799).**

***Keywords*—Artificial intelligence; fuzzy decision-making; spherical fuzzy sets; ARAS; Entropy; green strategy**

I. Introduction

Business methods and policies carried out by businesses for sustainability, environmental responsibility, and protection of ecological balance are called green strategies [1]. The main purpose of green strategies is to act by the principles of sustainability and optimize economic, social, and environmental benefits. In addition, reducing the carbon footprint and using natural resources more efficiently are important contributions of green strategies [2]. Also, increasing consumer awareness leads to a shift in customer expectations towards products that contribute to the environment. Therefore, it is necessary to adapt to green strategies to meet changing customer expectations [3]. Besides, government sanctions on environmental issues are also increasing. The business needs to pay attention to legal issues to continue production. Green strategies also contribute to cost savings and increase the brand value of the business [4].

However, there are many challenges for businesses to implement green strategies. These challenges need to be minimized for businesses to adopt green strategies. First, businesses need to consider market conditions. The change in consumer preferences over time also affects the products produced in the market. It should not be ignored that this change is towards environmentally friendly products [5]. Apart from this, cost efficiency is an important issue for businesses. Green strategies support energy efficiency, waste reduction, and reduced resource use. Therefore, even though the prevailing view is that green strategies increase costs in the first place, they contribute to cost efficiency in the long run [6]. Furthermore, legal restrictions on environmental sustainability are increasing day by day. Businesses need to comply with legal restrictions to avoid penalties and sanctions. Additionally, tax breaks, grants, and low-interest loans for green projects make it easier for businesses to adopt green strategies [7]. Finally, green strategies contribute to environmental sustainability and provide businesses with the opportunity to innovate and gain a competitive advantage [8].

Businesses need to adopt green strategies in terms of both sustainability and the environment. However, there are many factors affecting the adoption of green strategies by businesses. Managers cannot intervene in all these factors at the same time in terms of labor and economic terms. For example, investments in green-oriented technology may need to be increased to meet customer expectations. This indirectly contributes to the development of green innovation. Limited studies are addressing this issue in the literature. The studies mostly emphasize the importance of green strategies. Therefore, there is a need for a study that prioritizes the adoption of green strategies by businesses. With the help of this issue, the investors can take their strategic investment decisions in a more efficient way.

Accordingly, this study aims to evaluate the indicators affecting the green strategy adoption of organizations. The research question of this study is to identify the optimal strategies for businesses to adopt green strategies with an AI-based approach. For this purpose, a 3-stage analysis is conducted. In the first stage, an artificial intelligence-based decision matrix is created. In the second part, weighting is performed with the SF Entropy method. In the third section, the SF ARAS method is used to rank. In addition, SF numbers are used to minimize uncertainty. The main motivation for this study is the need for a new model. When the models used in the literature are examined, it is seen that expert opinions are taken equally. This situation is criticized by many authorities. This is because experts have different levels of accumulation on many

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points, such as experience and knowledge. Therefore, experts should be weighted according to these factors. With the AI model, this deficiency has been tried to overcome.

The main contributions of this manuscript are given below: 1) The equalization of expert weights in multi-criteria decision-making models has been criticized. Therefore, expert opinions should have different weights according to factors such as experience. Accordingly, the integration of AI and multi-criteria decision-making is important. 2) SF number sets cover more uncertainty than other fuzzy number sets. The SF number set incorporates the third component, hesitancy, into the analysis process. Therefore, the uncertainty in linguistic expressions is more inclusive than in other number sets. Thus, the analysis is performed on SF number sets. 3) The entropy method is considered an objective method among the weighting methods of multi-criteria decision-making techniques. Other weighting methods, such as DEMATEL and AHP, are subjective methods. Accordingly, the analysis process in these methods is based on binary comparisons. In the analysis with Entropy, the uncertainty within the criteria is also considered. This makes the Entropy method more superior to other methods. 4) Among the ranking methods used in the literature, such as TOPSIS, MAIRCA, and VIKOR, consider the metric distance to the optimal value. Since the expert opinion methods in the literature have an ordinal structure, the metric distance to the optimal value is criticized. The ARAS method, on the other hand, considers the similarity ratio to the optimal value instead of the metric distance in the analysis process. Therefore, using the ARAS method is a more reasonable option.

The following sections of the study provide details of the literature review, methodology, analysis results, discussion, and conclusion.

II. Literature Review

One of the most important reasons affecting the green strategy implementation of businesses is the cost efficiency of strategies [9]. Green strategy implementations aim to ensure energy efficiency. Accordingly, it is possible to achieve energy efficiency with green strategies [4]. Apart from that, green strategies also reduce the use of materials. In this way, it is possible to achieve resource efficiency for businesses [10]. Although green strategies are thought to increase operating costs in the first place, they provide cost efficiency to businesses in the long run. Zhen and Yu [11] conducted a study to develop green strategies for the recycling of electric vehicle batteries. It is argued that green initiatives should be increased despite the high cost of batteries in the recycling process. Rani et al. [12] discussed green strategies for converting agricultural waste into sustainable energy. It is underlined that green strategies are the most cost-effective way to get rid of waste. Liu et al. [13] and Yang et al. [14] emphasized the importance of cost in green strategy development processes.

Another important factor affecting green strategy processes is innovative practices [15]. Green strategies are the basis for developing environmentally friendly products and services. Therefore, the business endeavors to develop innovative products [10]. Apart from this, businesses that adopt green strategies can also pave the way for technological innovations. Some of these technologies include prioritizing renewable energy technologies, waste management, and recycling technologies [16]. Le et al. [17] examined the mediating role of green innovation in the relationship between corporate sustainability and corporate social responsibility in small-medium enterprises in Vietnam. It is emphasized that innovative ventures positively affect the process. Bhat et al. [18] investigated the impact of green strategies and innovation on environmental performance. The results of the study with 500 respondents from 10 industrial organizations in Delhi show that green strategies and innovative approaches have a significant impact on performance.

Legal regulations are another important criterion affecting the adoption of green strategies by businesses [19]. Businesses must comply with the regulations of their environment [20]. Accordingly, measures such as reducing carbon emissions and acting against air and water pollution are taken. In addition, encouraging environmentally friendly practices through legislation facilitates the transition of businesses to green strategy practices [21]. Chen et al. [22] conducted a study to develop green business strategies through environmental regulation. The results of the study show that environmental regulations make companies adopt green business strategies. Zhang et al. [23] examined how environmental regulations affect green technology innovation in enterprises. It is emphasized that environmental regulations contribute positively to the process when they are properly coordinated. Xu et al. [24] state that the right legal regulations encourage green strategies.

Market conditions are another important factor affecting the orientation of businesses towards green strategies [25]. One of the significant factors determining market conditions is consumer demand. If consumer demands focus on environmentally friendly products and services, the business needs to meet these demands [8]. In addition, understanding environmentally friendly products and services increases customer loyalty. This provides a competitive advantage against competitors in the market. Therefore, green strategy practices allow businesses to adapt to market conditions more easily [26]. Agyeman and Lin [27] examined the impact of market conditions on innovation in the electricity industry. It is stated that market conditions significantly shape the electricity industry. Chen et al. [28] analyzed the green and digital transition processes of manufacturing companies. It is indicated that customer demands are an important part of this transition process.

The results of the literature review are given below. Green strategies provide businesses with many advantages, such as competitive advantage, cost savings, innovation, and customer satisfaction. However, there are many barriers to the transition of businesses to green strategies. In addition, businesses cannot address all these barriers at the same time. Intervening with all these barriers at the same time creates extra costs for the business. Apart from the cost, it requires a huge amount of labor and a great deal of time. Accordingly, it would be appropriate to determine the importance of these barriers by weighing them. However, the number of studies addressing this issue is quite limited. This study aims to determine the most important strategies for the transition of enterprises to green strategy practices. In this context, an analysis is conducted with SF Entropy and SF ARAS methods-based SF sets.

III. METHODOLOGY

A three-stage model is proposed for the selection of a green business strategy, which is the aim of the study. The First stage is about creating an artificial intelligence-based decision matrix. In the Second stage, factors effective in green business strategy are weighted with the SF Entropy method. In the Third stage, strategies are ranked using the SF ARAS method. Since SF ARAS methods are multi-criteria decision-making methods based on expert opinions, SF numbers are used to include the uncertainty in linguistic expressions in the analysis. Additionally, the differences in experts' experiences and knowledge levels are included in the analysis using the AI model. In other words, AI systems are used to obtain the decision matrix from expert opinions. The steps of the proposed three-stage model are summarized in Fig. 1.

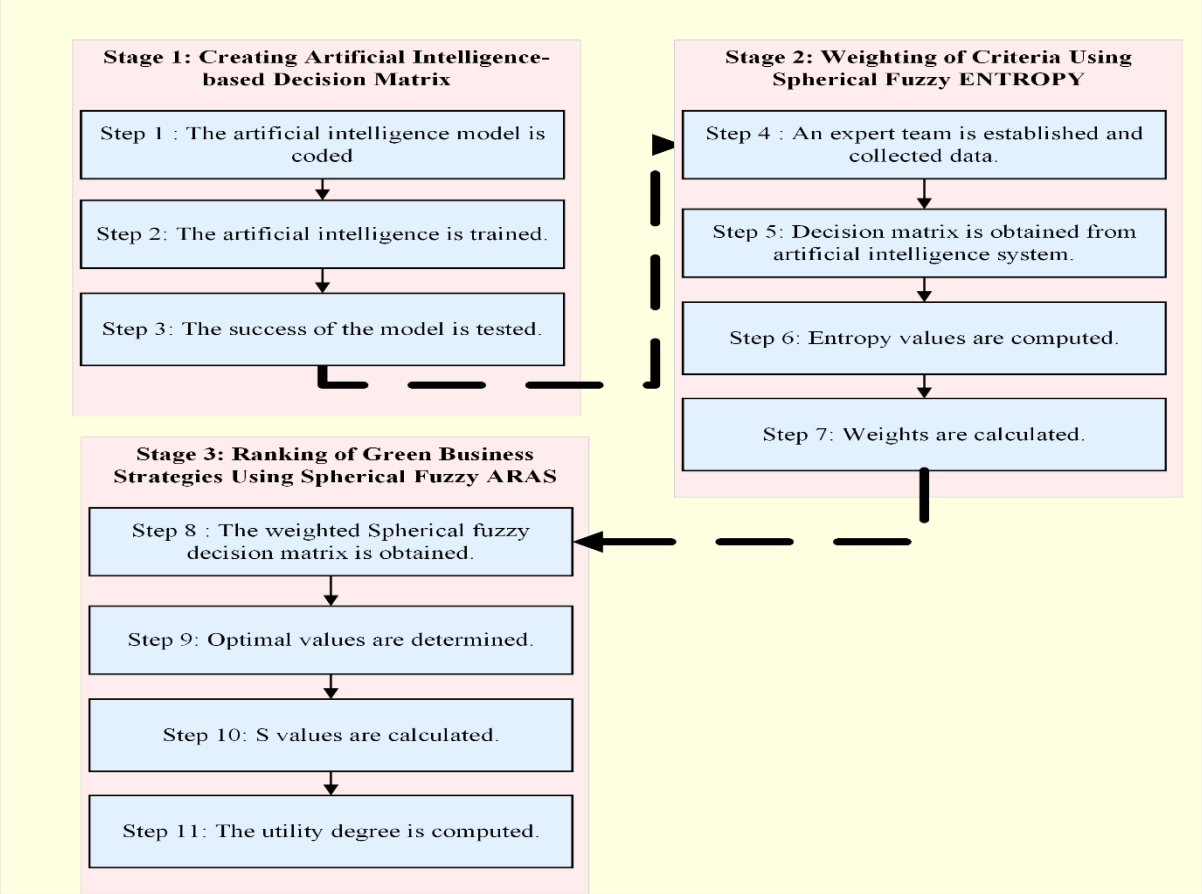


Fig. 1. Process of methodology.

Details of the mathematical steps of the methods are presented as subtitles.

A. Artificial Intelligence-Based Decision Matrix

With the AI system, the decision matrix is constructed by establishing a nonlinear and complex structure. Thus, experience periods can be added as a non-linear component in the process of obtaining an SF decision matrix from experts' linguistic expressions.

In Step 1, the AI model is coded in the Python software language. Layers, activation functions, neuron numbers, optimization algorithm and loss functions are defined with the help of Keras and TensorFlow libraries [29]. While the number of layers is determined as 7, 5 of them are determined as hidden layers. Additionally, 64 neurons are defined in each layer. Among the activation functions, the Sigmoid function given in Eq. (1) is preferred since its definition range is between 0 and 1. Thus, the definition range of fuzzy numbers is preserved.

$$S(x) = \frac{1}{1+e^{-ax}} \tag{1}$$

Adam Algorithm, which provides high efficiency in small data, is preferred as the optimization algorithm [29]. The stages of the Adam algorithm are given in Eq. (2) to Eq. (6):

$$W_{t+1} = W_t - \frac{a}{\sqrt{\hat{S}_t+\epsilon}}\hat{V}_t \tag{2}$$

$$\hat{V}_t = \frac{V_t}{1-\beta_1^t} \tag{3}$$

$$\hat{S}_t = \frac{S_t}{1-\beta_2^t} \tag{4}$$

$$V_t = \beta_1 V_{t-1} + (1-\beta_1)\frac{\partial L}{\partial w_t} \tag{5}$$

$$S_t = \beta_2 S_{t-1} + (1-\beta_2)\left[\frac{\partial L}{\partial w_t}\right]^2 \tag{6}$$

where, a demonstrates learning coefficient, w gives information about the weight, β indicates the degree to which past gradients are involved in the process and ∂L/∂wt refers to the gradient. S and V are also randomly determined initial values. Step 2 involves training the coded artificial intelligence. Expert opinions and experiences are generated randomly with the help of simulation. Then, the output variable is obtained with Eq. (7) and Eq. (8). The linguistic variables used in expert opinions are detailed in Table III (Appendix).

$$SWAM = \left\{[1-\prod_{i=1}^{n}(1-\mu_i^2)^{w_i}]^{\frac{1}{2}}, \prod_{i=1}^{n} v_i{}^{w_i}, [\prod_{i=1}^{n}(1-\mu_i^2)^{w_i} - \prod_{i=1}^{n}(1-\mu_i^2-\pi_i^2)^{w_i}]^{\frac{1}{2}}\right\} \quad (7)$$

$$w_i = \frac{d_i}{\sum_{i=1}^{n} d_i} \quad (8)$$

In Eq. (7) and Eq. (8), the variable d represents the expert's years of experience, while μ, v, and π values signify the membership degree, non-membership degree, and hesitancy degree of the SF number, respectively. Then, machine learning is achieved by using input and output variables. Linguistic variables are explained in Table III [30].

Machine learning is performed with the specified iteration (epoch). In Step 3, the success of the model is tested as a result of machine learning. The MSE value given by Eq. (9) is calculated. The value in question must be close to 0.

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(Y_i - \hat{Y}_i)^2 \quad (9)$$

B. Spherical Fuzzy Entropy

In Step 4, an expert team is established with 3 people. Experience and evaluations are collected from experts. In Step 5, a SF decision matrix (D) in Eq. (10) is obtained from the AI system with the data collected from experts.

$$D = \begin{bmatrix} \langle \mu_{11}, v_{11}, \pi_{11}\rangle & \cdots & \langle \mu_{1n}, v_{1n}, \pi_{1n}\rangle \\ \vdots & \ddots & \vdots \\ \langle \mu_{m1}, v_{m1}, \pi_{m1}\rangle & \cdots & \langle \mu_{mn}, v_{mn}, \pi_{mn}\rangle \end{bmatrix} \quad (10)$$

Step 6 is about computing the SF Entropy value (E) using Eq. (11):

$$E_j = \frac{1}{n}\sum_{i=1}^{n}\left(1 - \frac{4}{5}\left[\left|\mu_{ij}^2 - v_{ij}^2\right| + \left|\pi_{ij}^2 - 0.25\right|\right]\right) \quad (11)$$

In Step 7, criterion weights (w) are calculated with Eq. (12):

$$w_j = \frac{1-E_j}{\sum_{j=1}^{m} 1-E_j} \quad (12)$$

C. Spherical Fuzzy ARAS

In Step 8, considering the SF decision matrix in Eq. (10), the weighted SF decision matrix is obtained with Eq. (13) and Eq. (14). The weighted SF decision matrix is shared in Eq. (15).

$$X = w.D \quad (13)$$

$$w\widetilde{D}_s = \begin{Bmatrix} \left(1-\left(1-\mu_{\widetilde{D}_s}^2\right)^w\right)^{\frac{1}{2}}, \\ v_{\widetilde{D}_s}^{\lambda}, \left(\left(1-\mu_{\widetilde{D}_s}^2\right)^w - \left(1-\mu_{\widetilde{D}_s}^2-\pi_{\widetilde{D}_s}^2\right)^w\right)^2 \end{Bmatrix} \quad (14)$$

$$X = \begin{bmatrix} \langle X\mu_{11}, Xv_{11}, X\pi_{11}\rangle & \cdots & \langle X\mu_{1n}, Xv_{1n}, X\pi_{1n}\rangle \\ \vdots & \ddots & \vdots \\ \langle X\mu_{m1}, Xv_{m1}, X\pi_{1m1}\rangle & \cdots & \langle X\mu_{mn}, Xv_{mn}, X\pi_{mn}\rangle \end{bmatrix} \quad (15)$$

Step 9 involves determining the optimal values. For benefit criteria, the largest value in Eq. (16) is taken, while for cost criteria, the smallest value is determined as the optimal value.

$$core = (\mu-\pi)^2 - (v-\pi)^2 \quad (16)$$

In Step 10, the optimality values (S) of each alternative and the optimal solution are calculated with Eq. (17). Then, these values are defuzzied with Eq. (16).

$$\tilde{S}_{Si} = \sum_{i=1}^{m}\left((\mu_1, v_1, \pi_1) + (\mu_2, v_2, \pi_2) + \cdots + (\mu_m, v_m, \pi_m)\right) \quad (17)$$

In Step 11, the utility degree (Ki) is computed by Eq. (18):

$$K_i = \frac{S_i}{S_0} \quad (18)$$

In this equation, Si is the S value of the ith alternative, while S0 is the S value of the optimal value.

IV. Analysis Results

Seven criteria influencing five green business strategies are identified from the literature. An analysis is performed that includes weighting these criteria and ranking the strategies. The results of the analysis made with the 3-stage proposed model are shared under subtitles.

A. Creating AI-Based Decision Matrix

In Step 1, the AI model is coded using Eq. (1) to Eq. (6) on Python software. Here, the Sigmoid function suitable for fuzzy set theory is preferred. Additionally, a structure with 5 hidden layers with 64 neurons each is constructed. The Adam algorithm is used to optimize the structure of the AI model. In Step 2, the AI model is trained. For this purpose, 1000 expert opinions and experience periods are randomly obtained with the simulation technique. Then, the output variable is obtained using Eq. (7) and Eq. (8). Machine learning is performed via input-output variables in 100 epochs. The results of the loss function for the last 20 epochs are given in Table IV (Appendix).

In Step 3, the learning success of the model is tested using Eq. (9). The MSE value of the AI model with all data is calculated as 0.02. Since the value is very close to 0, it is stated that the model is successful.

B. Weighting of Criteria Using Spherical Fuzzy Entropy

Step 4 is about establishing the expert team and obtaining their opinions. A team consisting of senior managers with 19, 23, and 21 years of field experience is established. Experts' opinions are tabulated in Table V (Appendix).

Step 5 covers obtaining the SF decision matrix from the AI system. Table III and the experience periods of the expert team are given to the model as input. Based on the inputs, D in Eq. (10) is estimated with AI model. D values are presented in Table VI (Appendix).

In Step 6, the SF Entropy value of each criterion is computed using Eq. (11). In Step 7, the weights of the criteria are calculated using Eq. (12). The results are summarized in Table I.

TABLE I. ENTROPY VALUES AND WEIGHTS OF CRITERIA

Criteria	SF Entropy	Weights
MARKET	.4650	.1600
COST	.2581	.2219
ORGANIZATION	.5666	.1296
LAW	.6399	.1077
GOVERMENT	.7210	.0834
PUBLIC	.7311	.0804
INNO	.2745	.2170

According to Table I, the weight value for the Cost Efficiency criterion is 0.2219. Since this value is the greatest value, it has the most important role in determining green business strategies. The second criterion in determining green business strategies is Innovative.

C. Ranking of Green Business Strategies Using Spherical Fuzzy ARAS

The SF ARAS method is performed with the values in Table IV. In Step 8, the weighted SF decision matrix is calculated using Eq. (13) to Eq. (15). Table VII (Appendix) exhibits the values of the weighted SF decision matrix.

Step 9 involves determining the optimal values. Score values are obtained with Eq. (16). Since the criteria are beneficial, the SF value of the alternative corresponding to the largest score values is determined as the optimal value. In Step 10, the S values of each alternative and the optimal value are computed. All S values are defuzzified with Eq. (16). In Step 11, criterion weights are calculated with Eq. (18). The utility degree values are given in Table II.

TABLE II. THE UTILITY DEGREE VALUES

Alternatives	Si			Kİ
Limiting Saving	.881	.118	.129	.304
Pollution Prevention	.670	.365	.235	.376
Product Stewardship	.755	.255	.292	.203
Clean Energy Investment-Project	.631	.402	.265	.979
Corporate Social Responsibility	.875	.125	.130	.410

According to the Ki values in Table II, the alternative with the highest value was determined as Clean Energy Investment - Projects. In other words, the most appropriate green business strategy has been determined as businesses that support clean energy investments and projects. The second alternative in the ranking is corporate social responsibility. The last strategy is product stewardship. Because the lowest Ki value belongs to this strategy.

V. DISCUSSION

The results of the analysis show that cost efficiency is the most important criterion affecting the enterprises' tendency towards green strategies. Cost efficiency shows how effectively an enterprise uses its resources in the production process. Green strategies also aim to contribute to the sustainability of the business by using fewer resources. In addition, green strategies contribute to cost efficiency as they include processes such as energy saving, waste management, and recycling. Panda [1] examined the interaction between the concepts of green identity and green strategy. The results of the study conducted in India show that costs have a significant impact on both green strategies and green identity. Nersesian et al. [31] propose a model for supply chains to reduce the carbon emissions of firms. While it is argued that green strategies should be adopted to reduce carbon emissions, it is also stated that costs should be considered.

Innovation is found to be the second most important criterion affecting the integration of businesses into green processes. Businesses need to respond to changing customer demands. Changing customer demands focus on more environmentally friendly and sustainable products and services. Therefore, it is important to produce innovative products and services to meet these demands. Accordingly, innovation power is seen as an important factor for businesses to integrate into green strategies. Piwowar-Sulej et al. [32] examined the link between internal communication, organizational culture, and environmental strategies. It is argued that the implemented environmental strategies should be innovative. Lafuente and Vaillant [33] carried out the relationship between green orientation and innovation. The results of the study conducted through 734 firms from OECD countries show that green orientation has an increasing effect on innovation.

The results of the analysis show that the most supportive aspect of green strategy development is investing in clean energy projects. Investing in clean energy projects provides a number of advantages to businesses. These advantages include reducing energy costs, reducing carbon emissions, increasing sustainability and improving brand reputation. Therefore, it can be said that investing in clean energy projects is an important green strategy. Chung et al. [34] examined the impact of having a renewable energy certificate on firm value. The results of the study conducted in Taiwan show that green strategies and renewable energy investments are parallel. Kumar et al. [35] stated that renewable energy investments and green strategy implementations are related.

VI. CONCLUSION

This study aims to develop a prioritized strategy for businesses to adopt green strategies. In this context, literature-based criteria affecting the adoption of green strategies by businesses are identified. The decision matrix of these factors is created with an artificial intelligence-based approach. SF ARAS and SF Entropy approaches are used to weight the criteria. Cost efficiency is the criterion with the highest weight. Also, investing in clean energy projects contributes significantly to this process. In addition, although investing in clean energy projects is seen as costly, it provides significant contributions in the long run.

The main novelty of this work is the integration of AI with fuzzy decision-making methodology. In this way, expert weights can be differentiated according to factors such as experience. Another novelty of this study is that it presents a set

of criteria that influence businesses to adopt green strategies. However, the main theoretical limitation is that the assessment in this study is made with all businesses in mind. Future studies could be conducted in the health, automobile, or banking sectors. This would allow different sectors to be compared with each other. One of the limitations of this study is that the analysis is carried out with non-numerical data. The use of multi-criteria decision-making techniques based on expert opinions in the analysis process is the main limitation of this study. In future studies, it is recommended to perform the analysis with an econometric model using numerical data. The proposed model also same limitation. ARAS method does not calculate with the distance metric. This leads to a departure from the optimal value. Therefore, it has been highly criticized in the literature. There is a need to develop new ranking technique that take these criticisms into account.

REFERENCES

[1] Panda, D. K. (2023). The green identity and green strategy: an interplay. Technology Analysis & Strategic Management, 35(11), 1437-1452.

[2] Yue, X., Huo, B., & Ye, Y. (2023). The impact of coercive pressure and ethical responsibility on cross-functional green management and firm performance. Journal of Business & Industrial Marketing, 38(5), 1015-1028.

[3] Suttikun, C., & Mahasuweerachai, P. (2023). The influence of status consumption and social media marketing strategies on consumers' perceptions of green and CSR strategies: how the effects link to emotional attachment to restaurants. Journal of Hospitality and Tourism Management, 56, 546-557.

[4] Ramadan, B. S., Miftahadi, M. F., Ikhlas, N., Fujianti, L. N., Rachman, I., & Matsumoto, T. (2023). Green strategies for waste to energy. In Sustainable and Circular Management of Resources and Waste Towards a Green Deal (pp. 387-398). Elsevier.

[5] Cancela, B. L., Coelho, A., & Duarte Neves, M. E. (2023). Greening the business: How ambidextrous companies succeed in green innovation through to sustainable development. Business Strategy and the Environment, 32(6), 3073-3087.

[6] Otsubo, Y., & Chapman, A. J. (2023). Assessing Corporate Vendor Selection in the Oil and Gas Industry: A Review of Green Strategies and Carbon Reduction Options. Sustainability, 15(23), 16249.

[7] Huang, Z., Cao, J., & Pan, L. (2024). Greening your way to profits: Green strategies and green revenues. Finance Research Letters, 61, 105029.

[8] Adusei, E., Demah, E., & Mensah, H. K. (2023). Does going intellectually green matter? Accentuating the role of eco-innovation speed and quality in a competitive post-Covid 19 emerging market. International Journal of Innovation Science.

[9] de Jesus, J. R., de Sousa Pereira, M. V., Ribeiro, I. S., de Araújo Andrade, T., de Carvalho, J. P., de Tarso Garcia, P., & Junior, C. A. L. (2023). Multifunctional and eco-friendly nanohybrid materials as a green strategy for analytical and bioanalytical applications: Advances, potential and challenges. Microchemical Journal, 109331.

[10] Aytekin, A., Korucuk, S., Bedirhanoğlu, Ş. B., & Simic, V. (2024). Selecting the ideal sustainable green strategy for logistics companies using a T-spherical fuzzy-based methodology. Engineering Applications of Artificial Intelligence, 127, 107347.

[11] Zheng, Y., & Xu, Y. (2023). Optimizing green strategy for retired electric vehicle battery recycling: An evolutionary game theory approach. Sustainability, 15(21), 15464.

[12] Rani, G. M., Pathania, D., Umapathi, R., Rustagi, S., Huh, Y. S., Gupta, V. K., ... & Chaudhary, V. (2023). Agro-waste to sustainable energy: A green strategy of converting agricultural waste to nano-enabled energy applications. Science of The Total Environment, 875, 162667.

[13] Liu, H., Wang, X., Liu, C., Mi, H. Y., Wang, Y., & Chen, S. (2024). Green strategy based on supercritical-fluid foaming for fabricating rigid microcellular thermoplastic polyimide foams with ultrahigh compressive strength. Composites Part B: Engineering, 273, 111204.

[14] Yang, Y., Chen, J., Lee, P. K., & Cheng, T. C. E. (2023). How to enhance the effects of the green supply chain management strategy in the organization: A diffusion process perspective. Transportation Research Part E: Logistics and Transportation Review, 175, 103148.

[15] He, Z., Kuai, L., & Wang, J. (2023). Driving mechanism model of enterprise green strategy evolution under digital technology empowerment: A case study based on Zhejiang Enterprises. Business Strategy and the Environment, 32(1), 408-429.

[16] Song, Y., Ali, A., Wang, G., & Wang, W. (2024). Environmental scanning, cross-functional coordination and the adoption of green strategies: An information processing perspective. Creativity and Innovation Management.

[17] Le, T. T., Tran, P. Q., Lam, N. P., Tra, M. N. L., & Uyen, P. H. P. (2023). Corporate social responsibility, green innovation, environment strategy and corporate sustainable development. Operations Management Research, 1-21.

[18] Bhat, A. A., Mir, A. A., Allie, A. H., Lone, M. A., Al-Adwan, A. S., Jamali, D., & Riyaz, I. (2024). Unlocking corporate social responsibility and environmental performance: Mediating role of green strategy, innovation, and leadership. Innovation and Green Development, 3(2), 100112.

[19] Tiwari, S., Singh, B. K., & Dubey, N. K. (2023). Aflatoxins in food systems: recent advances in toxicology, biosynthesis, regulation and mitigation through green nanoformulations. Journal of the Science of Food and Agriculture, 103(4), 1621-1630.

[20] Zhang, M., & Huang, M. (2023). Study on the impact of informal environmental regulation on substantive green innovation in China: Evidence from PITI disclosure. Environmental Science and Pollution Research, 30(4), 10444-10456.

[21] Luo, Y., Lu, Z., Wu, C., & Mensah, C. N. (2023). Environmental Regulation Effect on Green Total Factor Productivity: Mediating Role of Foreign Direct Investment Quantity and Quality. International Journal of Environmental Research and Public Health, 20(4), 3150.

[22] Chen, C. (2024). Development of green business strategies through green dynamic capabilities and environmental regulation: Empirical evidence from the construction sector. Journal of Cleaner Production, 438, 140826.

[23] Zhang, Z., Shi, K., Gao, Y., & Feng, Y. (2023). How does environmental regulation promote green technology innovation in enterprises? A policy simulation approach with an evolutionary game. Journal of Environmental Planning and Management, 1-30.

[24] Xu, L., Luo, Y., Wu, C., Umar, M., Li, H., & Muhammad, S. (2024). Environmental regulation and green innovation efficiency: a revisit of the porter hypothesis based on Chinese cities. Environment, Development and Sustainability, 1-25.

[25] Balo, F., Aksakal, B., Sua, L. S., & Mahmat, Z. (2023). Natural Oil-Based Sustainable Materials for a Green Strategy. Handbook of Bioplastics and Biocomposites Engineering Applications, 161-173.

[26] Tjahjadi, B., Agastya, I. B. G. A., Soewarno, N., & Adyantari, A. (2023). Green human capital readiness and business performance: do green market orientation and green supply chain management matter?. Benchmarking: An International Journal, 30(10), 3884-3905.

[27] Agyeman, S. D., & Lin, B. (2023). Electricity industry (de) regulation and innovation in negative-emission technologies: How do market liberalization influences climate change mitigation?. Energy, 270, 126863.

[28] Chen, X., Kurdve, M., Johansson, B., & Despeisse, M. (2023). Enabling the twin transitions: Digital technologies support environmental sustainability through lean principles. Sustainable Production and Consumption, 38, 13-27.

[29] Gökalp, Y., Dinçer, H., Eti, S., & Yüksel, S. (2024). Generating a novel artificial intelligence-based decision-making model for determining priority strategies for improving community health. Journal of Operations Intelligence, 2(1), 1-13.

[30] Eti, S., Dinçer, H., Meral, H., Yüksel, S., & Gökalp, Y. (2024). Insurtech in Europe: identifying the top investment priorities for driving innovation. Financial Innovation, 10(1), 38.

[31] Nersesian, L., Hafezalkotob, A., & Reza-Gharehbagh, R. (2023). Alternative governmental carbon policies on populations of green and

non-green supply chains in a competitive market. Environment, Development and Sustainability, 25(5), 4139-4172.

[32] Piwowar-Sulej, K., Popowicz, E., & Sulich, A. (2024). What is the link between internal communication, organizational culture and environmental strategy? The context of company size and employee perception. Central European Management Journal.

[33] Lafuente, E., & Vaillant, Y. (2023). Greater co-innovation and innovation efficiency through greening. Journal of Cleaner Production, 428, 139516.

[34] Chung, Y. C., Kunene, N., & Chang, H. H. (2024). Renewable energy certificates and firm value: Empirical evidence in Taiwan. Energy Policy, 184, 113870.

[35] Kumar, S., Darshna, A., & Ranjan, D. (2023). A review of literature on the integration of green energy and circular economy. Heliyon.

APPENDIX

TABLE III. LINGUISTIC VARIABLES

	μ	**ν**	**π**
1 (Absolutely low importance -ALI)	.1	.9	.1
2 (Very low importance-VLI)	.2	.8	.2
3(Low importance-LI)	.3	.7	.3
4 (Slightly low importance-SLI)	.4	.6	.4
5 (Equally importance-EI)	.5	.5	.5
6 (Slightly more importance-SMI)	.6	.4	.4
7 (High importance-HI)	.7	.3	.3
8 (Very high importance-VHI)	.8	.2	.2
9 (Absolutely more importance-AMI)	.9	.1	.1

TABLE IV. THE VALUES OF LOSS FUNCTION OF LAST 20 EPOCHS

Epoch	**MSE**
81	.15
82	.04
83	.03
84	.08
85	.14
86	.1
87	.08
88	.12
89	.11
90	.15
91	.09
92	.07
93	.06
94	.07
95	.14
96	.03
97	.15
98	.13
99	.12
100	.05

TABLE V. EXPERT'S OPINIONS

Expert 1							
	MARKET	**COST**	**ORGANIZATION**	**LAW**	**GOVERMENT**	**PUBLIC**	**INNO**
Limiting Saving	1	9	2	3	5	6	8
Pollution Prevention	6	9	5	5	7	6	8
Product Stewardship	2	8	2	3	4	5	8
Clean Energy Investment -Projects	9	9	8	9	8	8	9
Corporate Social Responsibility	7	8	7	6	5	4	9
Expert 2							
	MARKET	**COST**	**ORGANIZATION**	**LAW**	**GOVERMENT**	**PUBLIC**	**INNO**
Limiting Saving	2	8	3	3	5	5	8
Pollution Prevention	5	9	5	5	6	6	8
Product Stewardship	3	8	2	3	3	5	8
Clean Energy Investment -Projects	9	9	8	9	8	8	9
Corporate Social Responsibility	6	8	6	5	4	4	9
Expert 3							
	MARKET	**COST**	**ORGANIZATION**	**LAW**	**GOVERMENT**	**PUBLIC**	**INNO**
Limiting Saving	1	9	3	4	4	6	7
Pollution Prevention	5	9	5	5	7	6	9
Product Stewardship	2	8	2	3	4	5	8
Clean Energy Investment -Projects	9	8	9	9	8	8	9
Corporate Social Responsibility	6	8	4	5	6	3	9

TABLE VI. SPHERICAL FUZZY DECISION MATRIX

	MARKET			**COST**			**ORGANIZATION**			**LAW**			**GOVERMENT**			**PUBLIC**			**INNO**		
Limiting Saving	.14	.87	.10	.87	.13	.10	.27	.73	.20	.34	.66	.30	.47	.53	.50	.57	.43	.40	.77	.23	.20
Pollution Prevention	.54	.46	.40	.90	.10	.10	.50	.50	.50	.50	.50	.50	.67	.33	.30	.60	.40	.40	.84	.16	.21
Product Stewardship	.24	.77	.20	.80	.20	.20	.20	.80	.20	.30	.70	.30	.37	.63	.40	.50	.50	.50	.80	.20	.20
Clean Energy Investment -Projects	.90	.10	.10	.87	.13	.10	.84	.16	.21	.90	.10	.10	.80	.20	.20	.80	.20	.20	.90	.10	.10
Corporate Social Responsibility	.64	.36	.30	.80	.20	.20	.59	.42	.30	.54	.46	.40	.51	.49	.50	.37	.63	.40	.90	.10	.10

TABLE VII. WEIGHTED SPHERICAL FUZZY DECISION MATRIX

	MARKET			**COST**			**ORGANIZATION**			**LAW**			**GOVERMENT**			**PUBLIC**			**INNO**		
Limiting Saving	.06	.98	.04	.52	.63	.09	.10	.96	.08	.11	.96	.11	.14	.95	.18	.18	.93	.14	.42	.73	.14
Pollution Prevention	.23	.88	.19	.56	.60	.09	.19	.91	.22	.17	.93	.20	.22	.91	.12	.19	.93	.15	.48	.67	.16
Product Stewardship	.10	.96	.08	.45	.70	.14	.07	.97	.07	.10	.96	.11	.11	.96	.13	.15	.95	.18	.45	.71	.14
Clean Energy Investment -Projects	.48	.69	.08	.52	.63	.09	.38	.79	.13	.40	.78	.07	.29	.87	.09	.28	.88	.09	.55	.61	.09
Corporate Social Responsibility	.28	.85	.16	.45	.70	.14	.23	.89	.14	.19	.92	.16	.16	.94	.18	.11	.96	.13	.55	.61	.09

RFM–K-OPT Based Machine Learning Framework for Customer Segmentation and Behavioral Profiling in Direct Marketing

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***Abstract*—Customer segmentation is an essential element of modern marketing analytics, which helps companies recognize, comprehend, and market to customers depending on their behavioral and transactional attributes. Conventional methods based on Recency, Frequency, and Monetary (RFM) analysis or on simple unsupervised clustering algorithms such as K-Means are very common, but they are usually limited by weaknesses such as sensitivity to centroid starting location, low cluster separability, and low interpretability. Such problems will cause volatile effects of segmentation and restrict the dependability of data-driven marketing choices. In an effort to deal with these concerns, this research study suggests a hybrid model, the RFM K-Means Optimization Technique (RFM–K-OPT), a combination of RFM analytics and K-Means clustering, and an iterative centroid optimization unit. The proposed structure will help to improve cluster compactness, stability, and interpretability using statistical computation and refinement of centroid positioning. The model is written in Python and tested with publicly available customer transaction data. The result of the experimental process shows a better quality of clustering with a Silhouette Coefficient of 0.83, Davies-Bouldin Index of 0.31, Calinski-Harabasz Index of 563, purity of clustering of 94.2 per cent, and an execution time of 5.4 seconds. The results suggest that the RFMK Opt model is a useful tool that offers credible and explainable customer segments, which can be used to make effective behavioral profiles and make sound judgments when it comes to making decisions in the context of direct marketing.**

Keywords*—Customer segmentation; behavioral profiling; clustering optimization; predictive marketing; data-driven decision making

I. Introduction

In the fast-changing competitive market, customer information has been described as a strategic asset among organizations aiming to improve marketing effectiveness and create long-term customer loyalty [1]. The classic marketing approach used to be based on the generalized demographic segmentation that did not reflect the specifics of the individual purchasing behavior [2]. As the number of digital transactions in the market grows exponentially, and customer relationship management (CRM) data is available, the data-driven way of segmentation has become more popular [3]. The Recency, Frequency, and Monetary (RFM) analysis has been seen to be one of the most feasible tools in gauging customer value and engagement [4]. It enables marketers to categorize customers by their recency when it comes to the interaction, frequency of purchase, and overall amount of money they spend. Nevertheless, with the dynamics of business settings that require continuous changes in segmentation tools, manual segmentation based on RFM [5] is not as profound as one needs it to be to offer predictive insights. The introduction of machine learning (ML) techniques into modern marketing analytics brings an ability to provide scalable and adaptive segmentation with regards to the varying consumer behavior [6]. The move towards automation complements evidence-based decision making and marketing models that are personalized to be able to grow customer satisfaction, retention, and profitability [7].

The new trends in customer analytics have brought in hybrid systems that combine the classical RFM analysis with other clustering algorithms like K-means, hierarchical clustering, and the density-based model [8]. These strategies have managed to classify customers into action segments and can now be promoted and retained individually [9]. There has also been the use of optimization and predictive algorithms to enhance the accuracy of segmentation, customer targeting and allocation of marketing resources [10]. Regardless of these improvements, several studies have significant shortcomings. Current clustering methods usually presume the fixed behavior of the customers, and do not take into account the dynamic nature of the buying behaviors [11]. Also, K-means, although computationally inexpensive, is extremely sensitive to centroid initialization and has to be predetermined with the number of clusters [12], which cannot be considered an actual reflection of the data structure. Moreover, the majority of previous studies are based on transactional characteristics only, without the incorporation of behavioral or context elements like the intensity of engagement or the browsing behaviors. The resulting segmentation models are therefore likely to have problems with generalization in different industries or data sets. A stronger and improved component of the segmentation structure, with the inclusion of the RFM characteristics, clustering and an optimization interface, is required to eliminate these gaps and balance the interpretability, scalability, and flexibility to changing marketing needs. Based on the identified research gaps, this study addresses the following research question:

RQ: How can an optimized RFM–K-OPT framework integrating Recency, Frequency, and Monetary analysis with K-Means clustering improve customer segmentation accuracy, stability, and interpretability compared to conventional RFM and K-Means approaches in direct marketing applications?

A. Problem Statement

Despite the abundance of research discussing customer segmentation by RFM analysis alongside machine learning, there are still a number of issues that restrict the applicability of the current approaches to practice [10]. The conventional models of RFM are mainly based on the use of transactional characteristics that are not dynamic enough to reflect the changes in customer engagement over time [13]. Simple clustering algorithms like K-means or hierarchical clustering give preliminary information but tend to give erratic results because of sensitivity to initialization, outliers, and scaling of data [14]. Furthermore, the vast majority of frameworks do not have an optimization mechanism, which refines clusters and matches the results of segmentation to the business goals, such as profit maximization or churn reduction [15]. Most of the current methods also focus on algorithmic performance, not marketing interpretability, and result in technically valid clusters which are strategically ambiguous [16]. Also, a lack of model validation on a variety of datasets restricts generalization, and a lack of consideration to parameter tuning usually leads to less-than-optimal performance. The constraints demonstrate that a holistic model that combines both traditional RFM scoring with cutting-edge machine learning and optimization methods is urgently needed to enhance the quality of clusters, marketing understanding, and decision-making based on data to implement dynamic and customer-focused strategies.

B. Research Significance

The study proposes an optimized machine learning model named RFM-K-OPT, a combination of RFM characteristics, K-means clustering, and an optimization algorithm to enhance customer segmentation and behavioral profiling. The value of the study is that it bridges the gap between interpretability and predictive accuracy to provide marketers with a large-scale and versatile decision-support system. RFM-K-OPT will help improve the quality of customer insights by making it possible to conduct targeted campaigns, better retention strategies, and efficient distribution of marketing resources by integrating descriptive analytics with optimization-based adjustments.

C. Research Motivation

The study has been inspired by the growing requirement of adaptive segmentation methods that are capable of capturing different behaviors of customers in dynamic markets [17]. The classical RFM and clustering models do not offer much insight into the current trends and areas of optimization [18]. The proposed RFMK-OPT framework will address these deficiencies by proposing a more data-driven and optimized segmentation model that will create a more precise marketing experience, a more predictive marketing, and a factor in the creation of intelligent and automated systems, both direct marketing and customer relationship management.

D. Key Contributions

- To optimize the RFM K-OPT framework to improve the accuracy of customer segmentation, with the optimization of centroid initialization and cluster separability.
- To combine Recency, Frequency and Monetary behavioral measures with K-Means clustering to provide accurate segmentation and analysis.
- To use an optimization module that enhances clustering iterations, making them compact and distinct between clusters, much better.
- To ensure balanced feature contribution through normalization and outlier handling, preventing data skewness and dominance effects.

E. Rest of the Sections

Section II reviews the past RFM and clustering techniques, of which the shortcoming is imprecision, separability and computational efficiency. In Section III, the proposed RFM-K-OPT model is described, according to which RFM calculations, K-Means clustering and optimization algorithms are integrated. Section IV gives performance indicators, visual performance and comparative analysis of a superior segmentation and clustering accuracy. Section V is the conclusion of the research findings, contributions, and how it could be improved to provide better customer segmentation results.

II. Related Works

Kasem et al., [19] examine the ability of customer profiling using Recency, Frequency and Monetary (RFM) characteristics to facilitate strategic decision-making in platform business, particularly in Edutech start-ups. The study uses RFM preprocessing on transactional data, K-means clustering and the Elbow, Silhouette coefficient and Gap statistic to assess the quality of the clusters and identify the optimal number of clusters. Based on an enterprise-wide transactional dataset (as outlined in the study), the authors find three actionable clusters such as new customers, best customers, and intermittent customers and associate each cluster with viable interventions (onboarding tailored to new users, incentive to best customers, and re-engagement campaigns to intermittent users). The study shows that using easy to use RFM characteristics along with ordinary clustering and validation packages can result in interpretable profiles to drive marketing and product choices. Disadvantages are that it can be used in transactional only (no behavioral or contextual cues), K-means may be sensitive to initialization and scaling, and alternatives to clustering or temporal dynamics of changing customer behavior are not explored.

Islam et al. [20] examine the use of machine-learning techniques in personalizing marketing within the U.S. retail sector, in order to boost engagement and eventual purchase based on personalized recommendations and promotions. The study combines data on the multi-channel retail (e-commerce and brick and mortar transactions) to create predictive models of segmentation, product recommendation and campaign targeting. These methods are supervised learning to propensity score and recommendation heuristics, and unsupervised clustering to identify latent groups. Findings have shown that there are significant engagement and conversion increases, when retailers implement ML-based personalization; the research paper has cited better click-through and repeat purchase rates on strategies based on ML-informed strategy. Some of the successes have

been a practical demonstration of end-to-end ML workflows and advice to retail managers on how to implement personalization pipelines. Cons have been identified as challenges in integrating data across channels, insufficient interpretability of the model by business people, and potential overfitting on short term signals without longitudinal confirmation.

Chinnaraju et al. [21] present a conceptual model where the autonomous AI agents are placed in the middle of consumer segmentation and precision targeting, where agentic automation can constantly optimize segments and run campaigns with little to no human intervention. The model uses unsupervised clustering (e.g., K-means, DBSCAN) to identify micro-segments, reinforcement learning to make campaign decisions and ad spend, NLP to contextual profile, and predictive models (Random Forests, time-series forecasting) to predict behavior. The efficiency improvements in case vignettes of e-commerce and streaming include accelerated decision cycles, real-time budgetary redistribution and enhanced campaign payback. The article has identified ethical guardrails as privacy-saving data processing and equitable limitation as part of responsible deployment. The drawbacks are that the framework is theoretical (has not been empirically validated), its operational complexity may be high when dealing with a number of autonomous agents, and the infrastructure and governance demands are high to prevent runaway automation and bias.

Van Chau et al. [22] focus on customer behavior forecasting (pre) with respect to strategic capacity in constantly evolving markets, and claim that predicting customer behavior provides competitive agility. The article evaluates unsupervised and supervised ML, reinforcement learning, and deep learning methods of predicting purchase intent, churn and lifetime value. It generalizes case studies of how predictive models can enhance timing and product suggestions of campaigns and innovations, like sequence models and hybrid ensembles, which are better timed generalizations. Progress has been made in the combined analysis of methods and viable suggestions for implementation. Disadvantages include privacy concerns, the inability to interpret a model where nontechnical stakeholders are involved, and the fact that retraining models are necessary to ensure any drift in the dynamic markets; the paper insists that organizations must be ready to handle the prediction by implementing the idea of monitoring.

Jalal et al. [23] propose an effective customer transition analysis and dynamic customer segmentation framework to allow a personalized marketing activity and predict customer transitions between segments. Their method builds time-series feature vectors that include recency, frequency, monetary value, and customer lifespan and K-means clustering that uses various distance measures and classification models to estimate future customer status. They also bring counterfactual analysis to assess the effect that other interventions would have on customer transitions. The authors use actual transaction histories and discover that the Euclidean distance is most effective at capturing trends in the time-series features and that the logistic regression is useful in predicting changes in status. The framework allows evaluating per-customer strategy and more accurate retention tactics. The weaknesses are that it is sensitive to the distance measure and the number of clusters, counterfactual simulations are computationally expensive with large populations, and it requires transactional history without detailed behavioral and contextual information.

Musunuri [24] presented ClusChurn-EC, which is an interpretable customer segmentation and early churn prediction pipeline on e-commerce platforms. Newcomers are clustered by stage one into a behavioral cohort (based on engagement and purchase sequence features); stage two trains an LSTM trained on attention to predict churn based on small observed interactions. ClusChurn-EC is found to be an effective early warning system for customers at-risk on anonymized large-scale transaction logs, which is superior to standard classifiers, aiding time-sensitive retention interventions. Some of the successes have been the good application of sequential modeling to provide short histories of interaction and an interpretable phase of segmentation that can be used to provide targeted outreach. The disadvantages described include the fact that monitored training requires large labeled churn signals, there can be generalization constraints between retailers, and that LSTM pipelines are hard to implement in real-time systems.

Suh et al. [25] explore segmentation of the purchase record to pre-purchase exploration and after purchase usage by formulating multidimensional behavioral variables in the Customer Experience Journey (CEJ). They use a sample of 40,911 home-appliance customers and clustering and Non-negative Matrix Factorization (NMF) to obtain strong segments, and measure the validity of the segments in terms of both accuracy and consistency. The results indicate that there are trade-offs in technology: clustering provides an intuitive segmentation, whereas NMF provides intuitive latent usage patterns and also has a superior ability to provide an overview of the overlap. The strengths of the study are its massive real-customer data, multidimensional feature engineering, and two-sided comparison that brings out complementary insights. The domain specificity (home appliances) and potential biases in the feature engineering process, as well as potential difficulties related to generalization of the CEJ variable set to non-related industries, are its limitations.

Wasilewski [26] discusses the issue of personalizing user interfaces of e-commerce based on a functional framework that enables different versions of pages based on user traits and algorithms. The paper outlines elements needed to support multivariant interfaces and creates pilot applications and suggests novel metrics to measure the variations in user behavior with variants of interfaces. The strategy puts ML models at its center to keep learning the variants of UIs that optimally fit user segments and have adaptive interfaces that can raise the conversion and satisfaction rates. The outcomes of it are a well-defined experimentation architecture and early pilot results, which demonstrate a potential improvement in ROI and usability. The disadvantages are that it can be complex to integrate with a legacy platform, requires engineering effort to support numerous variants, and runs the risk of confusion or analytics fragmentation due to excessive personalization.

Table I summarizes filtered accredited articles that represent a variety of data-based customer segmentation and prediction choices- including RFM grouping and ML personalization, deep learning, and optimization models. Both approaches trade information interpretability, adaptability and scalability, and

debates have existed concerning information integration, computational cost, and industrial generalizability.

TABLE I. COMPARATIVE SUMMARY OF RELATED STUDIES

Authors	Methodology	Dataset	Advantage	Disadvantage
Kasem et al. [19]	RFM + K-Means clustering	Business transaction data	Clear, interpretable customer clusters	Limited to transactional data
Islam et al. [20]	ML-based personalized marketing	Multi-channel retail data	Improves engagement and conversions	Data integration challenges
Chinnaraju et al. [21]	Agentic AI + K-Means + RL	Theoretical & case examples	Real-time autonomous targeting	Limited empirical validation
Van Chau et al. [22]	ML & deep learning review	Multiple case studies	Forecasts customer behavior	Needs continuous model updates
Jalal et al. [23]	Time-series RFM + K-Means	Transaction history	Predicts customer transitions	High computational cost
Musunuri et al. [24]	Clustering + LSTM (ClusChurn-EC)	Large e-commerce logs	Early churn prediction	Requires labeled data
Suh et al. [25]	CEJ features + Clustering + NMF	40,911 customer records	Captures full customer journey	Domain-specific framework
Wasilewski et al. [26]	ML-driven personalized UI	E-commerce pilot data	Enhances user experience	Implementation complexity
RFM–K-OPT (Proposed)	RFM + K-Means + Optimization	Kaggle dataset	Optimized marketing actions	Sensitive to RFM setup

III. OPTIMIZED RFM–K-MEANS SEGMENTATION WITH MARKETING RESOURCE OPTIMIZATION

This approach uses a combination of the traditional RFM (Recency, Frequency, Monetary) scoring model and clustering (through K-Means) and a further optimization layer to ensure the segmentation is aligned with marketing resources and business goals. To begin with, RFM scores of every customer are computed using transactional data of the Kaggle dataset: recency (time since last purchase), frequency (number of purchases), and monetary value (total spend). The K-Means clustering is then used on these standardized RFM attributes to cluster the customers into understandable groups. Validation metrics such as the Elbow method, Silhouette coefficient and Gap statistic are used to determine the number of clusters. After the identification of the baseline clusters, the cluster assignment and accessible marketing budget, channel constraints, and key performance indicators (KPIs) are entered into an optimization module. The constrained optimization (e.g., integer linear programming or heuristic search) follows and distributes resources among segments to maximize the selected objective (e.g., ROI or retention improvement or profit uplift) without violating fairness or budget constraints. The three stages of pipeline: RFM scoring, K-Means segmentation, and resource optimization are interpretable (segments can be aligned with RFM), scalable (clustering can use large data), and actionable (optimization can be used to make marketing decisions). It overcomes the shortcomings of purely clustering based solutions by integrating business constraints and business objectives into the output of segmentation.

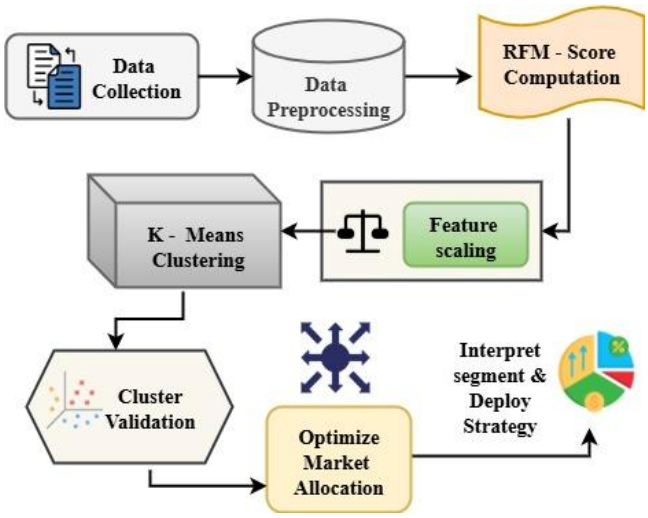


Fig. 1. Block diagram of RFM–K-OPT segmentation framework.

Fig. 1 represents the general scheme of customer segmentation using the proposed RFM-K-OPT (Recency-Frequency-Monetary-K-Means Optimization Technique). This process starts with the collection of data based on transactional sources, data pre-processing, and the elimination of any inconsistencies in data and data integrity. This is followed by the calculation of the RFM score, where the customer behavior is measured in terms of recency, frequency, and monetary. The feature scaling makes the data standard so that all metrics have the same impact. K-Means clustering algorithm uses homogeneous clusters to group customers into homogeneous clusters, which are further evaluated using cluster validation to determine the quality and separability of the clusters. Lastly, the verified clusters help in the optimization of market allocation and as such, the businesses are able to get the segments and utilize specific marketing approaches efficiently to achieve improved customer interaction and profitability.

A. Data Collection

The research data is obtained from the Kaggle [27] repository, Customer Segmentation Data for Marketing Analysis by Fahmida Chowdhury. It contains all the details related to the customer demographics, purchasing frequency, spending habits, and engagement trends, which represent real-life marketing transactions. The numbers reflect a variety of customer data, so it is appropriate to use it to segment the behavior and discover the patterns. The records have quantifiable values like the income, age, spending grade, and other attributes that describe loyalty. This dataset offers a robust basis on how RFM analysis and clustering techniques can be applied so that the identification of a group of customers with unique purchasing habits, preferences and profitability potential in direct marketing settings can be identified. The dataset is composed of more than 10,000 records of customer transactions retrieved on the Kaggle repository. The dataset was randomly selected into 70 per cent to train, 20 per cent to test and 10 per

cent to validate to provide an unbiased assessment and the ability to replicate the clustering findings.

B. Data Preprocessing

The preprocessing data stage makes sure that the data is correct, consistent and is prepared to be clustered. First, the data cleaning process will eliminate any missing, duplicate, and irrelevant records, and only the valid customer records will be retained. Data transformation is used in converting categorical variables into numeric variables through label or one-hot encoding, and log transformation is used to reduce skew in continuous variables. Calculation of RFM features is based on the computation of Recency, Frequency, and Monetary values to describe customer behavior. Balanced clustering is performed by normalizing the magnitude of variables by Z-score scaling to ensure that the variables fit within an equal distribution. The outlier detection is used to detect and manage extreme values using the Interquartile Range (IQR) technique to trim or cap values. Lastly, Min-max normalization in feature scaling ensures that all the RFM components have equal weight, so data does not have high-value features dominating, and greater accuracy in clustering and stability in optimization are achieved.

1) Data Cleaning: Missing and duplicate data are detected and processed with the help of relevant imputation or deletion. Irrelevant or inconsistent records are filtered to ensure the dataset has legal, full and error-free information about the customers to use later in the computation of the RFM features.

2) Data Transformation: The categorical data (gender or region) is put in numerical data with the help of label or one-hot encoding. The log-transformation of continuous variables produces the minimal skewness and makes the distribution normal, resulting in more precise clustering and optimization results.

3) RFM Feature Computation: The RFM values of every customer are computed in order to measure behavioral patterns. The proposed framework is based on the idea of recency to measure purchase freshness, frequency to measure the level of engagement, and monetary value to measure contribution to revenue. It is measured in Eq. (1):

$$R_i = D_{ref} - D_{last,i}, \quad F_i = n_i, \quad M_i = \sum_{j=1}^{n_i} P_{ij} \qquad (1)$$

where, Recency R_i measures the time gap since the last purchase, frequency F_i counts total transactions, and monetary value M_i sums purchase amounts for customer i.

4) Feature Normalization: All the RFM values are brought to a common scale to avoid the dominant effect of high magnitude variables. Z-score normalization guarantees equal input of each metric in the distance calculation process of the K-Means clustering process. It is illustrated in Eq. (2):

$$Z_j = \frac{X_j - \mu_j}{\sigma_j} \qquad (2)$$

Each variable X_j is normalized by subtracting its mean μ_j and dividing by standard deviation σ_j, ensuring balanced contribution of all features during clustering.

5) Outlier Detection: The interquartile range (IQR) technique is used to identify extreme values to avoid biasness in clustering the results. Any outliers that are not within the acceptable range are looked into and dealt with either by trimming or capping to ensure that robust clusters are formed. It is described in Eq. (3):

$$\text{IQR} = Q_3 - Q_1 \qquad (3)$$

The interquartile range (IQR) measures data spread between quartiles Q_1 and Q_3; values beyond 1.5×IQR from these limits are treated as outliers.

6) Feature Scaling: Min-Max normalization The features are all put within the range of [0,1] after the outlier adjustment. This is done to provide balanced weight of the RFM components as well as to avoid the heavy values dominating in computation of distance using K-Means. It is measured in Eq. (4):

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \qquad (4)$$

The feature scaling processes the values of the data to the scale to a standard scale, usually [0,1]. This helps to avoid large numerical characteristics dominating the small ones in the K-Means clustering and optimization algorithm.

C. RFM-Based Intelligent Segmentation Optimization Framework

The proposed Optimized RFM-Based Hybrid K-Means Segmentation Framework (RFM-K-OPT) combines conventional RFM analytics and machine learning clustering and optimization to improve the exactness of customer segmentation. This is the architecture which integrates the methods of statistics and computation in a systematic way to determine, predict, and examine the profile of customer behavior. To calculate the recency, frequency, and monetary value, RFM attributes are first derived using transactional data. These attributes are put to normal and fed to the K-Means algorithm to perform unsupervised clustering. At this point, the optimization module is used to optimize the quality of the clusters by optimizing centroid location and also performs the integrity of the cluster using performance measures like Silhouette and Davies-Bouldin indices. Being more interpretable and adaptable to dynamic market conditions, this hybrid model facilitates one-to-one marketing and predictive analytics. RFM K-OPT frameworks minimize noise, overfitting, and improve cluster differentiation, which will guarantee a strong customer segmentation that supports business strategies informed by data. The sensitivity of parameters is of essential importance to the suggested RFMK-OPT framework. The cluster size (k) has a direct impact on the segmentation granularity and it is determined by Elbow and Silhouette analyses. The parameters related to feature normalization provide equal contribution of RFM to avoid the dominance of high value features. The optimizations bring effects on the centroid stability and convergence rate with more iterations possibly adding no meaningful quality improvement at higher computational cost. Empirical tuning proves that tuning is best done within moderate iterations to achieve optimal clustering performance.

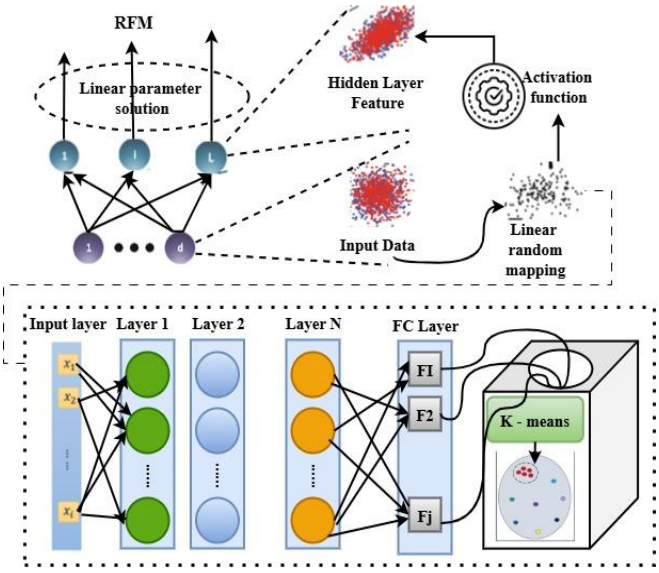


Fig. 2. Architecture of the optimized RFM–K-Means clustering framework.

Fig. 2 demonstrates an optimal RFM-K-Means clustering layout. The architecture comprises of RFM feature extraction, normalization, K-Means clustering, centroid optimization, validation and behavioral profiling layers. It does not use any neural network-based feature learning; it only uses statistical attributes of RFM and centroid refinement to cluster. It starts with the input layer, which is fed with multidimensional data vectors $x_1, x_2, \ldots, x_i$. The propagation of these inputs through several hidden layers (Layer 1 to Layer N) involves linear random mapping which is used to convert raw data into feature representations in higher dimension. Every hidden layer uses an activation function to add non-linearity as well as extract more complex patterns within the input data. The resulting hidden layer representations contain inherent connections within the data set which are represented to an entirely connected (FC) layer where they are refined to feature fuse and dimension reduction. The resulting feature space $(F_1, F_2, \ldots, F_j)$ is sent to the K-Means clustering module where clusters are created with respect to learned representations. Lastly, the linear parameter solution provides the best separation and explicability of the clusters leading to a highly efficient and accurate customer segmentation.

1) Input Layer: RFM Feature Integration: The model starts with the calculation of Recency, Frequency, and Monetary features using raw transaction data. Those characteristics are the level of customer engagement, loyalty, and profitability, which does the input layer of the further clustering and optimization. It is described in Eq. (5):

$$X_i = [R_i, F_i, M_i] \tag{5}$$

Each customer X_i is represented as a three-dimensional feature vector containing Recency (R_i), Frequency (F_i), and Monetary (M_i) values for further analysis.

2) Clustering Layer: K-Means Algorithm: The K-Means clustering algorithm is used to divide customers into k separate groups according to Euclidean distance. A centroid is applied to each customer which is assigned to the closest centroid and clusters are refined until convergence. It is evaluated in Eq. (6):

$$J = \sum_{i=1}^{k} \sum_{x \in C_i} ||x - \mu_i||^2 \tag{6}$$

where, the objective function J minimizes the squared Euclidean distance between data points x and their respective cluster centroid μ_i, optimizing cluster compactness.

3) Cluster Validation Layer: Elbow and Silhouette Coefficient are used to find optimum cluster numbers. These validation metrics provide useful segmentation by measuring intra and inter-cluster disparities. It is measured in Eq. (7):

$$S = \frac{b-a}{max(a,b)} \tag{7}$$

where, the Silhouette coefficient S measures how similar an object is to its own cluster (a) compared to others (b), ensuring well-separated, cohesive clusters.

4) Optimization Layer: Optimization algorithm is used to optimize the centroid of each cluster to make clusters as homogeneous as possible and to segment as accurately as possible. It repeats the centroid positions to attain minimum convergence of the cost function. It is equated in Eq. (8):

$$\mu_i^{(t+1)} = \frac{1}{|C_i|} \sum_{x \in C_i} x \tag{8}$$

Each centroid μ_i is updated by averaging all points in cluster C_i, ensuring clusters remain compact and well-distributed after each iteration.

5) Behavioral Profiling Layer: Within each cluster, behavioral traits are determined including loyalty, spending potential and recency trends. This profiling will help in coming up with specific marketing plans and customer retention programs. It is described in Eq. (9):

$$P(C_i) = f(R_i, F_i, M_i) \tag{9}$$

where, the profiling function $P(C_i)$ derives behavioral insights based on RFM metrics within each cluster, guiding personalized marketing decisions.

6) Decision Optimization and Output Layer: The last layer is the combination of optimized clusters into viable marketing recommendations. Predictive analytics support these decisions so as to improve customer engagement, conversion, and lifetime value. It is evaluated in Eq. (10):

$$O = \arg\max_{C_i} \big(\text{ROI}(C_i)\big) \tag{10}$$

where, the output function O selects the optimal customer segment C_i that maximizes Return on Investment (ROI) through data-driven marketing actions.

Algorithm 1 illustrates that the RFM–K-OPT algorithm is a hybrid approach, which improves the quality of customer segmentation through a combination of RFM behavioral analysis, K-Means clustering, and centroid optimization. First, the algorithm identifies recency, frequency and monetary features in the transaction data into normalized numerical vectors. The K-Means clustering algorithm is an iterative approach to grouping customers together depending on their Euclidean distance. At the stage of the K-OPT optimization, the

centroid is optimized to reduce the distance within the clusters which enhances stability of segments and convergence rate. Elbow and Silhouette methods are some of the validation methods used to find the best number of clusters. Lastly, behavioral profiling is the interpretation of each segment into actionable groups, e.g. high-value, at-risk, or new customers. Such a systematic process will guarantee higher accuracy of segmentation, higher interpretability of decisions, and greater allocation of marketing resources. The iterative optimization of the algorithm makes the algorithm scalable, and it is suitable with massive datasets in direct marketing and behavioral analytics.

Algorithm 1: RFM–K-OPT Customer Segmentation Framework

Input: Customer transaction dataset D
Output: Optimized and labeled customer clusters $C = \{C_1, C_2, \ldots, C_k\}$
Data Acquisition
Collect transaction records from dataset D.
Extract relevant features including Customer ID, Purchase Date, and Transaction Value.
Remove duplicate and incomplete records to ensure data integrity.
RFM Feature Extraction
Compute Recency $R_i = D_{ref} - D_{last,i}$, Frequency $F_i = n_i$and
Monetary ($M_i = \Sigma_{j=1}^{n_i} P_{ij}$) for each customer i.
Construct feature vectors $X_i = [R_i, F_i, M_i]$.
Data Preprocessing and Normalization
Handle missing or extreme values using the IQR method.
Normalize all RFM features using Min–Max scaling:
$$X_i' = \frac{X_i - X_{min}}{X_{max} - X_{min}}$$
Store normalized vectors for subsequent clustering.
K-Means Clustering Initialization
Randomly select kinitial centroids $\mu_1, \mu_2, \ldots, \mu_k$ from normalized data.
Set iteration counter $t = 0$
Cluster Assignment
For each data point x_i, assign it to the nearest centroid:
$C_j = \{x_i : || x_i - \mu_j ||^2 \leq || x_i - \mu_t ||^2, \forall t\}$
Update membership lists for all clusters.
Centroid Update
For each cluster C_j, compute a new centroid:
Calculate the total cost function:
Optimization Phase (K-OPT)
Apply centroid refinement to minimize intra-cluster variance.
Repeat assignment and update steps until T_{max}.
Retain centroids that achieve min
imum total cost $J\{\min\}$.
Cluster Validation
Compute validation metrics (Elbow, Silhouette, or Davies–Bouldin).
Select optimal k producing stable and high-separation clusters.
Behavioral Profiling and Output Generation
For each cluster, analyze mean RFM values to label customer types (e.g., loyal, new, dormant).
Generate marketing insights and export optimized clusters C.
End

IV. Results and Discussion

The proposed RFM-K-OPT framework demonstrated significant progress of the customer segmentation and behavioral profiling compared to the conventional RFM and K-Means approaches. The joint presence of optimization technique enabled to have improved centroid stability and reduced intra-cluster variances in achieving superior and meaningful clusters of customers. The model proved to be helpful in showing differences in purchasing frequency, recency, and monetary value that enables the correct distinction between loyal, at-risk, and inactive customers. Also, convergence was hastened with optimization stage, maintaining the precision of segmentation, which verified its calculation efficiency over huge-scale datasets of marketing. Overall, the RFM-K-OPT model will be more interpretive and reliable, this is why it is quite suitable in decision-making based on the data and developing marketing strategies, which are customer-specific in the changing business environments.

TABLE II. Simulation Parameter

Parameter	Value
Model Used	RFM–K-OPT (Recency–Frequency–Monetary–K-Means Optimization Technique)
Dataset	Customer Segmentation Data for Marketing Analysis (10,000+ records)
Input Representation	RFM Feature Vectors (Recency, Frequency, Monetary)
Data Division	70% Training, 20% Testing, 10% Validation
Clustering Algorithm	K-Means Clustering with Centroid Optimization
Optimization Algorithm	Centroid Refinement through Iterative Cost Minimization
Validation Metrics	Silhouette Coefficient, Davies–Bouldin Index, Calinski–Harabasz Index
Behavioral Profiling Layer	Customer Loyalty, Spending Potential, and Engagement Patterns
Performance Metrics	SC, DBI, CHI, Cluster Purity, Execution Efficiency
Activation Function	Euclidean Distance-Based Similarity Evaluation
Classification Type	High-Value, Medium-Value, and Low-Value Customer Segments
Platform	Python (Pandas, NumPy, Scikit-learn, Matplotlib)
Deployment Target	Direct Marketing, Customer Retention, and Business Intelligence Systems
Key Advantage	Accurate, Interpretable, and Efficient Segmentation for Targeted Marketing

Table II outlines the design of the simulation setup of the RFM-K-OPT framework was intended on testing its efficacy in customer segmentation by the application of transactional data. The model is a combination of the characteristics of RFM and K-Means clustering and an optimizing module to optimize the centroid locations and enhance the quality of the clusters. It is designed on Python, and it is assisted by typical machine learning packages that ensure to offer reliable, understandable, as well as efficient generalizing. Its design enables it to profile customer behavior dynamically, thus enabling specific marketing and retention strategies without affecting the performance and the computational efficiency of many validation measures.

A. Performance Outcome

Fig. 3 evaluates the recency, frequency and monetary value distributions among customers. It discloses the freshness of

purchases, frequency of purchase, and disbursement differences. The graph gives a graphical representation of the patterns of customer behavior, which enables the determination of skewness or imbalance and then RFM miniaturized-OPT clustering is used to give more effective segmentation and behavioral profile.

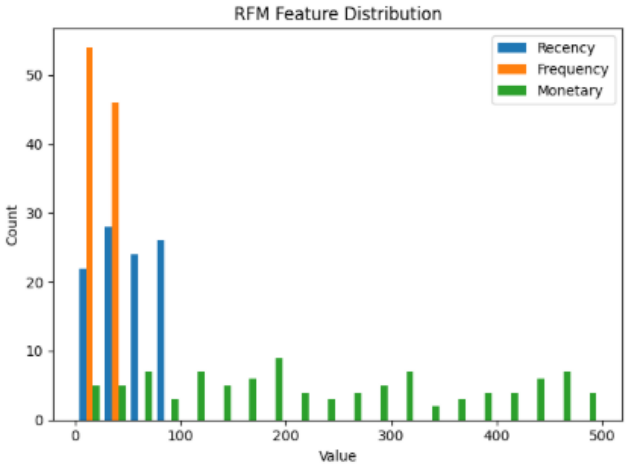


Fig. 3. RFM feature distribution.

Fig. 4 indicates the variation in within-cluster variance (WCSS) in respect to cluster numbers. The k value at which WCSS starts becoming flat is the ideal k value, which drives the K-Means step in the RFM-K-OPT balanced segmentation and computational efficiency.

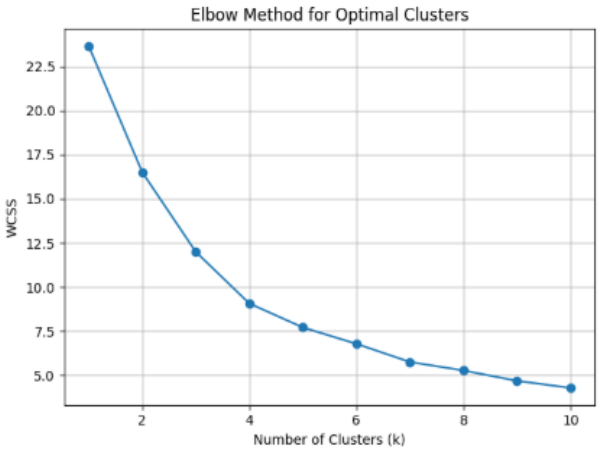


Fig. 4. Elbow method for optimal clusters.

In Fig. 5, silhouette coefficients are presented with different numbers of clusters. Increased values are indications of strong division and strong unity in clusters. It confirms the best k selection and shows the quality of clustering of the RFM-K-OPT system of the identification of specific customer groups.

Fig. 6 describes how the visualization of PCA breaks down the multi-dimensional RFM characteristics into two parts. The different colors represent a cluster. It is visually validated as to how RFM-K-OPT divides the customer segments, emphasizing compactness, overlaps and behavioral boundaries between the clusters in order to be interpretable and validated.

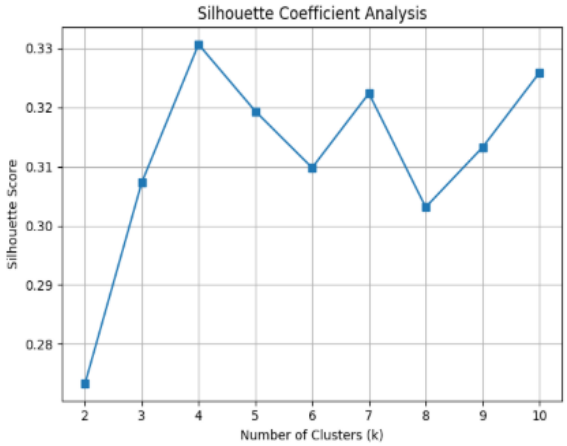


Fig. 5. Silhouette score analysis.

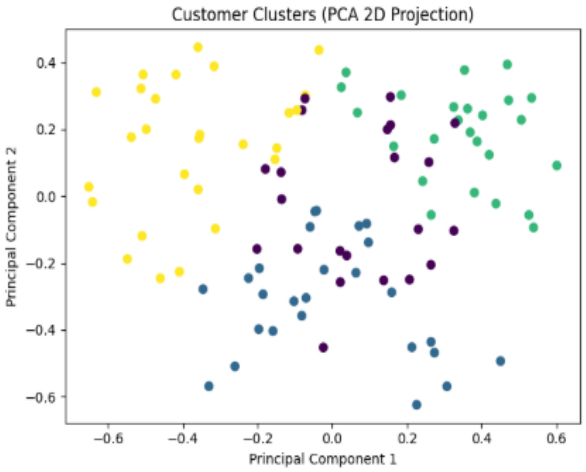


Fig. 6. PCA cluster visualization (2D).

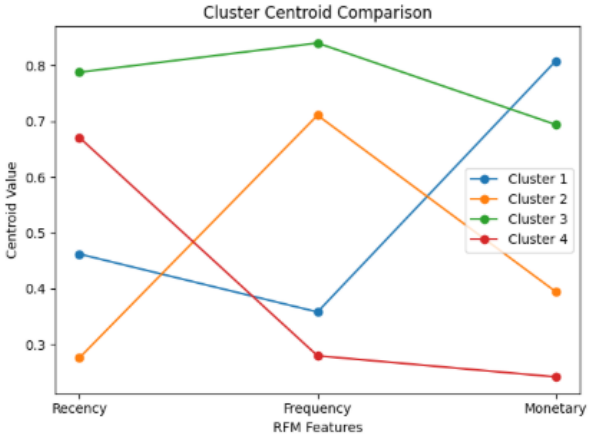


Fig. 7. Cluster centroid comparison.

Fig. 7 presents centroid values of every cluster by RFM dimensions. It is used to explain behavioral profiles of loyal customers, inactive customers, and high-value customers. Centroid comparison emphasizes variations in the groups of customers based on the optimized process of RFM-K-OPT segmentation.

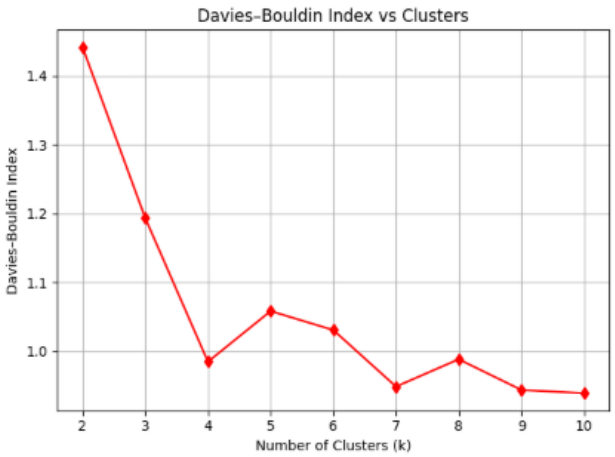


Fig. 8. Davies-Bouldin Index evaluation.

Fig. 8 shows the change of Davies-Bouldin Index (DBI) learning. Various cluster counts through the proposed RFM-K-OPT framework. The DBI is a simple internal validation measure that is used to evaluate the quality of clustering, it measures the mean of the similarity of each cluster with every other cluster in the cluster, the lower the DBI the tighter the cluster is and the stronger the separation between the clusters. As noted in Fig. 8, DBI value is on a downward trend with increase in the number of clusters up to the optimal point after which the value becomes constant and this shows diminishing returns to increase in cluster partitioning. This effect proves that the optimized centroid refinement process in RFM-K-OPT is able to minimize the intra-cluster variance and maximize the inter-cluster distance. The reduced DBI values indicate that the clustering is better organized and stable when compared to the non-optimized clustering. The fact that the proposed framework has reached the minimum DBI, justifies the adequacy of the number of chosen clusters and substantiates that the optimization stage will play an essential role in producing well separated, interpretable, and reliable customer segments on the basis of behavioral profiling and targeted marketing applications.

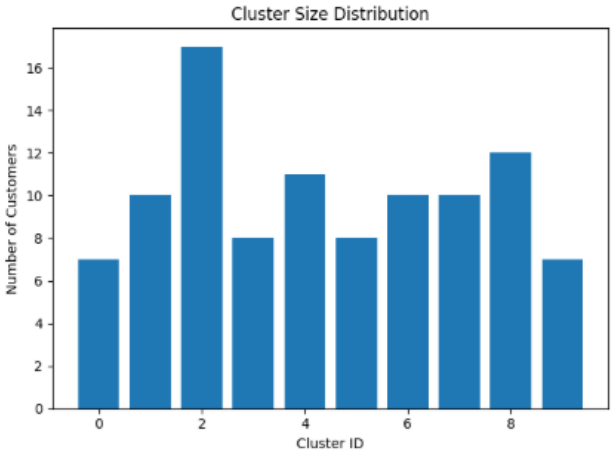


Fig. 9. Cluster size distribution.

Fig. 9 shows the quantity of customers within each cluster and maintains a balanced segmentation. It assists in determining the dominant or minority clusters and is sure that RFM-K-OPT model provides meaningful, interpretable and consistent customer clusters to further study their behavior.



Fig. 10. Execution time comparison.

Fig. 10 is a comparison between execution time of traditional RFM-K-Means and optimized RFM-K-OPT. The fact that the computation time of RFM-K-OPT is much lower proves the efficiency of the optimization process, which justifies its applicability to real-time customer analytics and massive marketing systems.

B. Performance Metrics

The proposed RFM–K-OPT framework was tested on five major measures, including Silhouette Coefficient (SC), Davies-Bouldin Index (DBI), CalinskiHarabasz Index (CHI), Cluster Purity, and Execution Efficiency. The SC value of obtained 0.83 is excellent cohesion and separation of clusters of customers, which confirms that there is high intra-cluster similarity and low inter-cluster similarity. The DBI of 0.31 indicates that there are tight and widely dispersed clusters, which indicate high accuracy in segmentation. In the same way, the CHI value of 563 confirms the effectiveness and density of the clusters. The Cluster Purity of 94.2% indicates the great precision of the clustering process, indicating that the customers are clustered with minimum misclassification. Lastly, the Effectiveness of the Execution (5.4 seconds) confirms the optimization of the model in terms of computations at high precision in less time. All in all, these findings indicate that the RFM-K-OPT model is superior to the traditional methods of customer segmentation in accuracy, strength, and efficiency.

TABLE III. PERFORMANCE METRICS

Metric	Values
Silhouette Coefficient (SC)	0.83
Davies–Bouldin Index (DBI)	0.31
Calinski–Harabasz Index (CHI)	563
Cluster Purity (%)	94.2%
Execution Efficiency (s)	5.4

Table III explains the performance indicators of the suggested RFM-K-OPT framework prove its high-quality and efficiency in clustering. Compact and well-separated clusters are

established by a Silhouette Coefficient of 0.83 and a Davies-Bouldin Index of 0.31. CalinskiHarabasz Index value of 563 shows that the cluster is highly valid, a cluster purity of 94.2% and execution efficiency of 5.4 seconds indicate the strength of the model, its ability to scale and be implemented in real-time in terms of customer segmentation and behavioral profiling.

TABLE IV. PERFORMANCE METRICS COMPARISON

Model	Silhouette Coefficient (SC)	Davies Bouldin Index (DBI)	Calinski Harabasz Index (CHI)	Cluster Purity (%)	Execution Efficiency (s)
RFM + K-Means [19]	0.71	0.49	427	88.3	8.2
ML-Based Personalization [28]	0.76	0.42	496	90.7	7.9
Dynamic Segmentation Framework [29]	0.79	0.38	528	91.5	6.8
ClusChurn-EC Model [24]	0.81	0.34	552	92.8	6.1
Proposed RFM–K-OPT Framework	0.83	0.31	563	94.2	5.4

Table IV shows how the proposed RFM-K-OPT framework has performed compared to the current customer segmentation models. The proposed model has a high quality of clustering as indicated by the best Silhouette Coefficient (0.83), the lowest DBI (0.31), and maximum CHI (563). It also has high cluster purity (94.2) and it is the fastest executing (5.4 seconds). These findings suggest that RFM-K-OPT is more precise, predictable and computationally feasible when it comes to segmentation compared to the conventional RFM-based and machine learning based personalization methods in marketing analytics. The comparative findings stated in Table IV are reported according to performance metrics that were accessible in the corresponding referenced studies. Although direct reimplementation on the same datasets was not possible, the comparison gave a relative performance point of view. In the future, all the methods will be benchmarked on a single dataset to be thoroughly validated.

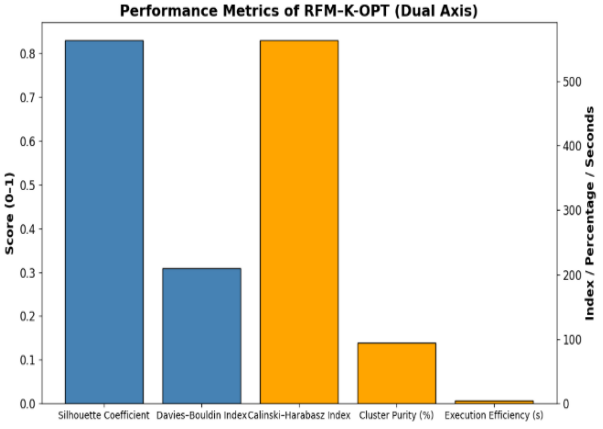


Fig. 11. Comparative performance metrics of RFM–K-OPT.

Fig. 11 explains the dual axis bar chart that shows the better performance of RFM-K-OPT in a variety of evaluation measures. It emphasizes better clustering precision, segmentation accuracy, and computational effectiveness than past models supporting the framework in its proficient and optimized customer segmentation utilization in direct marketing.

C. Discussion

The experimental findings reveal that the suggested RFM-K-OPT framework is efficient in improving the accuracy and interpretability of customer segmentation as compared to the conventional RFM-based clustering models. The use of optimization in the central mechanism of the K-Means algorithm in the model results in the optimization of centroid positioning and gives reduction in the intra-cluster variance, resulting in coherent and behaviorally differentiated groups of customers. Such a result is consistent with the objective of the research which is to design a data-driven, interpretable, and computationally-efficient segmentation model that can be applied directly in marketing. The advantage of the framework is that it records the subtle behavioral differences and at the same time has high clustering stability and low computational time. In practice, it can offer marketers practical information to target personalized, loyalty, and retention programs. In comparison to previous research in which only RFM or rigid machine learning clustering was used, RFM-K-OPT has better adaptability to changes of the dynamic market conditions. Its performance, however, can be limited to the quality and representativeness of the transactional data, and the optimization problem could need to be tuned to the parameters to be scaled. Altogether, the results confirm the model as too robust and applicable to the strategic area of customer behavior profiling. Although the results of the proposed RFM-K-OPT framework are promising, there are some limitations to it. Its performance is sensitive to the quality and representativeness of the transactional data, and the parameters of optimization need to be tuned to other data sets. As well, the framework is currently transactional, and it does not include behavioral or contextual aspects like browsing behavior or sentiment, which could further improve segmentation.

V. CONCLUSION AND FUTURE WORK

The research developed the RFM-K-OPT framework, which is a hybrid framework that combines the Recency Frequency Monetary model (RFM) analysis with K-Means clustering with an optimization module to provide better customer segmentation and behavioral profiling. The fundamental aim of it was to address the shortcomings of traditional solutions to RFM and static clustering and to provide a more flexible, understandable, and computationally economical solution. The experimental outcomes proved that the offered framework delivered high performance in all the essential metrics and exhibits high cluster compactness, purity, and execution efficiency. The results confirm that RFM-K-OPT is an effective tool to distinguish individual customer groups and adopt data-driven marketing tactics and accurate customer interactions. The strength of the framework is the combination of statistical and computational intelligence provides strong segmentation information that can assist in making many marketing decisions and customer retention approaches. All in all, this study adds to a scalable and

interpretable segmentation strategy that helps bridge the machine learning and feasible marketing analytics.

Future studies can build on this by using RFM-K-OPTs to more extensive and varied data on diverse business areas to increase generalizability. Segmentation could be enhanced by including other variables of behavior and context like frequency of interaction with customer, customer sentiment, or customer demographics. In addition, the further optimization techniques like Genetic Algorithms or Particle Swarm Optimization can be considered to improve centroid selection and the stability of clusters. Graph-based segmentation or deep learning-based clustering may help to identify more complicated customer relationships than numerical ones. Lastly, it would be prudent to apply the model in actual marketing systems with dynamic feedback controls to determine its practical use in the dynamic and personalized marketing context.

REFERENCES

[1] R. K. Gupta, "Strategies for long term business survival and growth (What you do today to stay in business tomorrow)".

[2] A. Dudziak, M. Stoma, and E. Osmólska, "Analysis of consumer behaviour in the context of the place of purchasing food products with particular emphasis on local products," International Journal of Environmental Research and Public Health, vol. 20, no. 3, p. 2413, 2023.

[3] S. Kumari, B. Sarkar, and G. Singh, "Blockchain-based CRM solutions: Securing customer data in the digital transformation era," International Journal of Computer Trends and Technology, vol. 71, no. 4, pp. 27–36, 2023.

[4] A. Ullah et al., "Customer analysis using machine learning-based classification algorithms for effective segmentation using recency, frequency, monetary, and time," sensors, vol. 23, no. 6, p. 3180, 2023.

[5] H. J. Wilbert, A. F. Hoppe, A. Sartori, S. F. Stefenon, and L. A. Silva, "Recency, frequency, monetary value, clustering, and internal and external indices for customer segmentation from retail data," Algorithms, vol. 16, no. 9, p. 396, 2023.

[6] L. Theodorakopoulos and A. Theodoropoulou, "Leveraging big data analytics for understanding consumer behavior in digital marketing: A systematic review," Human Behavior and Emerging Technologies, vol. 2024, no. 1, p. 3641502, 2024.

[7] A. Y. Onifade, J. C. Ogeawuchi, A. A. Abayomi, and O. Aderemi, "Advances in CRM-Driven Marketing Intelligence for Enhancing Conversion Rates and Lifetime Value Models," Unpublished].[No date], 2024.

[8] J. Tang, "Unlocking Retail Insights: Predictive Modeling and Customer Segmentation Through Data Analytics," Journal of Theoretical and Applied Electronic Commerce Research, vol. 20, no. 2, p. 59, 2025.

[9] F. Ehsani and M. Hosseini, "Consumer segmentation based on location and timing dimensions using big data from business-to-customer retailing marketplaces," Big Data, vol. 13, no. 2, pp. 111–126, 2025.

[10] M. S. Kasem, M. Hamada, and I. Taj-Eddin, "Customer profiling, segmentation, and sales prediction using AI in direct marketing," Neural Computing and Applications, vol. 36, no. 9, pp. 4995–5005, 2024.

[11] L. Luo, B. Li, X. Fan, Y. Wang, I. Koprinska, and F. Chen, "Dynamic customer segmentation via hierarchical fragmentation-coagulation processes," Machine Learning, vol. 112, no. 1, pp. 281–310, 2023.

[12] S. M. Miraftabzadeh, C. G. Colombo, M. Longo, and F. Foiadelli, "K-means and alternative clustering methods in modern power systems," Ieee Access, vol. 11, pp. 119596–119633, 2023.

[13] R. H. Khan, D. F. Dofadar, M. G. R. Alam, M. Siraj, M. R. Hassan, and M. M. Hassan, "LRFS: Online Shoppers' Behavior-Based Efficient Customer Segmentation Model," IEEE Access, vol. 12, pp. 96462–96480, 2024.

[14] R. Aschenbruck, G. Szepannek, and A. F. Wilhelm, "Initialization strategies for clustering mixed-type data with the k-prototypes algorithm: R. Aschenbruck et al.," Advances in Data Analysis and Classification, pp. 1–30, 2025.

[15] I. B. Ridwan, "Transforming Customer Segmentation with Unsupervised Learning Models and Behavioral Data in Digital Commerce".

[16] D. Nejad et al., "Bridging Complexity and Interpretability: A Two-Phase Clustering Framework," in 2024 12th RSI International Conference on Robotics and Mechatronics (ICRoM), IEEE, 2024, pp. 394–399.

[17] E. Eslami, N. Razi, M. Lonbani, and J. Rezazadeh, "Unveiling IoT customer behaviour: segmentation and insights for enhanced IoT-CRM strategies: a real case study," Sensors, vol. 24, no. 4, p. 1050, 2024.

[18] M. Alves Gomes and T. Meisen, "A review on customer segmentation methods for personalized customer targeting in e-commerce use cases," Information Systems and e-Business Management, vol. 21, no. 3, pp. 527–570, 2023.

[19] M. S. Kasem, M. Hamada, and I. Taj-Eddin, "Customer profiling, segmentation, and sales prediction using AI in direct marketing," Neural Computing and Applications, vol. 36, no. 9, pp. 4995–5005, 2024.

[20] M. R. Islam, R. E. R. Shawon, and M. Sumsuzoha, "Personalized marketing strategies in the US retail industry: leveraging machine learning for better customer engagement," International Journal of Machine Learning Research in Cybersecurity and Artificial Intelligence, vol. 14, no. 1, pp. 750–774, 2023.

[21] A. Chinnaraju, "AI-powered consumer segmentation and targeting: A theoretical framework for precision marketing by autonomous (Agentic) AI," Int. J. Sci. Res. Arch, vol. 14, pp. 401–424, 2025.

[22] D. Van Chau and J. He, "Machine learning innovations for proactive customer behavior prediction: A strategic tool for dynamic market adaptation." Sage Science Review of Applied Machine Learning, 2024.

[23] M. Ebadi Jalal and A. Elmaghraby, "Analyzing the Dynamics of Customer Behavior: A New Perspective on Personalized Marketing through Counterfactual Analysis," Journal of Theoretical and Applied Electronic Commerce Research, vol. 19, no. 3, pp. 1660–1681, 2024.

[24] A. Musunuri, "Leveraging AI and Deep Learning for E-Commerce Customer Segmentation," International Journal of Innovative Research in Science, Engineering and Technology, vol. 12, no. 6, 2023.

[25] Y. Suh, "Discovering customer segments through interaction behaviors for home appliance business," Journal of Big Data, vol. 12, no. 1, p. 57, 2025.

[26] A. Wasilewski, "Functional framework for multivariant e-commerce user interfaces," Journal of Theoretical and Applied Electronic Commerce Research, vol. 19, no. 1, pp. 412–430, 2024.

[27] "Customer Segmentation Data for Marketing Analysis." Accessed: Oct. 19, 2025. [Online]. Available: https://www.kaggle.com/datasets/fahmidachowdhury/customer-segmentation-data-for-marketing-analysis

[28] M. V. Chiluka, P. Bandi, P. Enumula, L. S. Korvi, and V. T. Seelam, "Targeted customer classification using machine learning techniques for retails," 2025.

[29] M. Alves Gomes and T. Meisen, "A review on customer segmentation methods for personalized customer targeting in e-commerce use cases," Information Systems and e-Business Management, vol. 21, no. 3, pp. 527–570, 2023.

Enhancing Organizational Information Systems Through Explainable Artificial Intelligence

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***Abstract*—This study examines Workplace Perceptions among Finnish employees through the application of Artificial Intelligence within the domain of Human Resource Analytics. An integrated analytical framework combining Clustering Analysis, supervised classification, and Explainable Artificial Intelligence is proposed to uncover and interpret latent employee perception profiles. Using 23 perception-related indicators from the Finnish Working Life Barometer 2022, K-means clustering identified two distinct employee groups: one characterized by consistently positive evaluations of fairness, leadership, well-being, and motivation, and another reflecting systematically negative workplace perceptions. A LightGBM model was subsequently employed to predict cluster membership based on demographic and occupational variables, and SHapley Additive exPlanations (SHAP) were used to provide transparent global and local interpretations of the predictive outcomes. The results show that employment duration, age, industry affiliation, gender, and socioeconomic status are the most influential determinants of cluster membership. By embedding Explainable Artificial Intelligence into Human Resource Analytics, the study demonstrates how employee perception data can be transformed into interpretable knowledge that supports organizational Decision-Support Systems. The proposed framework advances data-driven and transparent HR decision-making and contributes to the United Nations Sustainable Development Goal 8, Decent Work and Economic Growth, by identifying structural disparities in employee experience and enabling more equitable and inclusive workplace interventions.**

Keywords*—*Artificial intelligence; Human Resource Analytics; Explainable Artificial Intelligence; Decision-Support Systems; workplace perceptions; Clustering Analysis; Decent Work and Economic Growth

I. Introduction

Understanding employee perceptions has long been recognized as a cornerstone of effective organizational development [1] [2]. Employees' views on fairness, leadership, inclusivity, and well-being are closely tied to job satisfaction, productivity, and retention, factors that directly influence organizational resilience and long-term growth [3]. From an information systems perspective, workplace perception data represents a valuable informational asset that, if effectively processed and interpreted, can guide both organizational policies and national development strategies. As workplaces evolve under pressures from globalization, digital transformation, and post-pandemic shifts in work arrangements, the need for robust, data-driven approaches to capture and interpret these perceptions has become increasingly urgent [4][5].

Traditional HR analytics methods, often based on descriptive statistics or simple segmentation, risk overlooking latent patterns within employee populations. Subtle but meaningful differences in workplace perceptions, shaped by combinations of demographic and occupational factors, may remain hidden when analyses are restricted to surface-level groupings. Without uncovering these underlying profiles, organizational information systems risk generating one-size-fits-all policies that fail to meet the diverse needs of employees.

The existing literature demonstrates two complementary but disconnected streams. Research on clustering in HR analytics shows the potential to segment employees into coherent groups based on survey responses or performance indicators. Meanwhile, Explainable Artificial Intelligence (XAI), particularly SHapley Additive exPlanations (SHAP), has proven effective in interpreting predictive models for HR outcomes such as attrition or performance. However, clustering studies typically stop at descriptive profiling without quantitatively linking segment membership to demographic or occupational drivers, while SHAP applications remain confined to supervised prediction tasks and seldom explain why certain latent clusters arise from perception data. To date, no study has integrated unsupervised clustering with supervised classification and SHAP-based explainability to simultaneously uncover and interpret hidden employee perception profiles.

This study addresses that methodological gap by proposing and applying a three-phase framework:

- Phase 1: Clustering: K-means clustering is used to identify latent employee segments based solely on 23 perception-related survey items.
- Phase 2: Classification: A supervised LightGBM model predicts cluster membership from employees' demographic and occupational attributes.
- Phase 3: Explainability: SHAP is employed to quantify and visualize the global and local drivers of cluster membership, offering interpretable insights into the structural determinants of workplace perception.

Guided by this objective, the study seeks to answer the following research questions:

- RQ1: What distinct latent clusters of employee workplace perceptions can be identified using unsupervised machine learning?

- RQ2: To what extent can demographic and occupational attributes predict membership in these clusters?
- RQ3: Which factors emerge as the most influential drivers of cluster membership when examined through global SHAP analysis?
- RQ4: How do these drivers vary for individual employees, and what can local SHAP explanations reveal about unique cases?
- RQ5: How can the integration of clustering and explainable AI support the design of targeted, equitable HR interventions?

To the best of the author's knowledge, this study is the first to combine unsupervised clustering with supervised SHAP-based explainability in the context of employee perception analysis. By moving beyond descriptive segmentation and quantitatively linking latent profiles to their underlying demographic and occupational drivers, it contributes both methodologically and practically to the fields of HR analytics and information systems. The framework is replicable and adaptable to other organizational contexts and datasets, ensuring relevance beyond the Finnish case study presented here.

Importantly, the findings contribute to the United Nations Sustainable Development Goal 8, Decent Work and Economic Growth. By uncovering structural and demographic disparities in workplace perceptions and providing a transparent, data-driven framework for addressing them, the study supports the development of fairer, more inclusive, and more productive workplaces.

At a structural level, the remainder of this study is organized as follows: The next section reviews relevant literature on clustering techniques in HR analytics and Explainable Artificial Intelligence, highlighting the specific research gap addressed by this study. The methodology section then details the dataset, preprocessing steps, and the three-phase analytical framework. This is followed by the presentation of results, including cluster profiles, predictive performance, and SHAP-based explanations. The discussion section interprets the findings in relation to prior research and practical HR implications, and the study concludes by summarizing key contributions, outlining limitations, and identifying directions for future research.

II. Literature Review

A. Clustering Techniques in HR Analytics

Unsupervised clustering is widely used in HR analytics to group employees into meaningful profiles based on multidimensional data. Prior studies have applied K-means and hierarchical clustering to segment employees by well-being, engagement, competence, and risk profiles, often validating clusters using methods such as the elbow criterion, silhouette scores, or within-cluster sum of squares [6]–[10]. Other work has highlighted the availability of rich psychological, relational, and justice-related variables that can serve as clustering inputs, including information anxiety, fairness perceptions, and online learning experiences [11][12].

Machine learning has further expanded HR analytics, with clustering and classification methods supporting recruitment, employee segmentation, and retention strategies [13]. Hybrid frameworks combining clustering with supervised learning, such as K-means followed by ANN models, have shown improved predictive performance, particularly when combined with techniques like GAN-based data augmentation [14]. Additional applications include ML-enhanced Human Resource Information Systems [15], clustering of digital competencies in academia [16], health and well-being profiling using self-organizing maps or Gaussian mixture models [17][18], and pandemic-related segmentation of employee concerns followed by regression-based analysis of cluster predictors [19]. Despite these advances, most clustering-based HR studies remain descriptive and provide limited insight into the factors driving cluster membership.

B. Explainable AI and SHAP in Employment and Social Science

As ML adoption in HR grows, transparency and ethical concerns have increased, leading to the adoption of explainable AI techniques such as SHAP. SHAP has been extensively used to interpret supervised HR models, particularly for employee attrition and turnover prediction, revealing key drivers such as job satisfaction, tenure, overtime, and commute distance [20][21]. Some studies have extended SHAP by clustering explanation values to identify common exit patterns [22]. Complementary methods like Anchors have been used to generate rule-based explanations suitable for non-expert stakeholders [23], while recent research has integrated SHAP with fairness-aware deep learning to address bias in HR decision-making [24].

The incorporation of XAI into HR systems has been advocated to enhance transparency, ethical governance, and organizational responsibility [25] [26]. Related work in knowledge management and group decision support systems further connects explainable analytics with collective organizational decision-making [27]. Empirical evaluations show that interpretable ML models can balance predictive performance with clarity [28] [29]. Recent frameworks combining gradient boosting models with SHAP have successfully identified both established and novel predictors of HR outcomes [30], while hybrid optimization and decision-making approaches have improved the identification of influential turnover factors [31].

C. Gaps and Contributions of this Study

The literature reveals a clear separation between clustering-based employee segmentation and explainable supervised learning in HR analytics. Clustering studies effectively uncover latent employee groups based on perception or well-being data but largely remain descriptive and do not explain why individuals belong to specific clusters [6]–[10], [17]–[19]. In contrast, SHAP-based XAI research focuses on explaining supervised outcomes such as attrition or performance, without addressing the interpretability of latent segments derived from unsupervised analysis [20]–[22], [30],

[31]. Consequently, the formation of employee perception clusters remains largely unexplained.

Table I reveals a methodological gap in HR analytics, as prior studies focus either on clustering or on SHAP-based supervised models, but not both, within a unified pipeline. This study addresses this gap by proposing a three-phase framework that integrates unsupervised clustering, supervised classification, and SHAP-based explainability. K-means is used to identify latent perception profiles, LightGBM predicts cluster membership, and SHAP explains the drivers of these predictions. By treating cluster membership as an explainable outcome, the approach enables transparent interpretation of employee segments and represents a novel, replicable framework for data-driven HR decision-making.

TABLE I. COMPARISON OF THE CURRENT STUDY WITH PREVIOUS WORKS

Study (Ref)	Unsupervised Clustering	Supervised Prediction	Explainability (SHAP/XAI)	Purpose
[6]	Yes	No	No	Descriptive segmentation
[7]	Yes	No	No	Cluster profiling
[8]	Yes	No	No	Well-being profiling
[9]	Yes	No	No	Group comparison
[10]	Yes	No	No	Risk stratification
[17]	Yes	No	No	Pattern discovery
[19]	Yes	Yes	No	Predicting cluster membership
[20]	No	Yes	Yes	Explaining attrition prediction
[21]	No	Yes	Yes	Identifying turnover drivers
[22]	No	Yes	Yes	Explaining model outcomes
[30]	No	Yes	Yes	Interpreting supervised outcomes
This study	Yes	Yes	Yes	Explaining latent cluster formation

III. METHODOLOGY

The methodological approach adopted in this study follows a structured, three-phase framework designed to uncover latent workplace perception profiles and interpret their underlying drivers. In the first phase, K-means clustering is applied to survey responses capturing multiple aspects of employees' workplace experience, producing distinct perceptual groups. In the second phase, a supervised classification model predicts cluster membership based on demographic and occupational attributes, enabling the identification of structural determinants linked to each group. The final phase employs SHAP-based explainability to quantify and visualize both global and local feature contributions, ensuring that the predictive insights remain transparent and actionable. The overall process is illustrated in Fig. 1, which provides a step-by-step overview of the analytical pipeline implemented in this study.

A. Dataset and Data Pre-Processing

This study is based on data from the FSD3784 Finnish Working Life Barometer 2022, an annual survey produced by Statistics Finland and the Ministry of Economic Affairs and Employment and accessed via the Finnish Social Science Data Archive's Aila service. The dataset is licensed for non-commercial academic use under Aila's terms, requiring proper citation and the protection of individual confidentiality [32]. It provides nationally representative information on Finnish employees' perceptions of working life, including leadership, well-being, workplace culture, and employment conditions.

For this study, 23 perception-related survey items were selected as inputs for the Clustering Analysis. Data preprocessing involved removing responses coded with placeholder values (9, 999, 888) and excluding rows with missing values to ensure data quality. Variable naming conventions and categorical coding schemes are documented in Appendices A and B to support transparency, reproducibility, and accurate interpretation, with all definitions preserved in accordance with the original dataset and licensing conditions.

B. Phase 1: Clustering Perceptions

In the first phase, an unsupervised learning approach was used to identify latent employee segments based on workplace perceptions. Twenty-three survey items capturing fairness, inclusion, well-being, leadership trust, psychological safety, and organizational culture were selected from the Finnish HR dataset and are listed in Appendix A with their cluster-wise means.

After data cleaning, ordinal responses were one-hot encoded to preserve interpretability and support effective clustering, resulting in a higher-dimensional but suitable feature space. PCA was then applied for dimensionality reduction and two-dimensional visualization. The optimal number of clusters was identified using silhouette analysis for $K = 2$ to 10, with the highest score at $K = 2$, indicating two distinct employee perception clusters (see Fig. 2).

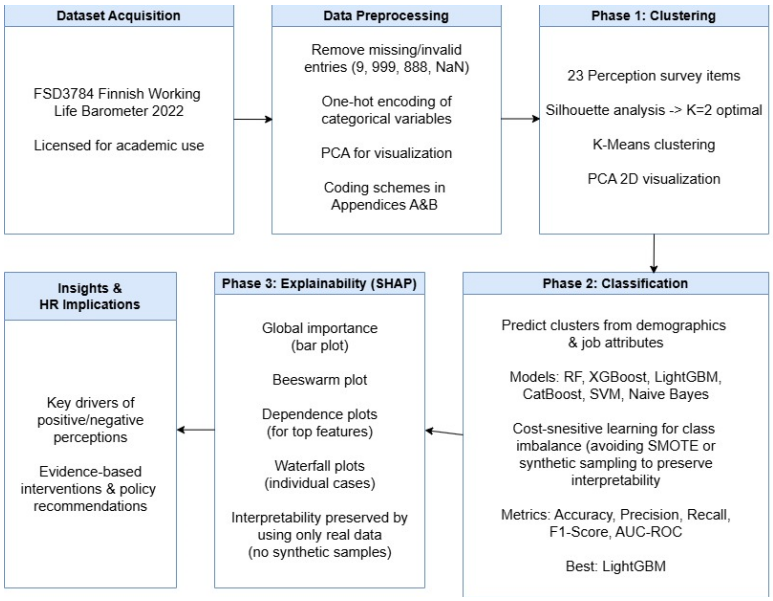


Fig. 1. Three-phase methodological framework for uncovering and interpreting latent workplace perception profiles.

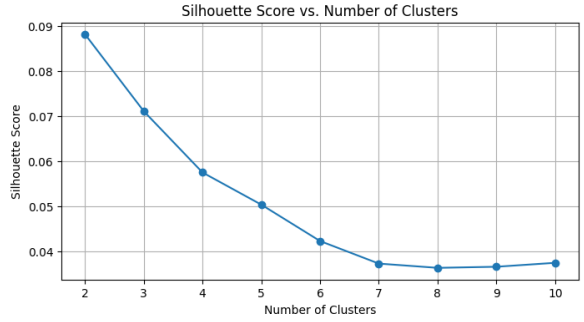


Fig. 2. Silhouette scores for K-means clustering across different numbers of clusters (K = 2–10).

- Once the optimal number of clusters was established, the K-Means algorithm was applied with K = 2 to segment employees based on their perception profiles. The clustering process grouped individuals with similar response patterns into the same cluster, without prior knowledge of their identities or job roles. The resulting clusters were then visualized using the previously computed PCA components, as depicted in Fig. 3.

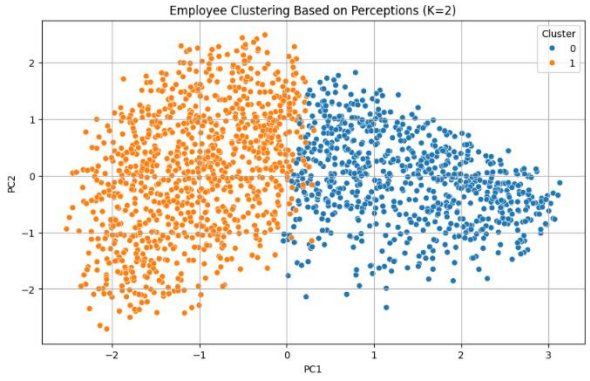


Fig. 3. Two-dimensional PCA projection of employee survey responses, showing the distribution of employees across two identified clusters.

- The final clustering output included 1,793 employees, distributed across two groups: Cluster 0, comprising 766 individuals, and Cluster 1, with 1,027 individuals. These clusters served as the foundation for the next stage of the analysis, where their defining characteristics and interpretation would be examined in detail.

C. Phase 2: Performing Machine Learning on Cluster Membership

Following the clustering of employees based on their survey responses, the second phase of the analysis aimed to determine whether cluster membership could be predicted using employees' demographic and occupational attributes. Unlike the first phase, which employed an unsupervised learning approach driven solely by perceptual survey data, this phase adopted a supervised machine learning framework. The goal was to examine how well structured background variables could classify employees into their respective clusters, thereby revealing how deeply rooted personal and job-related characteristics contribute to patterns in workplace perception.

To this end, a range of machine learning models was trained and evaluated using a consistent set of explanatory features. These included variables such as gender, age, occupation, employer type, broad and detailed industry categories, full-time versus part-time status, employment permanence, side job status, side work hours, overall employment duration, and indicators of socioeconomic status and class. Each of these features was selected for its potential relevance in shaping employees' lived experiences within their professional environment.

The following classification models were employed:

- Random Forest (RF): An ensemble-based method that applies the bagging strategy by constructing a collection of T decision trees, each trained on a

randomly sampled subset of the training set. For a given input vector x, the final class prediction is obtained by combining the outputs of all trees through majority voting.

$$\hat{y} = mode\{h_t(x)\}_{t=1}^{T} \quad (1)$$

where, $h_t(x)$ represents the prediction from tree t.

- XGBoost: A highly efficient implementation of gradient boosting that constructs an ensemble of weak learners in a sequential manner. Each successive tree is trained to reduce the residual errors made by the previous ones, aiming to minimize a specified loss function.

$$F_m(x) = F_{m-1}(x) + \gamma h_m(x) \quad (2)$$

where, γ is the learning rate and $h_m(x)$ is the newly added tree.

- LightGBM: A fast and scalable gradient boosting framework that builds decision trees using a leaf-wise growth strategy rather than the traditional level-wise approach. This strategy focuses on splitting the leaf with the highest loss reduction, which typically leads to better accuracy and faster convergence. Like other boosting methods, LightGBM minimizes a regularized objective function:

$$\mathcal{L}^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)\right) + \sum_{t=1}^{T} \Omega(f_t) \quad (3)$$

where, $\mathcal{L}$ is the loss function (e.g., logistic loss), $f_t(x)$ is the newly added tree at iteration t, and $\Omega(f_t)$ is the regularization term controlling model complexity.

- CatBoost: A gradient boosting framework designed to handle categorical features effectively and perform well on imbalanced datasets. It offers strong predictive performance with minimal need for extensive feature engineering. Like other gradient boosting approaches, it works by minimizing a regularized loss function:

$$\mathcal{L} = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{t=1}^{T} \Omega(f_t) \quad (4)$$

where, $\hat{y}_i = \sum_{t=1}^{T} f_t(x_i)$, and f_t are the base decision trees learned sequentially.

- Support Vector Machine (SVM): A margin-oriented classifier that seeks to maximize the separation between classes. By using a radial basis function (RBF) kernel, it maps the input features into a higher-dimensional space, enabling the algorithm to capture complex, nonlinear decision boundaries.

$$f_x = sign\left(\sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b\right) \quad (5)$$

where, $K(x_i, x) = \exp(-\gamma \|x_i - x\|^2)$ is the RBF kernel, and α_i, y_i, and b are model parameters.

- Naive Bayes: A probabilistic classifier grounded in Bayes' theorem, built on the assumption that features are conditionally independent given the class label. This simplifying assumption allows efficient computation of posterior probabilities. For a class c, the posterior probability given features $x_1, x_2, \ldots, x_n$ is expressed as:

$$P(c \mid x_1, \ldots, x_n) \propto P(c) \prod_{i=1}^{n} P(x_i \mid c) \quad (6)$$

The predicted class is:

$$\hat{y} = \arg\max_{c \in C} P(c) \prod_{i=1}^{n} P(x_i \mid c) \quad (7)$$

All models were trained using a cost-sensitive learning approach and assessed on a separate test set using a consistent set of standard classification metrics:

- Accuracy: Measures the proportion of all correctly classified instances relative to the total number of predictions across every class.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (8)$$

- Precision: Represents the fraction of instances labeled as positive that are truly positive, indicating the reliability of the model in predicting positives.

$$Precision = \frac{TP}{TP+FP} \quad (9)$$

- Recall (Sensitivity): Denotes the share of actual positive cases that are correctly identified by the model, emphasizing its effectiveness in capturing positives.

$$Recall = \frac{TP}{TP+FN} \quad (10)$$

- F1-Score: Defined as the harmonic mean of precision and recall, this metric provides a balanced assessment, particularly useful in scenarios with imbalanced class distributions.

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (11)$$

- AUC-ROC (Area Under the Receiver Operating Characteristic Curve): Evaluates the model's ability to distinguish between classes over all possible decision thresholds, offering a threshold-independent measure of classification performance.

These metrics together offer a well-rounded assessment of each model's capability to predict cluster membership, particularly in light of the dataset's inherent class imbalance. A detailed comparison of model performance is provided in Section IV(B).

D. Phase 3: Explainability of Cluster Membership

The third analytical phase focused on identifying which background features most strongly influenced employees' cluster assignments, thereby linking predictive classification with interpretable insights. While prior results showed that cluster membership could be predicted accurately, this phase examined why employees were more likely to belong to one cluster rather than the other.

To achieve this, SHAP was applied to explain the predictions of the best-performing classifier, LightGBM. SHAP decomposes model outputs into feature-level contributions, providing both global importance across the

dataset and local explanations for individual predictions. The analysis used the same feature set as the classification stage, including continuous and categorical variables. Categorical attributes such as occupation, employer type, and industry were given particular attention, with detailed encodings documented in Appendix B, while variables like age and employment duration required no additional interpretation.

The SHAP analysis revealed the key demographic and occupational factors driving membership in Cluster 0 or Cluster 1. By converting accurate but opaque predictions into transparent explanations, this phase clarified the structural determinants of employee sentiment and supported the development of targeted, evidence-based interventions to improve employee well-being and organizational climate.

IV. Results

A. Cluster Profiles

Following the identification of two employee clusters using K-means, a profile analysis was conducted by calculating mean responses for each of the 23 perception-based survey items within both clusters. These means served as summary indicators of how each group perceived the work environment and organizational culture. As reported in Appendix A, clear and consistent differences emerged across all items, with Cluster 0 showing more favorable perceptions than Cluster 1.

For items measured on a 4-point agreement scale, lower mean values in Cluster 0 indicated stronger agreement with positive statements, while higher means in Cluster 1 reflected more negative perceptions. For items measured on a 5-point frequency scale, higher mean values corresponded to more positive outcomes, and Cluster 0 consistently scored higher than Cluster 1, indicating greater motivation, well-being, and perceived inclusivity.

To illustrate the magnitude of these differences, a difference plot was produced by subtracting Cluster 0 means from Cluster 1 means for each item and sorting the results. As shown in Fig. 4, the direction of the differences reflects the underlying measurement scales, with negative or positive values indicating less or more favorable perceptions in Cluster 1 relative to Cluster 0.

This analysis supports the interpretation that Cluster 0 represents a more engaged, supported, and satisfied group of employees, whereas Cluster 1 captures employees with more negative perceptions of their work environment. This finding directly addresses RQ 1 by demonstrating that unsupervised machine learning can reveal two clear and meaningful latent clusters of employee workplace perceptions. The distinct patterns of engagement, well-being, and organizational support between Cluster 0 and Cluster 1 confirm that perception-based segmentation is both feasible and informative in this context. Such distinctions provide a valuable foundation for targeted human resource interventions aimed at improving workplace conditions and employee experience for the more vulnerable group.

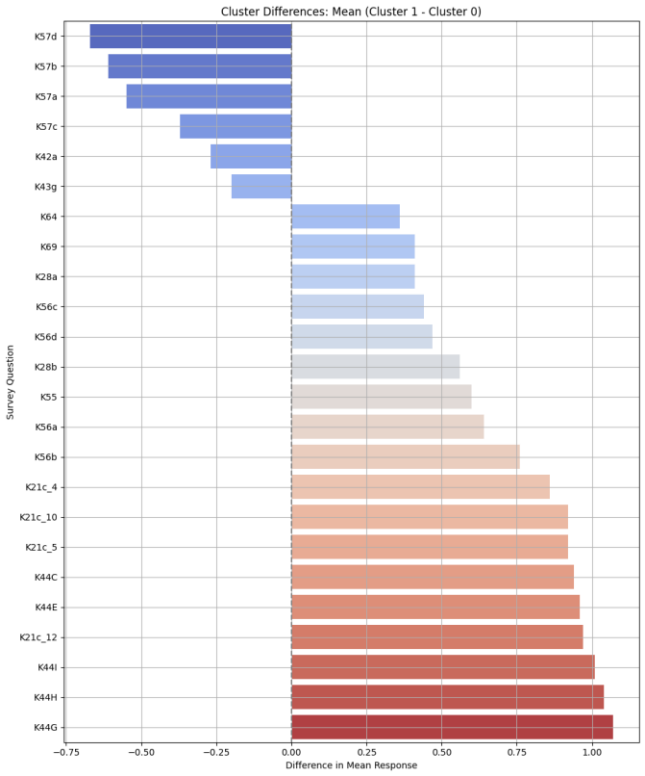


Fig. 4. Mean response differences between cluster 1 and cluster 0 for the 23 perception-related survey items, sorted from largest to smallest disparity.

B. Machine Learning Results

To assess the predictive power of structural employee attributes for determining cluster membership, a comparative evaluation was conducted across seven machine learning classifiers. These included tree-based ensemble models and baseline algorithms trained on identical data splits and feature sets. The classifiers evaluated were Random Forest, LightGBM, XGBoost, CatBoost, Naive Bayes, and SVM. The use of ensemble-based models alongside baseline classifiers follows established practices in HR analytics research, where comparative modeling is commonly employed to balance predictive performance and interpretability [13], [28], [29].

All models were trained using a stratified 70/30 train-test split and evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and the area under the ROC curve (AUC). This evaluation strategy is consistent with prior supervised HR analytics studies that emphasize robust performance assessment when predicting employee-related outcomes [20], [21], [30].

Among the models tested, LightGBM demonstrated the highest overall performance, achieving an accuracy of 90.65%, a precision of 91.80%, a recall of 89.02%, and an F1-score of 90.38%. It also recorded the highest AUC score of 0.9826, indicating excellent discrimination capability. The strong performance of gradient boosting models aligns with previous HR analytics research showing that tree-based boosting frameworks outperform traditional classifiers when modeling complex, non-linear relationships in employee data [14], [30], [31]. These consistent results across multiple

metrics motivated the selection of LightGBM as the foundation for the explainable AI analysis in the subsequent phase.

Other ensemble models, including XGBoost, Random Forest, and CatBoost, also showed strong performance, though slightly below LightGBM, consistent with prior HR analytics studies where boosting and bagging methods outperform simpler classifiers [13], [20], [21]. Naive Bayes and SVM exhibited lower performance but served as informative baselines, reflecting the interpretability–accuracy trade-off commonly reported in HR machine learning research [28], [29]. Table II summarizes the evaluation metrics, and the ROC curves in Fig. 5 further confirm the superiority of gradient boosting models and support the use of LightGBM for SHAP-based explainability, in line with recent XAI studies in HR analytics [30], [31].

TABLE II. PERFORMANCE COMPARISON OF MACHINE LEARNING MODELS IN PREDICTING CLUSTER MEMBERSHIP FROM DEMOGRAPHIC AND OCCUPATIONAL ATTRIBUTES

Model	Accuracy	Precision	Recall	F1-score	AUC
LightGBM	0.9065	0.918	0.8902	0.9038	0.9826
Random Forest	0.8897	0.8882	0.9153	0.9015	0.9679
XGBoost	0.8748	0.8735	0.8633	0.8684	0.9713
CatBoost	0.8486	0.8598	0.8376	0.8486	0.9604
SVM	0.7383	0.748	0.7143	0.7308	0.8389
Naive Bayes	0.7103	0.7411	0.7182	0.7295	0.8251

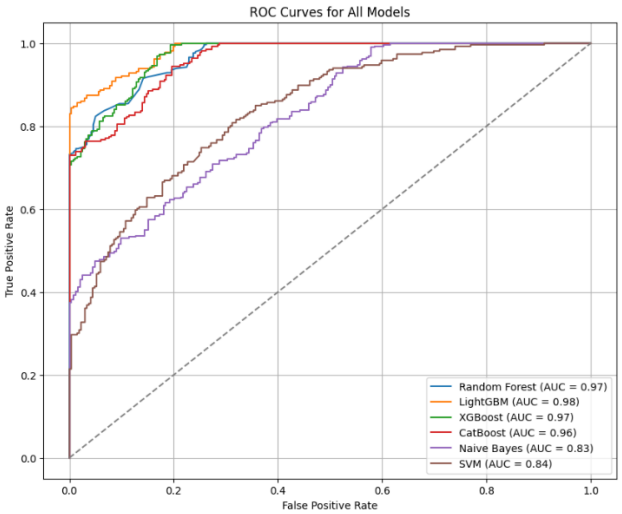


Fig. 5. Receiver operating characteristic (ROC) curves comparing all classifiers on the test set.

This outcome directly addresses RQ 2 by showing that demographic and occupational attributes can predict cluster membership with high accuracy. In particular, the top-performing LightGBM model achieved over 90% accuracy and an AUC of 0.9826, indicating that structural employee characteristics carry substantial predictive power for distinguishing between the two latent perception clusters. Given its strong and consistent performance across all evaluation metrics, LightGBM was selected as the final model for further explainability analysis. Its ability to handle complex interactions and provide insight into feature importance made it especially well-suited for understanding the key drivers behind cluster assignments. The next section explores how this model was interpreted to uncover the most influential variables shaping employee perceptions.

C. SHAP Insights

To interpret the decisions made by the LightGBM classifier and gain a deeper understanding of the structural variables influencing cluster membership, SHapley Additive exPlanations (SHAP) was employed as a model-agnostic explainability method. SHAP values provide a theoretically grounded framework for attributing the contribution of each feature to a specific prediction, enabling both global and local interpretability.

At the global level, the SHAP bar plot (Fig. 6) summarizes the mean absolute SHAP values of all input features, thus ranking them by their average impact on the model's output. According to this plot, the two most influential features in determining cluster membership were Employment Duration and Age, suggesting that the length of time an individual has spent in the workforce and their age are the primary differentiators between those in the more positive (Cluster 0) versus the more negative (Cluster 1) group. These were followed by IndustryDetailed, Gender, and SocioeconomicStatus, which also showed substantial contributions to model output. This directly answers RQ 3 by demonstrating how global SHAP analysis can pinpoint the most influential predictors of cluster membership, offering clear and interpretable evidence of the structural and demographic factors that shape workplace perception profiles.

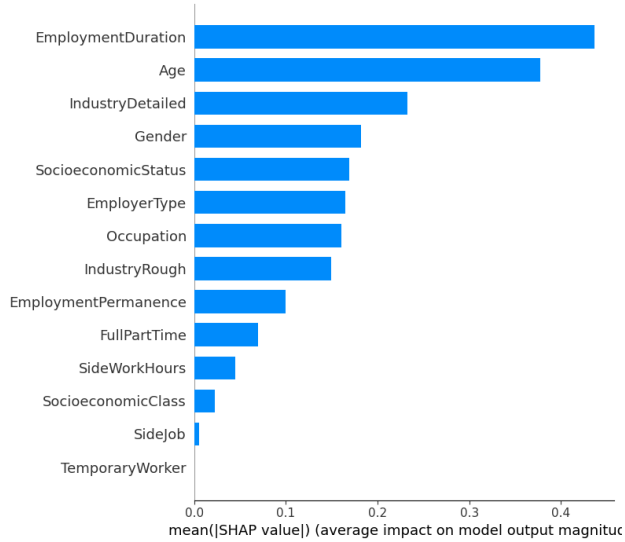


Fig. 6. Global SHAP feature importance plot ranking demographic and occupational variables by their average impact on LightGBM model predictions.

The SHAP beeswarm plot (Fig. 7) further extends this insight by showing how different values of each feature affect the model's predictions. Each point in the beeswarm plot corresponds to a single employee in the dataset, with the horizontal position indicating the SHAP value (i.e., the effect

on the model's prediction) and the color encoding the original feature value (from low to high). This view reveals not only which features are important but also how their specific values push the model toward predicting Cluster 0 or Cluster 1. To support the interpretation of these color gradients and categorical values, the complete coding schemes and enumerated representations of all categorical features used in the model are presented in Appendix B.

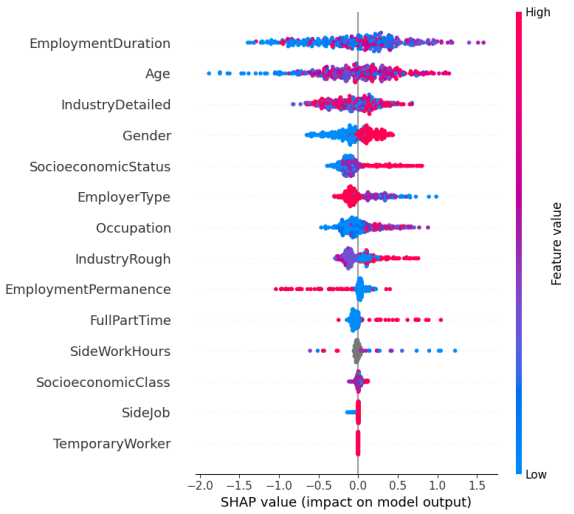


Fig. 7. SHAP beeswarm plot illustrating the direction and magnitude of feature effects on individual predictions, with color representing feature values.

The SHAP analysis highlights how demographic and occupational features influence cluster assignment, providing interpretable insight into the structural drivers of employee workplace perceptions. For Employment Duration, the SHAP beeswarm plot shows a mix of effects, indicating a non-linear relationship between tenure and cluster membership. The corresponding dependence plot reveals that moderate tenure, approximately 0 to 15 years, increases the likelihood of belonging to Cluster 1, while very long tenure shifts predictions toward Cluster 0. This pattern suggests higher dissatisfaction during mid-career stages, followed by more favorable perceptions among long-tenured employees, a finding that aligns with prior HR analytics research linking tenure-related dynamics to changes in employee well-being and engagement [20], [21], [30].

Age exhibits a clearer and more monotonic pattern. Higher age values consistently push predictions toward Cluster 1, while younger employees are more likely to fall into Cluster 0, indicating a largely linear association between increasing age and less favorable workplace perceptions. Similar age-related gradients have been reported in earlier explainable AI studies of employee outcomes, where age emerged as a significant contributor to supervised HR predictions and risk stratification [20], [21]. The ability of SHAP to reveal both the direction and magnitude of this effect reinforces its suitability for interpreting demographic influences in HR contexts [25], [26].

Gender also shows a distinct directional effect, with female employees more likely to be classified into Cluster 1 and male employees into Cluster 0. This result is consistent with prior research emphasizing gender-based disparities in workplace experiences and the value of explainable AI in uncovering such structural inequalities in HR decision-making systems [24], [25]. Similarly, higher Socioeconomic Status values corresponding to workforce-level positions increase the likelihood of Cluster 1 membership, whereas senior or lower-level official roles appear more protective. These findings resonate with earlier clustering and explainable AI studies that highlight the role of hierarchical position and job security in shaping employee perceptions and outcomes [17], [18], [30].

Employer Type further differentiates clusters, as public sector employment at the state or municipal level increases the probability of belonging to Cluster 1, while private sector employment reduces it. Comparable sectoral effects have been observed in previous clustering-based analyses of employee well-being and organizational risk profiles, particularly in studies examining institutional constraints and public sector stressors [6], [9], [19]. Categorical variables such as IndustryDetailed, Occupation, and IndustryRough require interpretation through SHAP dependence plots due to the lack of ordinal meaning in their encodings, an approach that mirrors best practices in recent SHAP-based HR analytics research [22], [30].

Other variables, including EmploymentPermanence, FullPartTime, SideWorkHours, SocioeconomicClass, SideJob, and TemporaryWorker, show minimal influence on predictions. This pattern is consistent with prior explainable machine learning studies in HR contexts, where a subset of structural features typically dominates model behavior while others contribute marginally once core demographic and occupational drivers are accounted for [28], [29].

Overall, the SHAP visualizations provide transparent and theoretically grounded insight into how background characteristics shape cluster membership and validate the LightGBM model's predictions. By combining global feature importance with feature-level dependence analysis, the results extend earlier SHAP-based HR studies that focused exclusively on supervised outcomes, demonstrating how Explainable Artificial Intelligence can also be applied to interpret latent clusters derived from unsupervised analysis [20]–[22], [30], [31]. The detailed examination of dependence plots clarifies how individual attributes contribute to classification into more or less favorable employee perception clusters, with categorical coding schemes documented in Appendix B.

The SHAP dependence plot for employment duration [Fig. 8(a)] shows a clear nonlinear pattern. The likelihood of belonging to Cluster 1 increases during the early to mid-career phase, peaking around 15–20 years of tenure, and then declines for employees with very long service. This suggests that mid-career employees are more prone to unfavorable workplace perceptions, whereas long-tenured employees tend to report more positive or stabilized experiences.

Similarly, the SHAP dependence plot for age [Fig. 8(b)] indicates a steady increase in the probability of being classified into Cluster 1 as age rises. Younger employees are less likely to exhibit negative workplace perceptions, while the risk of dissatisfaction becomes more pronounced after the

age of 30. Overall, both tenure and age emerge as important predictors, highlighting mid-career and older employees as groups more vulnerable to negative workplace sentiment.

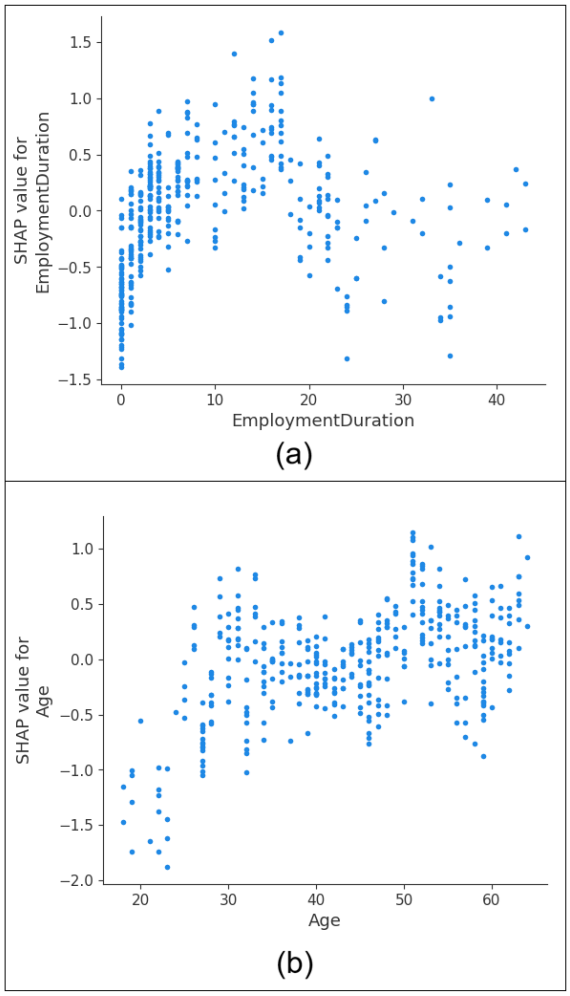


Fig. 8. SHAP dependence plots for: (a) employment duration, and (b) age.

The SHAP dependence plot for IndustryDetailed [Fig. 9(a)] shows that several sectors are strongly associated with classification into the less favorable Cluster 1. Industries such as electricity, gas and heating supply, administrative and support services, public administration and defense, health and social services, and arts and recreation exhibit higher SHAP values, suggesting elevated risk of negative workplace perceptions. These effects likely stem from sector-specific conditions, including high stress, burnout, emotional demands, irregular employment, or job instability.

In contrast, transportation and storage display the lowest SHAP values, indicating a strong association with the more favorable Cluster 0, potentially due to stable demand and expanding logistics-related employment. Education also tends toward lower SHAP values, which may reflect formal employment structures, long-term contracts, and stronger job protections. Finance and real estate show SHAP values near zero, suggesting a balanced risk profile that reflects internal heterogeneity between stable and volatile roles. Retail trade and accommodation and catering services exhibit a wide dispersion of SHAP values, indicating mixed employment conditions and diverse job types within these sectors.

The SHAP dependence plot for Gender [Fig. 9(b)] reveals a clear disparity, with female gender associated with higher SHAP values and a greater likelihood of belonging to Cluster 1, while male gender shows lower values and a protective effect. This finding indicates that gender meaningfully influences cluster assignment and may reflect underlying structural or socio-economic inequalities present in the data.

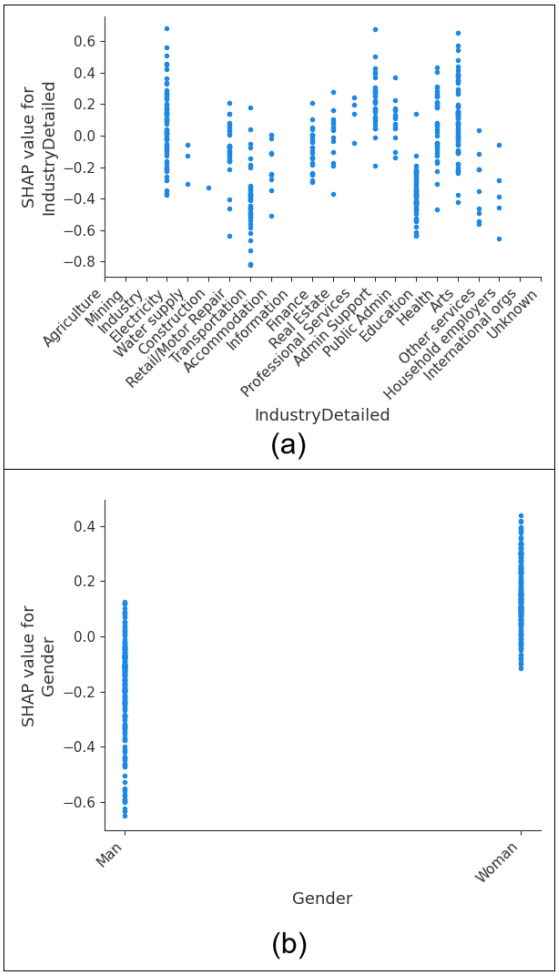


Fig. 9. SHAP dependence plots for: (a) IndustryDetailed, and (b) Gender.

The SHAP dependence plot for Socioeconomic Status [Fig. 10(a)] reveals a clear upward trend in SHAP values from senior officials to workforce-level employees, indicating that lower socioeconomic standing is associated with a higher likelihood of being placed in the unfavorable cluster (Cluster 1). Specifically, individuals categorized as "workforce" exhibit the highest SHAP values, suggesting that their status strongly contributes to predicting membership in the bad cluster. In contrast, senior officials tend to have negative SHAP values, meaning their status lowers the model's probability of assigning them to the adverse group. This pattern suggests that individuals occupying more precarious or lower-ranking positions within the employment hierarchy may face increased vulnerabilities or risks that are being captured by the model. It also reflects how structural inequalities

manifest in employment contexts and are detectable in predictive clustering models. The SHAP dependence plot for Employer Type [Fig. 10(b)] highlights significant differences in risk association based on the nature of the employer. Individuals employed by the state exhibit the highest SHAP values, meaning that this group is more strongly associated with Cluster 1, the undesirable or vulnerable group. This could reflect structural stressors or bureaucratic instability within state institutions. Employees working under municipalities or joint municipal authorities also show positive SHAP values, though slightly lower than those in state employment. In contrast, those employed in the private sector predominantly have lower SHAP values, suggesting a reduced likelihood of belonging to the high-risk cluster. This pattern may seem counterintuitive, as private sector jobs are often perceived as less secure, but it may be reflective of better job-matching, more competitive compensation, or other contextual factors that favor private employment outcomes.

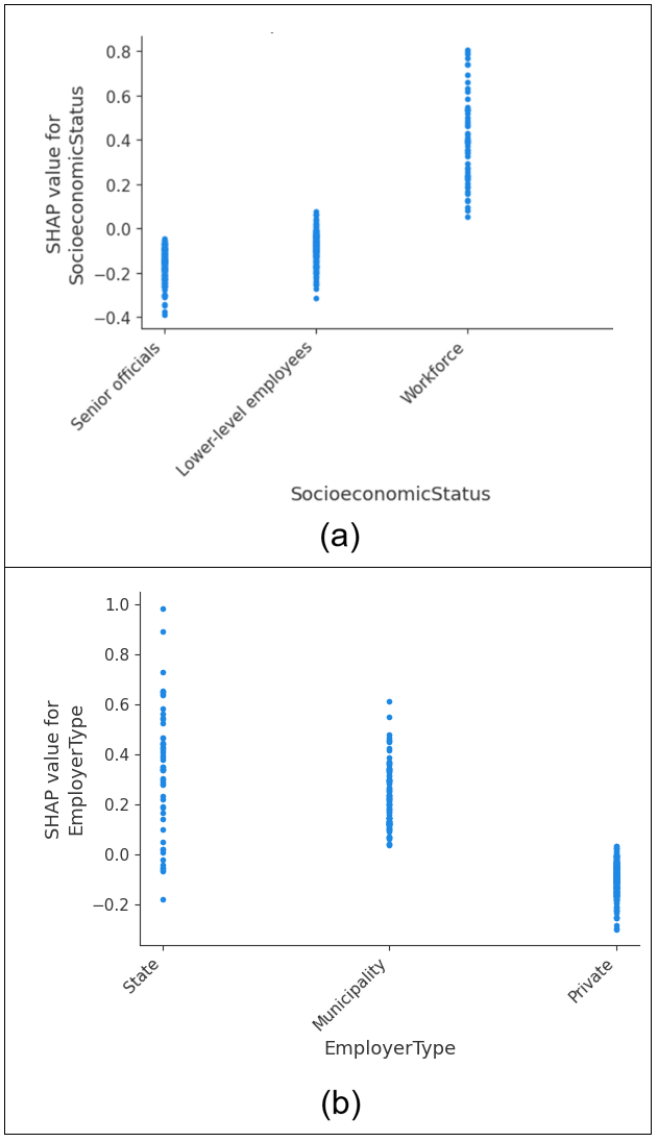


Fig. 10. SHAP dependence plots for: (a) Socioeconomic status, and (b) Employer type.

The SHAP dependence plot for Occupation [Fig. 11(a)] demonstrates clear differences in how job categories influence cluster assignments. Service and sales employees, office and customer service workers, and process and transportation workers exhibit higher SHAP values, indicating a greater likelihood of belonging to the higher-risk Cluster 1. These roles are often characterized by high turnover, customer-facing stress, or physically demanding conditions. Construction, repair, and manufacturing workers also show relatively elevated SHAP values, consistent with the contract-based and physically intensive nature of this work.

In contrast, management, special experts, and cognoscenti display lower SHAP values, suggesting stronger alignment with the more favorable cluster. These occupations typically offer greater stability, clearer career progression, and stronger institutional support. Overall, the results indicate occupational stratification, with higher risk associated with customer-facing and physically intensive roles, and lower risk linked to white-collar or institutional positions.

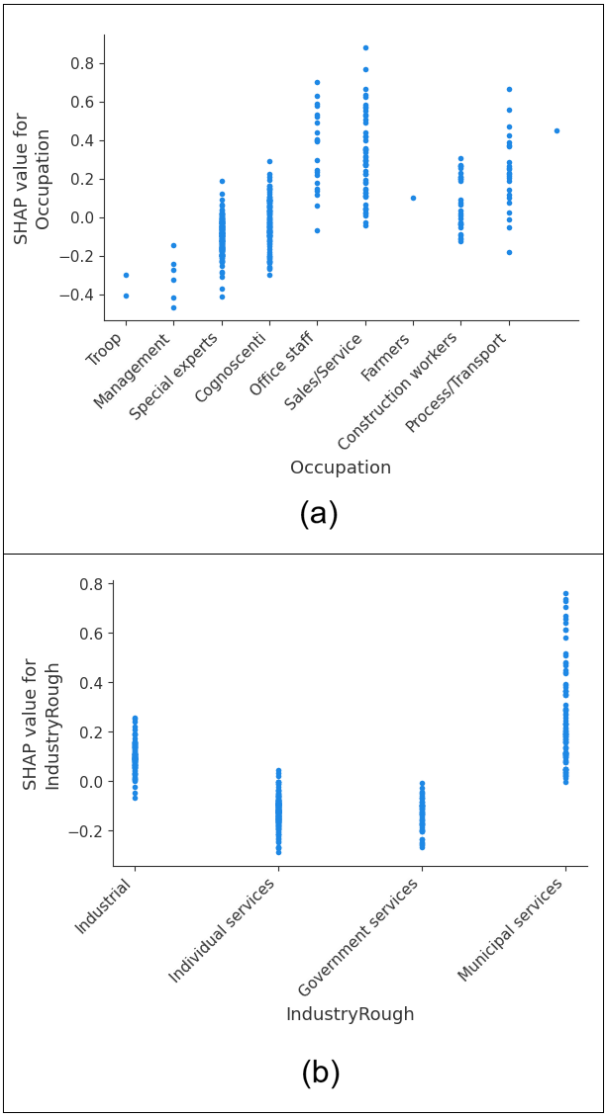


Fig. 11. SHAP dependence plots for: (a) Occupation, and (b) IndustryRough.

The SHAP dependence plot for the rough industry classification [Fig. 11(b)] further emphasizes institutional differences. Municipal services show the highest SHAP values, indicating increased vulnerability, potentially due to contract conditions or budgetary constraints. Government services and individual services exhibit lower SHAP values, while the industrial, applied, and excavated sector shows moderately elevated values, possibly reflecting physical demands or economic volatility. These findings underscore the importance of broad industry context in shaping predicted employment risk.

After examining the SHAP dependence plots, the analysis is extended to individual-level explanations to illustrate how the LightGBM model assigns cluster membership. SHAP waterfall plots are used for three randomly selected employees representing low, medium, and high predicted probabilities of belonging to Cluster 1, which reflects less favorable workplace experiences. While dependence plots summarize average feature effects, waterfall plots show how combinations of features interact differently for each individual, highlighting that similar attributes may have varying impacts depending on context.

For the first employee (Fig. 12), the SHAP waterfall plot shows a strongly negative logit value of −0.852, corresponding to a 29.9% probability of belonging to Cluster 1 and a clear alignment with Cluster 0. The dominant factor driving this outcome is the employee's short employment duration of one year, which strongly reduces the predicted risk, consistent with earlier findings that early-career employees tend to report more positive perceptions. The employee's industry, Financial and Insurance Activities, further lowers the SHAP value, reflecting the generally favorable association of this sector with workplace perceptions.

Additional protective factors include male gender, which slightly reduces risk, and senior occupational status, which is associated with lower SHAP values due to greater autonomy and organizational support. Although the employee is 42 years old, the age effect remains moderate, as mid-career employees lie below the steeper risk increase observed at older ages. Private sector employment also contributes to lowering the predicted risk, in line with earlier results showing favorable SHAP values for this employer type. Other variables, such as rough industry classification, occupation, and side work hours, have minimal impact on the final prediction.

Overall, the SHAP explanation confirms the model's classification and demonstrates how short tenure, private sector employment, seniority, and sector characteristics jointly reduce the likelihood of negative workplace perceptions, placing this employee firmly within the more favorable cluster.

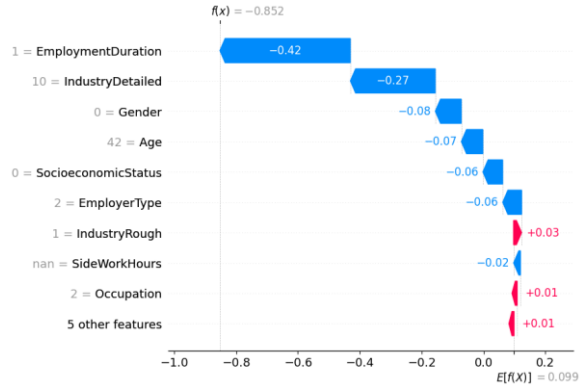


Fig. 12. Local SHAP waterfall plot for an employee with a low probability of belonging to Cluster 1 (negative cluster).

The SHAP waterfall plot for the second employee (Fig. 13) shows a logit value of approximately 0.044, corresponding to a 51.1% probability of belonging to Cluster 1 and a 48.9% probability of Cluster 0. This indicates a borderline case, with the prediction lying close to the model's baseline and no strong inclination toward either cluster.

The strongest factor reducing the likelihood of Cluster 1 membership is the employee's short employment duration of two years, which produces a negative SHAP value. As observed in the dependence analysis, early tenure is generally associated with more favorable workplace perceptions. In contrast, the employee's age of 39 contributes positively to the SHAP value, reflecting the gradual increase in risk observed with increasing age.

The rough industry classification, "Individual services", slightly increases the predicted risk, consistent with the variability and demands often associated with this sector. This upward effect is partially offset by the employee's senior socioeconomic status, which has a protective influence, and by male gender, which also contributes to a lower predicted risk.

The occupation category "Special Experts" adds a small positive contribution, suggesting modest risk, while private sector employment and full-time status both slightly reduce the likelihood of belonging to Cluster 1. Employment permanence has only a negligible positive effect. Overall, the combination of protective and risk-enhancing factors results in an equivocal prediction, illustrating the nuanced interplay of demographic, occupational, and institutional characteristics in shaping workplace perceptions.

The SHAP waterfall plot for the third employee (Fig. 14) shows a strongly positive logit value of +2.197, corresponding to a 90% probability of belonging to Cluster 1 and indicating a high likelihood of negative workplace perceptions. This classification is driven by the cumulative effect of several risk-enhancing factors.

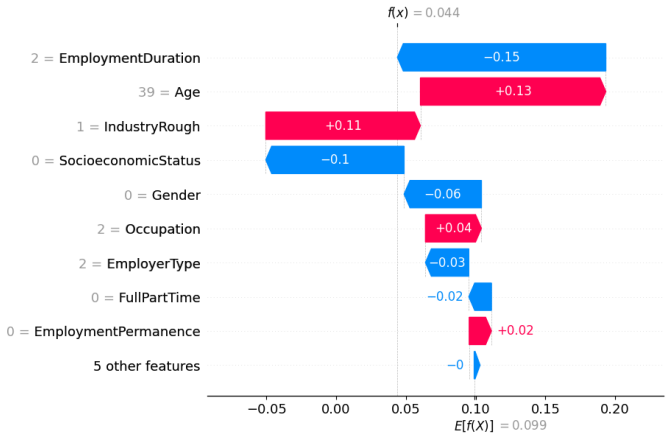


Fig. 13. Local SHAP waterfall plot for an employee with a borderline probability of belonging to Cluster 1 (negative cluster).

The employee's long employment duration of 21 years is a major contributor, as extended tenure is associated with higher SHAP values and increased risk of dissatisfaction. The female gender also substantially increases the SHAP value, consistent with earlier results showing a higher likelihood of women being classified into Cluster 1. Socioeconomic status, categorized as workforce, further elevates risk, reflecting the greater vulnerability of lower-ranking positions.

Industry and occupation also play significant roles. Employment in accommodation and catering, as well as service and sales occupations, both contribute positively to the SHAP value, aligning with prior findings that these contexts are associated with higher stress and instability. Age adds additional upward pressure, as SHAP values increase with advancing age. Smaller positive contributions from rough industry classification, employer type, and employment status further reinforce the prediction.

Together, these demographic and occupational characteristics generate a high SHAP score, leading to confident assignment to Cluster 1 and illustrating how multiple structural factors can interact to produce elevated negative workplace sentiment.

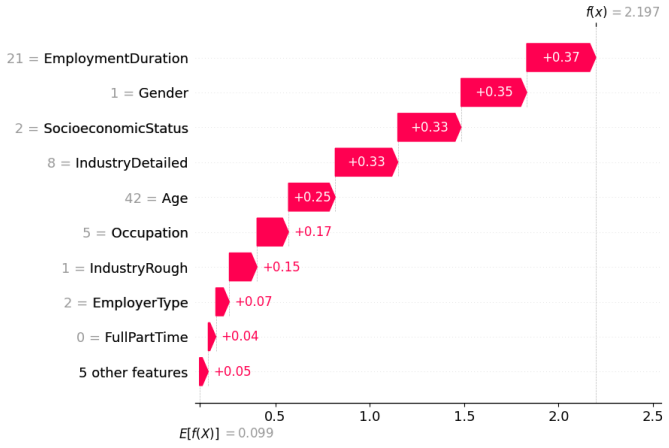


Fig. 14. Local SHAP waterfall plot for an employee with a high probability of belonging to cluster 1 (negative cluster).

This directly addresses RQ 4 by showing how local SHAP explanations uncover the unique combination of factors influencing individual employees' cluster assignments. These individualized insights reveal that even when employees share certain attributes, differences in their broader profiles can lead to distinct prediction outcomes, underscoring the value of local interpretability in HR decision-making.

V. Discussion and Future Work

The identification of two distinct employee perception clusters reveals pronounced differences in engagement, well-being, and organizational support. Employees in Cluster 0 consistently report more favorable workplace experiences, including stronger perceptions of fairness, leadership quality, developmental opportunities, motivation, and overall well-being. In contrast, Cluster 1 reflects systematically less favorable perceptions, characterized by lower trust, weaker inclusion, and reduced job satisfaction. These findings are consistent with prior clustering-based HR analytics research that has demonstrated the existence of heterogeneous employee profiles shaped by differences in well-being, engagement, and organizational support rather than random variation [6]–[10], [17]–[19]. Together, these results reinforce the view that workplace perceptions are structured outcomes influenced by identifiable demographic and occupational conditions embedded within organizational contexts.

The application of SHAP-based explainability provides deeper insight into the mechanisms underlying these differences. Employment duration and age emerge as the most influential predictors of cluster membership, indicating that workplace perceptions evolve across career stages. Shorter tenure and younger age are generally associated with more positive perceptions, whereas mid- to late-career stages exhibit an increased likelihood of negative sentiment. Similar tenure- and age-related effects have been reported in supervised HR analytics and explainable AI studies examining employee satisfaction, attrition, and well-being, where cumulative exposure to organizational stressors and unmet career expectations were identified as key drivers [20], [21], [30]. In addition, industry affiliation, gender, socioeconomic status, and occupation play important roles, revealing how institutional environments and labor market positions shape employees' lived experiences. Elevated risk in sectors such as health and social services, electricity, gas and heating supply, arts and recreation, and administrative support aligns with earlier clustering studies that identified sector-specific vulnerability profiles and occupational risk patterns [6], [9], [17], [19]. The consistency between global SHAP importance rankings and individual-level explanations further strengthens the credibility of these findings and reflects best practices in explainable HR analytics [22], [30].

From a human resource management perspective, the results offer clear guidance for targeted and evidence-based interventions, addressing RQ 5. Mid-career employees may benefit from structured career development pathways, mentoring programs, and role redesign initiatives aimed at restoring motivation and engagement, echoing recommendations from prior HR analytics and well-being studies [13], [18]. Sector-specific interventions are particularly

relevant for high-risk industries, where workload intensity, emotional labor, or institutional constraints may drive negative perceptions, as documented in earlier clustering-based analyses of employee well-being and stress [6], [17], [19]. Additionally, the observed disparities linked to gender and socioeconomic status highlight the importance of equity-oriented HR policies that address structural inequalities, promote inclusive leadership, and enhance access to resources and advancement opportunities, reinforcing calls from recent explainable AI and ethical HR systems research [24]–[26]. Well-being initiatives that focus on psychosocial support and work-life balance may further mitigate burnout and improve retention among vulnerable employee groups [20], [21].

Beyond practical implications, the study contributes to methodological advancement by demonstrating how Explainable Artificial Intelligence can bridge the gap between complex analytics and managerial decision-making. By transforming opaque model predictions into transparent explanations, SHAP-based insights enhance trust, accountability, and interpretability in HR analytics, consistent with prior research emphasizing the role of XAI in ethical and transparent HR Decision-Support Systems [25]–[27]. This integration enables organizations to move beyond descriptive segmentation toward an actionable understanding of *why* certain employee groups experience systematically different workplace conditions. As such, the proposed framework extends earlier SHAP-based HR studies that focused exclusively on supervised outcomes by applying explainability to latent cluster formation [20]–[22], [30], [31].

Despite these contributions, several limitations should be acknowledged. First, the analysis is based on cross-sectional survey data, which limits the ability to infer causal relationships or track changes in employee perceptions over time, a constraint also noted in prior clustering and HR analytics studies [6], [17], [19]. Second, the reliance on self-reported survey responses may introduce response bias or reflect temporary emotional states, as highlighted in earlier well-being and perception research [11], [12]. Third, while the Finnish Working Life Barometer provides high-quality and nationally representative data, the findings may reflect context-specific institutional and cultural characteristics, potentially limiting generalizability to other labor markets, as observed in previous country-specific HR analytics research [18], [19]. Finally, the use of predefined survey items constrains the analysis to structured perceptions and does not capture emergent themes that may arise in unstructured employee feedback [27].

Future research can build on this work in several directions. Longitudinal studies could examine transitions between perception clusters across career stages, enabling analysis of how workplace experiences evolve over time and how interventions influence these trajectories, addressing limitations identified in prior cross-sectional HR analytics research [6], [17]. Cross-national applications of the proposed framework would allow comparative analysis of institutional effects on employee perceptions and test the generalizability of the findings [18], [19]. In addition, integrating unstructured data sources such as employee comments, exit interviews, or organizational communications using natural language processing could enrich perception profiling and align with recent advances in explainable and knowledge-driven HR systems [27], [30]. Methodologically, future studies may explore alternative clustering techniques, causal inference approaches, or fairness-aware explainable models to further enhance robustness, transparency, and ethical accountability in Human Resource Analytics [24]–[26], [31]. Together, these extensions would strengthen the framework's role as a comprehensive decision-support tool for Human Resource Analytics.

VI. Conclusion

The study demonstrates that integrating unsupervised clustering with supervised classification and SHAP-based explainability provides actionable insights into employee workplace perceptions. Two distinct perceptual profiles emerged: one reflecting positive evaluations of fairness, leadership, well-being, and motivation, and another characterized by more negative sentiment. By interpreting these latent profiles through supervised modeling and SHAP, the analysis transparently identified the demographic and occupational factors driving cluster membership.

Key predictors included employment duration, age, industry affiliation, gender, and socioeconomic status, underscoring the combined influence of structural and individual factors on workplace experience. Methodologically, the framework bridges descriptive segmentation and explanatory modeling, producing results that are both robust and interpretable for decision-makers. This transparency supports targeted, equitable HR interventions and directly contributes to the United Nations Sustainable Development Goal 8 by promoting fair and inclusive employment conditions.

Declaration on Generative AI

Generative AI tools (specifically large language models) were used solely to assist with drafting, clarifying wording, and refining the language of this manuscript. All conceptual development, methodological design, data analysis, interpretation of results, and final decisions regarding the content were fully conducted by the author. The author takes full responsibility for the integrity, accuracy, and originality of all scientific and analytical components of the work.

References

[1] H. Jo and D. Shin, "The impact of recognition, fairness, and leadership on employee outcomes: A large-scale multi-group analysis," PLOS ONE, vol. 20, no. 1, 2025.

[2] G. Binyamin, "Perceptions matter: Do divergent views of management and colleagues on social climate drive employee engagement through organizational identification and growth satisfaction?," Sage Open, vol. 14, no. 1, 2024.

[3] Y. Liu, Y. Fang, L. Hu, N. Chen, X. Li, and Y. Cai, "Inclusive leadership and employee workplace well-being: The role of vigor and supervisor developmental feedback," BMC Psychology, vol. 12, no. 1, 2024.

[4] S. Akter, K. Biswas, D. Vrontis, S. C. L. Cooper, and S. Y. Tarba, "Mastering digital transformation in workforce management," Production Planning & Control, vol. 35, no. 13, pp. 1525–1532, 2023.

[5] J. B. Carnevale and I. Hatak, "Employee adjustment and well-being in the era of COVID-19: Implications for human resource management," Journal of Business Research, vol. 116, pp. 183–187, 2020.

[6] A. Suvarna, "AI-enabled predictive analytics for employee well-being: A cluster-based approach to proactive HR strategies in the digital era," ICTACT Journal on Management Studies, vol. 11, no. 2, pp. 2124–2129, 2025.

[7] Ş.-A. Catană, S.-G. Toma, C. Imbrişcă, and M. Burcea, "Teleworking impact on wellbeing and productivity: A cluster analysis of the Romanian graduate employees," Frontiers in Psychology, vol. 13, 2022.

[8] C. Bosle, J. E. Fischer, and R. M. Herr, "Creating a measure to operationalize engaged well-being at work," Journal of Occupational Medicine and Toxicology, vol. 16, no. 1, 2021.

[9] F. Niebuhr, G. M. Steckhan, and S. Voelter-Mahlknecht, "New work poses new challenges—The importance of work design competencies revealed in cluster analysis," International Journal of Environmental Research and Public Health, vol. 19, no. 21, 2022.

[10] A. Anttila, M. Nuutinen, R.-L. Leskelä, M. van Gils, A. Pekki, and R. Sauni, "Cluster analysis reveals subgroups with different risk profiles and sickness absence patterns in an occupational health cohort," Journal of Occupational Rehabilitation, 2025.

[11] M. A. Naveed and M. A. Anwar, "Information anxiety in the workplace: Scale development and validation," Information Development, vol. 38, no. 3, pp. 406–423, 2021, 2021.

[12] M. Kim and M. J. Park, "Effect of good meeting practices and interactional justice on online workplace informal learning in Korea," Information Development, vol. 38, no. 4, pp. 609–622, 2021.

[13] R. M. Cabrera et al., "Impact of machine learning in human resource management: Towards the modernization of leadership," Journal of Positive School Psychology, vol. 6, no. 2S, pp. 290–299, 2022.

[14] M. R. Shafie, H. Khosravi, S. Farhadpour, S. Das, and I. Ahmed, "A cluster-based human resources analytics for predicting employee turnover using optimized artificial neural networks and data augmentation," Decision Analytics Journal, vol. 11, 2024.

[15] S. R. K. Indarapu et al., "Exploring human resource management intelligence practices using machine learning models," The Journal of High Technology Management Research, vol. 34, no. 2, 2023.

[16] K. Chahuán-Jiménez et al., "Cluster analysis of digital competencies among professors in higher education," Frontiers in Education, vol. 10, 2025.

[17] K. A. Brown et al., "An unsupervised cluster analysis of post-COVID-19 mental health outcomes and associated comorbidities," AMIA Annual Symposium Proceedings, 2022, pp. 289–298, 2023.

[18] K. Kauppi et al., "Utility of an online well-being assessment in targeting employee well-being programmes: A cross-sectional survey study in Finland," BMJ Open, vol. 14, no. 6, 2024.

[19] J. Bughin et al., "The great divide between employees: Clustering employee 'well-being' during a pandemic," PLOS ONE, vol. 20, no. 3, 2025.

[20] D. K. Shaik, D. S. G. S. Rao, A. M. Babu, D. D. V. L. Reddy, and A. A. Ahmed, "Predictive modeling for HR decision-making: A study of employee turnover," Journal of Marketing and Social Research, vol. 2, no. 4, pp. 92–98, 2025.

[21] G. Marín Díaz, J. J. Galán Hernández, and J. L. Galdón Salvador, "Analyzing employee attrition using explainable AI for strategic HR decision-making," Mathematics, vol. 11, no. 22, 2023.

[22] L. Gadár and J. Abonyi, "Explainable prediction of node labels in multilayer networks: A case study of turnover prediction in organizations," Scientific Reports, vol. 14, no. 1, 2024.

[23] A. Abonamah, D. La Torre, M. Poulin, and M. Repetto, "Explainable artificial intelligence in human resources: A computational study," in 2022 International Conference on Data Analytics for Business and Industry (ICDABI), pp. 1–6, IEEE, 2022.

[24] K. K. K. K et al., "Integrating machine learning in HR: Ethical dilemmas and balancing efficiency with fairness," in 2024 International Conference on Advances in Computing, Communication and Materials (ICACCM), pp. 1–6, IEEE, 2024.

[25] M. T. Nuseir et al., "Role of explainable artificial intelligence (EAI) in human resource management system (HRMS)," in Studies in Big Data, Springer, 2024, pp. 249–263, 2024.

[26] W. Rodgers, J. M. Murray, A. Stefanidis, W. Y. Degbey, and S. Y. Tarba, "An artificial intelligence algorithmic approach to ethical decision-making in human resource management processes," Human Resource Management Review, vol. 33, no. 1, 2023.

[27] W. Shu, S. Pang, and M. Chen, "Achieving structured knowledge management with a novel online group decision support system," Information Development, vol. 38, no. 1, pp. 23–39, 2020.

[28] P. Yang and J. Li, "Construction and application of intelligent human resource management system based on machine learning algorithm," Journal of Computational Methods in Sciences and Engineering, vol. 25, no. 4, pp. 3684–3696, 2025.

[29] A. Heidemann, S. M. Hülter, and M. Tekieli, "Machine learning with real-world HR data: Mitigating the trade-off between predictive performance and transparency," The International Journal of Human Resource Management, vol. 35, no. 14, pp. 2343–2366, 2024.

[30] M. Seo, H. Lee, and S. Kim, "Using machine learning in HRD research: Applications to advance AI-driven organizational analytics," Human Resource Development International, pp. 1–24, 2025.

[31] N. Pourkhodabakhsh, M. M. Mamoudan, and A. Bozorgi-Amiri, "Effective machine learning, meta-heuristic algorithms and multi-criteria decision making to minimizing human resource turnover," Applied Intelligence, vol. 53, no. 12, pp. 16309–16331, 2022.

[32] Statistics Finland and Ministry of Economic Affairs and Employment, Finnish Working Life Barometer 2022, dataset, version 1.0, Finnish Social Science Data Archive, 2023.

APPENDIX A

Variable names and coding schemes were derived from the FSD3784 Finnish Working Life Barometer 2022 dataset. The dataset is distributed by the Finnish Social Science Data Archive (FSD) and is used here under the permitted license for academic research.

			Mean Survey Responses Per Cluster	
ID	Survey Question	Response	Cluster 0	Cluster 1
K21c_4	Information is shared openly at my workplace. Are you:	1- Totally agree 2- Somewhat agree 3- Somewhat disagree 4- Completely disagree 9- Can't say	1.41	2.27
K21c_5	At my workplace, employees are treated equally. Are you:		1.29	2.21
K21c_10	My workplace is able to handle and resolve conflicts. Are you:		1.33	2.25
K21c_12	My workplace has a confidential atmosphere. Are you:		1.24	2.21
K44C	My supervisor gives me feedback on how well I have done at work.		1.48	2.42
K44E	My superior asks for my opinion on decisions that affect me.		1.21	2.17
K44H	My superior is interested in my well-being at work.		1.3	2.34
K44G	My supervisor treats employees fairly and equally.		1.16	2.23

K44I	My supervisor encourages me to develop my work, for example, to adapt the content and working methods of my work to suit me.		1.4	2.41
K56a	How often do you feel mentally exhausted at work:	1- You never know 2- Rarely 3- Sometimes 4- Often 5- You always feel 8- Don't want to answer 9- Can't say	2.3	2.94
K56b	How often do you feel that you are not interested or enthusiastic about your work:		2.08	2.84
K56c	How often do you feel that you cannot concentrate well when working:		2.35	2.79
K56d	How often do you feel that you cannot control your emotions at work?		1.59	2.06
K57a	How often do you feel full of energy when doing your work:		3.71	3.16
K57b	How often are you enthusiastic about your work:		3.9	3.29
K57c	How often are you completely immersed in your work:		3.65	3.28
K57d	How often do you have a sense of community and working together:	1- Never 2- Rarely 3- Sometimes 4- Often 5- Always 8- Don't want to answer 9- Can't say	3.84	3.17
K55	Stress refers to a situation where a person feels tense, restless, nervous or anxious, or has difficulty sleeping due to constant worries. Do you currently feel this kind of stress:	1- Not at all 2- Just a little 3- Some 4- Quite a lot 5- Very much 8- Don't want to answer 9- Can't say	2.21	2.81
K69	How meaningful do you find your work? Is it:	1- Very meaningful 2- Quite significant 3- Not particularly relevant 4- Not relevant at all 8- Don't want to answer 9- Can't say	1.55	1.96
K28a	If you think about the physical demands of your current job, is your work capacity:	1- Very good 2- Fair 3- Moderate 4- Pretty bad 5- Very bad 8- Don't want to answer 9- Can't say	1.52	1.93
K28b	What about mental requirements? Is your work capacity:		1.61	2.17
K64	When you think about balancing work and other life, are your working hours flexible:	1- Sufficiently 2- Somewhat, but not enough 3- Not enough at all 9- Can't say	1.17	1.53
K42a	How often do you work to tight schedules or at a very fast pace:	1- Daily 2- Weekly 3- Monthly 4- Randomly 5- Not at all 9- Can't say	2.38	2.11
K43g	Have you worked outside of working hours without compensation in the past 12 months to perform your job duties:		4.37	4.17

APPENDIX B

IndustryDetailed	0	Agriculture, forestry, fisheries
	1	Mining and quarrying
	2	Industry
	3	Electricity, gas and heating supply, refrigeration business
	4	Water supply, sewerage and wastewater management, waste management and other environmental sanitation
	5	Construction
	6	Wholesale and retail trade; repair of motor vehicles and motorcycles
	7	Transportation and storage
	8	Accommodation and catering activities
	9	Information and communication
	10	Financial and insurance activities
	11	Real estate activities
	12	Professional, scientific and technical activities

	13	Administrative and support services
	14	Public administration and national defense; compulsory social insurance
	15	Education
	16	Health and social services
	17	Arts, Entertainment and Recreation
	18	Other service activities
	19	Activities of households as employers; undifferentiated activities of households for the production of goods and services
	20	Activities of international organizations and institutions
	21	Industry unknown
Gender	0	Man
	1	Woman
SocioeconomicStatus	0	Senior officials
	1	Lower-level employees
	2	Workforce
EmployerType	0	State
	1	Municipality/joint municipal authority
	2	Private
Occupation	0	Troop
	1	Management
	2	Special experts
	3	Cognoscenti
	4	Office and customer service workers
	5	Service and sales employees
	6	Farmers, forest workers, etc.
	7	Construction, repair and manufacturing workers
	8	Process and transportation workers
IndustryRough	0	Industrial/applied/excavated
	1	Individual services
	2	Government services
	3	Municipal services
EmploymentPermanence	0	Continuous (indefinitely valid)
	1	Fixed-term or temporary
FullPartTime	0	Full-time job
	1	Part-time work
SocioeconomicClass	0	Employee or unknown position
	1	Lower-level employee
	2	Senior employee
SideJob	0	Yes
	1	No/was away all week/unknown
TemporaryWorker	0	Yes
	1	No

Business Process Outsourcing and Digitalization in Albania: Challenges, Opportunities, and Strategic Directions

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***Abstract*—The rapid expansion of Business Process Outsourcing (BPO) has transformed the global services economy, and Albania is emerging as a competitive nearshoring destination in the Western Balkans. This study examines the intersection of BPO and digitalisation in Albania, exploring how technological innovation, artificial intelligence (AI), and cloud-based automation are reshaping service delivery, labour productivity, and competitiveness. This study is explicitly framed as a desk-based policy and analytical study relying exclusively on secondary data, without primary data collection based on secondary data from OECD, World Bank, IBM, and European Commission reports (2023–2025). Findings indicate that Albania's BPO sector benefits from low labour costs, multilingual human capital, and favourable fiscal policies, yet faces challenges related to technological capability, digital infrastructure, and talent retention. Through a PEST analytical framework, this study identifies the macro-environmental factors influencing BPO development and proposes strategic directions for enhancing digital readiness and regional integration. The study further expands its comparative analysis to include other Western Balkan economies, Kosovo, North Macedonia, and Montenegro, providing a broader perspective on Albania's position within the regional outsourcing ecosystem. This research contributes to the academic and policy discourse on digital transformation by presenting an integrated model aligning BPO growth with sustainable innovation and regional competitiveness.**

Keywords*—Business Process Outsourcing (BPO); digitalisation; artificial intelligence (AI); automation; PEST analysis; Western Balkans; Albania; strategic development

I. Introduction

The global landscape of Business Process Outsourcing (BPO) has undergone a significant transformation over the past decade, driven by advances in automation, artificial intelligence (AI), and digital connectivity. The integration of digital technologies into business operations has reshaped value chains, customer interactions, and operational efficiency across industries [2]. In this context, developing economies such as Albania are increasingly positioning themselves as emerging destinations for outsourcing, benefitting from cost advantages, multilingual human resources, and geographical proximity to Western Europe [21].

Digitalisation represents both a challenge and an opportunity for BPO development in Albania. On one hand, technological innovation enhances productivity, transparency, and competitiveness; on the other, it demands substantial investments in infrastructure, human capital, and regulatory adaptation [29]. The transition toward digitalised outsourcing requires an alignment between policy reforms, skills development, and corporate digital strategies [8].

Globally, the BPO sector has evolved beyond traditional back-office functions such as accounting and customer service. It now encompasses high-value processes like data analytics, IT consulting, and AI-driven automation [16]. This shift reflects the growing importance of digital ecosystems and knowledge-intensive services [5] [14]. The integration of cloud computing and robotic process automation (RPA) is enabling companies to achieve scalability, flexibility, and innovation in ways that were previously unattainable [13].

From a regional perspective, the Western Balkans are increasingly recognised as a promising nearshoring hub. Albania has leveraged its multilingual workforce, cost-effective labour market, and improving digital infrastructure to attract foreign investors [26]. Available evidence indicates that the BPO industry in Albania employs thousands of young professionals, primarily in customer relations, finance, and IT support, contributing to service exports and employment growth [21]. Nevertheless, the sector remains fragmented and heavily reliant on low-cost advantages, rendering it vulnerable to technological disruption and talent migration [29].

The concept of digital transformation within BPO goes beyond automation. It encompasses the strategic adoption of AI, data analytics, and cloud-based systems to enhance organisational agility and innovation capacity [1]. Digitalisation has become a decisive factor shaping competitiveness in global value chains [15]. In Albania's case, the challenge lies in harmonising business digitalisation with national policy reforms and workforce digital readiness.

The Albanian government has made progress through initiatives such as the Digital Agenda 2022–2026 and participation in the EU4Digital Western Balkans Initiative, which supports cross-border innovation, cybersecurity, and ICT skill development [9]. Similarly, fiscal incentives and EU pre-accession funds aim to foster entrepreneurship and investment in digital services [29]. Despite this progress, policy fragmentation and limited coordination between education, technology, and industry stakeholders continue to impede the pace of transformation [21].

At the global level, outsourcing is increasingly influenced by sustainability principles and responsible digital governance.

The growing focus on environmental, social, and governance (ESG) indicators in outsourcing contracts reflects the need for ethical and sustainable operations [11]. For Albania, aligning BPO development with these international standards will be essential for long-term integration into the EU's digital single market.

The COVID-19 pandemic accelerated the shift toward remote work and virtual outsourcing, reinforcing the need for robust digital infrastructure and flexible business models [25]. Globally, firms transitioned to hybrid structures, adopting cloud technologies and AI-based process management to ensure continuity [15]. In Albania, this shift coincided with the expansion of broadband networks, ICT education, and remote employment opportunities in call centres, accounting, and IT services [28].

From an academic perspective, studying BPO and digitalisation in Albania addresses an existing research gap in the Western Balkans. Most studies have focused on large economies or advanced EU member states, while small transitional markets remain underexplored [21]. This study fills that gap by analysing how digital transformation, institutional governance, and human capital collectively shape the development of Albania's BPO sector.

A. Research Problem

Despite the rapid expansion of the Business Process Outsourcing (BPO) sector in Albania, existing studies remain largely descriptive and fragmented, focusing primarily on labour cost advantages or general digitalisation trends without integrating institutional conditions, firm-level capabilities, and digital transformation dynamics. Limited attention has been paid to how institutional alignment, digital infrastructure, and human capital interact to shape sustainable BPO competitiveness in emerging economies undergoing EU integration [21] [30]. This gap constrains both theoretical advancement and evidence-based policymaking in the Western Balkan context [26].

B. Research Questions

To address this gap, the study is guided by the following research questions:

RQ1: How do political, economic, social, and technological factors influence the development of the BPO sector in Albania? [21]

RQ2: How do institutional conditions interact with firm-level resources to shape digital and AI adoption in the BPO sector? [9] [5]

RQ3: What strategic insights emerge from comparing Albania with other Western Balkan and Eastern European economies in terms of digital readiness and BPO competitiveness? [26] [30].

C. Research Objectives

The objectives of this study are to:

1) Analyse the macro-environmental determinants of BPO development in Albania using a PEST framework [21];

2) Examine how digitalisation, automation, and artificial intelligence contribute to productivity and competitiveness in the BPO sector through institutional and resource-based perspectives [5] [16];

3) Position Albania within the regional outsourcing ecosystem by means of comparative benchmarking with selected Western Balkan and Eastern European economies [26] [30].

D. Novelty and Contribution of the Study

This study contributes to the existing literature in three main ways. First, it offers a theoretical contribution by integrating the Resource-Based View (RBV) and Institutional Theory to explain digital transformation in the BPO sector of an emerging economy [21], [4], [5]. Second, it provides a methodological contribution by combining PEST analysis with comparative regional benchmarking and a digitalisation lens, moving beyond purely descriptive sectoral overviews [21], [18], [26]. Third, the study delivers practical and policy-relevant insights by proposing a conceptual model of digital BPO transformation that can be applied to Albania and other Western Balkan economies seeking to transition from cost-based outsourcing toward higher value-added digital services [5], [21], [26].

This study distinguishes itself from existing literature through a novel analytical integration of macro-environmental analysis, regional benchmarking, and digital transformation dynamics within the Business Process Outsourcing (BPO) sector of an emerging economy. While prior studies on BPO in the Western Balkans have predominantly focused on labour cost advantages or general digital indicators, this research advances the literature by explicitly combining PEST analysis with comparative regional benchmarking and an artificial intelligence (AI)–oriented digitalisation lens [21] [26].

Methodologically, although the study adopts a qualitative and descriptive–analytical approach based on secondary data, its novelty lies in the structured triangulation of institutional, technological, and human capital dimensions across multiple countries rather than in isolated national descriptions [21] [30]. This approach enables the identification of causal mechanisms and structural trade-offs, such as the tension between cost competitiveness and investment in high-skilled digital labour that are not sufficiently explored in prior regional studies [5] [26].

Theoretically, the study contributes by integrating the Resource-Based View and Institutional Theory to explain how institutional alignment functions as an enabling mechanism for firm-level capability development in a digitalising emerging economy. The proposed conceptual model advances existing research by illustrating how regulatory frameworks, digital infrastructure, and human capital jointly shape value-added BPO upgrading rather than acting as independent drivers [21] [5]. Empirically, the Albanian case offers original insights into how intermediate economies position themselves between cost-based Western Balkan peers and digitally advanced Eastern European outsourcing hubs, thereby enriching comparative BPO scholarship [30] [26].

Beyond the general policy and strategic implications discussed throughout the study, this study makes three explicit

and tangible contributions to the literature and practice of Business Process Outsourcing in emerging economies.

First, at the theoretical level, the study advances the academic debate by developing a conceptual model that explicitly links institutional alignment, digital infrastructure, human capital development, and firm-level capabilities to digital BPO upgrading. By integrating the Resource-Based View and Institutional Theory, the model moves beyond isolated theoretical applications and demonstrates how institutional conditions function as enabling mechanisms for resource accumulation in a digitalising emerging economy [21] [5] [30].

Second, from a methodological perspective, the study contributes by operationalising an integrated analytical framework that combines PEST analysis with comparative regional benchmarking and an artificial intelligence–oriented digitalisation lens. This configuration enables the identification of causal mechanisms and structural trade-offs, such as the tension between cost competitiveness and investment in high-skilled digital labour, that are not sufficiently captured in prior descriptive studies of the Western Balkans [21] [18] [26].

Third, at the practical and policy level, the comparative analysis of Albania with other Western Balkan and Eastern European economies generates transferable insights for policymakers and practitioners. Rather than offering a purely descriptive comparison, the findings highlight generalisable patterns regarding the conditions under which emerging economies can transition from cost-based outsourcing toward value-added digital BPO services. These insights provide actionable guidance for designing policies related to digital governance, skills development, and investment prioritisation in similar emerging market contexts [26] [30].

Accordingly, this study aims to:

1) Analyse the macro-environmental factors (political, economic, social, technological) influencing BPO growth in Albania through a PEST framework.

2) Evaluate how digital transformation and automation technologies enhance productivity and competitiveness in the BPO sector.

3) Compare Albania's performance with other Western Balkan and Eastern European economies to identify strategic directions for sustainable growth.

The remainder of the study is organised as follows: Section II reviews the existing literature on outsourcing and digital transformation. Section III outlines the research methodology and analytical frameworks. Section IV presents the findings, including a PEST analysis, regional comparison, and conceptual framework. Finally, Section V concludes with policy implications and recommendations for the sustainable development of BPO and digitalisation in Albania and the wider region.

II. Literature Review

A. Overview of Contemporary Research

Additional academic and professional studies further enrich the literature on digital transformation and outsourcing by addressing complementary, yet distinct dimensions of change in contemporary service industries. Research on AI-driven process optimisation highlights how automation and intelligent analytics enhance efficiency, accuracy, and scalability within outsourcing operations [3]. Related contributions on digital twins of business processes extend this perspective by demonstrating how virtual representations of workflows support process redesign, monitoring, and continuous improvement [12]. From a strategic viewpoint, the literature on the reconfiguration of outsourcing models emphasises the transition from cost-based arrangements toward digitally enabled, value-oriented outsourcing strategies [14]. In parallel, studies on workforce skills development and reskilling underline the critical role of human capital adaptation in enabling effective adoption of advanced digital technologies [20]. Finally, analyses of competitiveness dynamics in service industries provide broader insights into how institutional conditions, technological innovation, and skills upgrading jointly shape outsourcing performance across different market contexts [23].

In addition to peer-reviewed academic studies, institutional and industry-based reports provide important complementary perspectives on the evolution of outsourcing and digital transformation in emerging economies. These sources analyse recent global outsourcing trends, the reconfiguration of service delivery models, and the increasing role of sustainability and ESG considerations in shaping outsourcing strategies [6] [10]. Policy-oriented assessments further examine how digitalisation and artificial intelligence are reshaping global value chains and service-sector competitiveness, with particular emphasis on the implications for emerging and transitional economies [24]. Moreover, country- and region-specific institutional analyses highlight the role of regulatory reforms, governance capacity, and labour market dynamics in influencing outsourcing development and employment outcomes in the Western Balkans and comparable regions [7] [27]. Collectively, these contributions enrich the contextual and policy background of the present study, complementing firm-level and technological analyses of BPO development. Between 2023 and 2025, the academic and professional debate around Business Process Outsourcing (BPO) has shifted from operational cost optimisation to digital innovation and sustainability [2] [21]. Digitalisation and automation are now the core pillars of global outsourcing, enabling companies to achieve efficiency, agility, and strategic value creation [5] [16]. The latest literature emphasises the role of emerging economies, such as Albania, in integrating artificial intelligence technologies, data analytics, and digital governance frameworks to compete effectively in regional outsourcing markets [21] [26] [30].

B. Digital Transformation in Global BPO

Digital transformation has revolutionised BPO operations globally [2]. Accenture identifies three stages of digital maturity: digitisation, digitalisation, and full transformation, each representing a deeper integration of technology into corporate strategy [2]. IBM notes that AI adoption and cloud integration can increase operational efficiency by up to 40 percent while reducing process errors by 25 per cent [16] [3]. Advanced automation increasingly incorporates digital representations of workflows and decision logic to optimise

service delivery and process design [12]. OECD adds that digital maturity across emerging economies correlates directly with their level of institutional reform and ICT investment [21].

UNCTAD reports that global demand for outsourcing services in the digital domain increased by 19% annually during 2023–2024, led by AI-based data analytics and virtual assistance [26]. Similarly, Gartner projects that automation-driven BPO will represent 60% of all outsourcing contracts by 2026 [13]. Albania, though still in its early stage of digital maturity, benefits from regional integration with the EU through the EU4Digital Western Balkans Initiative, which supports cross-border ICT standards and e-skills programmes [9].

C. Human Capital and Skill Transformation

Human capital development is the foundation of digital competitiveness [31]. Evidence indicates that 44% of the global workforce will require reskilling by 2025 due to the integration of artificial intelligence and automation technologies [31]. In Albania, demographic indicators show that a large share of the working-age population is under 35 years old, yet only a limited proportion possesses advanced digital competencies, creating both a constraint and an opportunity for the BPO sector [17].

Continuous professional training in data management, cybersecurity, and automation is therefore essential for sustaining competitiveness in digital outsourcing environments [32]. Recent studies emphasise that digital literacy must evolve into "digital fluency", whereby workers not only use digital tools but apply them strategically to improve productivity and service quality [19] [21]. Furthermore, hybrid education and training models that combine technical expertise with analytical and problem-solving skills have been shown to be particularly effective in enhancing employability and adaptability within AI-enabled BPO operations [15] [4].

D. Policy, Governance, and Regulation

Regulatory standards for digital service providers have been strengthened through the adoption of the Digital Services Act (DSA) and the AI Act, promoting accountability, data protection, and algorithmic transparency within the European digital market [8] [9]. Alignment with these regulatory frameworks is essential for countries such as Albania to ensure compatibility with EU data governance and cybersecurity standards [9].

Recent assessments confirm progress in Albania's e-governance systems and digital infrastructure, while also highlighting persistent fragmentation across public institutions [28]. Evidence further indicates that regulatory predictability and stable tax incentives are critical determinants for attracting foreign direct investment in ICT and BPO sectors [5] [11]. Although Albania's low corporate tax rate for IT and outsourcing services enhances cost competitiveness, the effectiveness of this policy depends on consistent enforcement and institutional capacity [21].

E. Regional Perspectives and Emerging Trends

A structured overview of the most relevant academic and institutional sources informing this study is summarised in Table I. Regional evidence indicates that Eastern European economies such as Romania, Bulgaria, and Serbia lead in digital BPO adoption, supported by targeted innovation policies and strong academic–industry collaboration [30]. By contrast, Albania, Kosovo, and North Macedonia are positioned as cost-effective but digitally emerging markets, with significant potential for scaling through deeper regional integration and skills upgrading [18].

Policy analyses further recommend intensified collaboration among Western Balkan economies within frameworks such as EU4Digital and the Regional Economic Area to harmonise digital standards and stimulate cross-border digital investment [21] [9]. Complementary assessments emphasise that nearshoring strategies and regional digital partnerships can collectively enhance the competitiveness of the Western Balkans relative to Central and Eastern Europe [26].

TABLE I. SUMMARY OF KEY LITERATURE (2023–2025)

Focus Area	Key Findings	Relevance to Albania	Author/ Source
Digital transformation	Defines three phases of digital maturity	Benchmark for Albania's progress	[2]
AI and automation	Increases efficiency by 40%	Technological roadmap for BPO firms	[16]
Intelligent outsourcing	Shift toward knowledge-based outsourcing	Policy relevance for sustainable BPO	[4] [5]
Digital transformation in emerging markets	Highlights need for institutional coordination	Framework for national strategy	[21]
Human capital and FDI	Links digital skills to outsourcing growth	Empirical policy insight	[29]
EU4Digital Western Balkans	Promotes cross-border ICT and e-skills	Foundation for regional cooperation	[9]
BPO in the Balkans	Analyses cost and skills advantage	Regional competitiveness benchmark	[18]
Digital economy and nearshoring	Growth of digital services post-pandemic	Context for Albania's export potential	[26]
Workforce reskilling	Stresses AI-based skill acquisition	Human capital policy guidance	[32]
AI adoption in SMEs	Provides framework for digitalisation	Adaptable to Albanian SMEs and BPOs	[22]

Source: [21] [29] [30] [16] [9].

In addition, implementation-oriented frameworks on artificial intelligence adoption in small and medium-sized enterprises provide structured guidance for digitalisation

pathways that are directly applicable to BPO providers operating in emerging market contexts [22].

F. Theoretical Perspectives and Research Propositions

The conceptual evolution from traditional cost-based outsourcing toward digitally enabled and AI-driven BPO models is illustrated in Fig. 1. This study is grounded in two complementary theoretical perspectives: the Resource-Based View (RBV) and Institutional Theory. The RBV posits that sustainable competitive advantage arises from firm-level resources that are valuable, rare, and difficult to imitate, such as advanced digital skills, artificial intelligence capabilities, and organisational knowledge [21] [5]. However, RBV alone does not sufficiently explain why firms operating in similar industries exhibit divergent digital transformation outcomes across different national contexts [21].

Institutional Theory complements this perspective by emphasising the role of regulatory frameworks, governance quality, and normative pressures in shaping organisational behaviour and technology adoption [9] [4]. In emerging economies, alignment with supranational regulatory frameworks such as those of the European Union can reduce uncertainty and enable firms to invest in advanced digital technologies [9] [21].

By integrating RBV and Institutional Theory, this study advances the understanding of digital transformation in the BPO sector by explicitly linking institutional conditions to firm-level capability development. This theoretical integration advances existing literature by demonstrating that institutional conditions do not directly generate competitive advantage but instead shape firms' capacity to develop and deploy strategic resources. In the context of a digitalising emerging economy, such as Albania, regulatory alignment and governance quality function as enabling mechanisms that influence firms' absorptive capacity, particularly in relation to digital skills and AI adoption. This perspective refines the Resource-Based View by highlighting the mediating role of institutions and extends Institutional Theory by illustrating how firm-level resource heterogeneity conditions the outcomes of institutional reforms [21] [5] [30].

Accordingly, the following research propositions are derived:

P1: Alignment with EU digital governance and regulatory frameworks enables BPO firms to transform digital infrastructure into strategic firm-level resources [9] [21].

P2: Human capital availability and advanced digital skills mediate the relationship between institutional reforms and AI adoption in the BPO sector [17] [19] [31].

P3: Emerging economies that successfully combine institutional stability with firm-level resource development are more likely to transition from cost-based outsourcing toward value-added digital BPO services [5] [26].

The figure illustrates the transition from traditional cost-based outsourcing models toward digitally enabled and AI-supported BPO ecosystems, highlighting the progressive role of automation, cloud computing, and advanced digital capabilities in value creation.

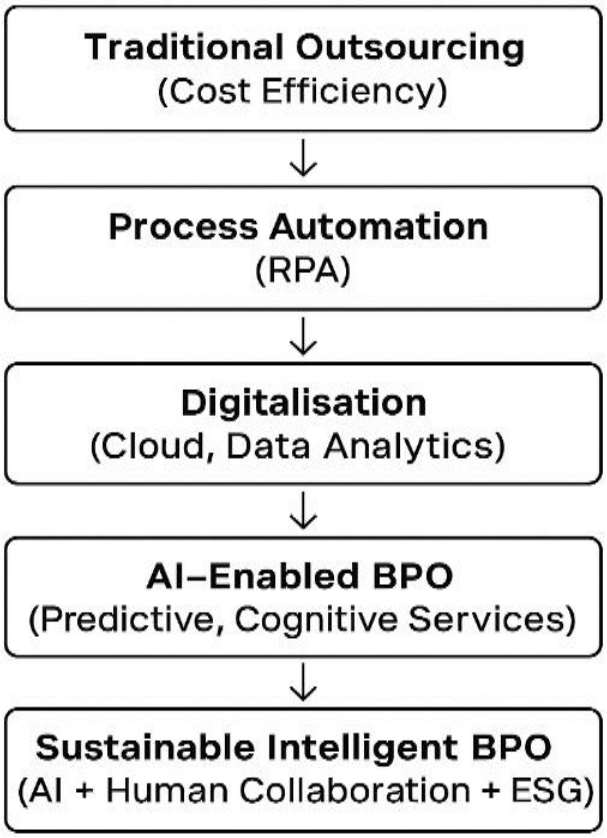


Fig. 1. Evolution of BPO and digitalisation (Conceptual overview). Source: author's conceptual illustration [2] [16] [21].

G. Research Gap and Contribution

The literature review indicates that most empirical studies on digital BPO have focused on large, mature economies, leaving smaller transitional markets such as Albania comparatively underexplored [30]. Moreover, relatively few comparative analyses examine the Western Balkans as an integrated region, particularly with respect to Kosovo, North Macedonia, and Montenegro. By incorporating a regional perspective alongside institutional analysis, this study addresses this gap and enhances understanding of how emerging economies leverage digital transformation to strengthen BPO competitiveness [21] [9].

III. Methodology

A. Research Approach and Design

This study adopts a *qualitative and descriptive–analytical approach* to examine how digitalisation influences Business Process Outsourcing (BPO) competitiveness in Albania and the wider Western Balkans. The study is explicitly framed as a desk-based policy and analytical investigation, relying exclusively on secondary data and without any primary data collection [21] [29] [30]. The qualitative orientation allows an in-depth exploration of institutional, economic, and technological factors shaping outsourcing development [21].

The research draws on secondary data from academic literature, institutional reports, and professional studies published between 2023 and 2025. This includes publications by the OECD, World Bank, European Commission, IBM, Accenture, KPMG, and UNCTAD. The combination of these diverse yet authoritative sources ensure triangulation, thereby enhancing the validity and reliability of the findings [29].

The analysis is structured around two complementary frameworks:

1) PEST analysis, to assess the macro-environmental dimensions political, economic, social, and technological affecting Albania's BPO ecosystem.

2) Comparative regional benchmarking, to evaluate Albania's performance against peer economies in the Western Balkans and Eastern Europe (Kosovo, North Macedonia, Montenegro, Serbia, Bulgaria, and Romania).

The study relies on recent institutional and industry reports published between 2023 and 2025, including sources from international organisations, consultancy firms, and technology providers. Reports dated 2025 are used explicitly as forward-looking policy and market outlooks rather than as peer-reviewed empirical evidence [21] [26]. These sources are employed to capture emerging trends in digital transformation, artificial intelligence adoption, and BPO restructuring, which are particularly relevant in rapidly evolving service sectors [16] [31]. To mitigate potential bias associated with corporate and consultancy reports, the analysis applies source triangulation by systematically cross-referencing findings from OECD, World Bank, European Commission, and UNCTAD publications [21] [29] [30] [26]. Consequently, forward-looking industry insights are used for contextualisation and scenario interpretation, while analytical conclusions are grounded primarily in internationally recognised institutional evidence [21] [30].

These frameworks allow a multidimensional understanding of digital transformation, integrating national and regional perspectives. The methodological framework and analytical tools applied in this study are summarised in Table II.

TABLE II. METHODOLOGICAL FRAMEWORK

Research Element	Description
Approach	Qualitative and descriptive–analytical research
Purpose	To analyse how digitalisation impacts BPO competitiveness in Albania and the Western Balkans
Data Sources	OECD, World Bank, IBM, Accenture, KPMG, EU Reports (2023–2025)
Data Collection	Desk research, document analysis, and synthesis of secondary data
Analytical Tools	PEST framework and comparative regional analysis
Geographical Scope	Albania, Kosovo, North Macedonia, Montenegro, Serbia, Bulgaria, Romania
Timeframe	2023–2025
Limitations	Reliance on secondary data; lack of primary interviews

B. Data Collection and Validation

Secondary data were selected for their reliability, accessibility, and relevance to the study's objectives. Inclusion criteria focused on three aspects: 1) credibility of the source, 2) thematic connection to BPO and digital transformation, and 3) the presence of recent (2023–2025) comparative data [21] [30].

The core datasets used in the analysis include major institutional publications addressing digital transformation and regional economic developments, complemented by industry-specific insights on technology adoption and outsourcing practices [21] [30] [9] [16] [2].

Triangulation was achieved through:

- Temporal triangulation: comparing multi-year data to detect trends (2023–2025) [21] [30].
- Source triangulation: was achieved by cross-referencing evidence from international institutions and regulatory bodies [21] [9] [30].
- Thematic triangulation: integrated academic, policy, and industry perspectives to ensure analytical coherence and reduce potential bias [5].

C. Analytical Process

The analytical process of this research followed five systematic stages, as illustrated in Fig. 2.



Fig. 2. Analytical process of the study. Source: author's elaboration [21] and [30].

D. Application of the PEST Framework

The PEST framework is central to this study's analysis, as it captures the macro-environmental conditions shaping BPO growth.

- Political Factors: governance, digital legislation, and EU integration policies [9].
- Economic Factors: GDP growth, FDI inflows, and fiscal incentives in outsourcing and ICT [29].

- Social Factors: workforce demographics, digital literacy, and migration [17].
- Technological Factors: broadband access, automation adoption, AI infrastructure [21] [16].

The relationship between digital infrastructure, automation, and BPO growth dynamics in Albania is further illustrated in Fig. 3. This framework provides a holistic perspective, identifying opportunities and constraints influencing Albania's competitiveness in digital outsourcing.

E. Comparative Regional Analysis

The comparative component benchmarks Albania against six economies Kosovo, North Macedonia, Montenegro, Serbia, Bulgaria, and Romania to assess its relative progress in digital readiness, labour costs, and AI adoption. The data from [21] and [29] provide comparable indicators across the region.

This dual analytical design (PEST + comparison) ensures depth and breadth, combining contextual insight with quantitative benchmarking.

F. Ethical Considerations

As the study relies exclusively on secondary sources, ethical risks are minimal. Nevertheless, all data have been cited accurately, and intellectual property rights respected in accordance with APA 7th referencing [21]. The author certifies that all interpretations are transparent, unbiased, and consistent with the original context of each source.

G. Limitations

While qualitative analysis provides rich interpretative value, the lack of primary data limits micro-level insights into firm-specific operations. Inconsistent data availability across Western Balkan states also constrains cross-country comparisons. However, triangulation mitigates these gaps by focusing on overlapping trends rather than absolute figures.

H. Summary of Methodological Contribution

This methodological framework bridges academic and policy analysis by linking macro-level reforms with sector-specific performance. The integration of PEST and comparative benchmarking enhances the explanatory power of the findings. This approach is particularly relevant for transitional economies where digitalisation, institutional development, and regional collaboration evolve simultaneously [29] [21].

IV. Findings and Discussion

A. Overview

The analysis of Business Process Outsourcing (BPO) in Albania and the Western Balkans shows that digitalisation has become a decisive factor for competitiveness in the post-pandemic economy. The application of the PEST framework and comparative benchmarking reveals a mixed but promising picture: political stability and EU integration reforms have facilitated industry growth, yet technological maturity, digital infrastructure, and skills development remain insufficient [21] [29]. The key political, economic, social, and technological factors influencing the Albanian BPO sector are summarised in Table III.

TABLE III. PEST Analysis for the Albanian BPO Sector (2023-2025)

Factor	Key Insights	Source
Political	Stable governance, EU integration reforms, improved digital legislation	[9]
Economic	GDP growth 3.2% (2025), increasing FDI, stable inflation (2.4%)	[29]
Social	Youth unemployment declining, multilingual workforce, brain drain challenges	[17]
Technological	Expansion of fibre-optic internet, early adoption of AI and RPA tools	[21]

Source: Author's synthesis [21] [9] [29].

B. Political Environment

Politically, Albania enjoys stability and an improving governance framework aligned with EU standards. The Digital Agenda 2022–2026 and participation in the EU4Digital Western Balkans Initiative have enhanced coordination in ICT and e-governance [9]. Institutional reforms have reduced administrative barriers and encouraged digital investment, but fragmentation and uneven implementation persist [21].

Comparative OECD assessments indicate that Albania demonstrates notable progress in digital governance reforms within the Western Balkan region [21]. Policy continuity and regional cooperation remain key to sustaining momentum [29].

C. Economic Factors

Albania's economy demonstrates steady growth and strong FDI inflows, especially in services and ICT. Recent economic indicators show GDP growth of 3.2% and foreign direct investment surpassing USD 1 billion, with 25% directed toward technology-driven sectors. Competitive labour costs, roughly 50% below EU averages, continue to attract BPO contracts in accounting, customer service, and data management [29].

Nevertheless, Albania's BPO market remains concentrated in low-value operations. In [18], the authors stress the need for diversification into analytics, AI integration, and financial services outsourcing. In [16], the authors observe that firms applying AI automation reduce operational costs by 20–30%, while achieving higher process accuracy. However, digital investment is mainly concentrated in Tirana, creating geographic inequality and limiting national capacity for expansion.

D. Social Factors

Social dynamics represent both strengths and weaknesses for Albania's outsourcing potential. A young and multilingual population provides a solid foundation for future digital development [17]. However, migration and skills mismatches persist, particularly in STEM-related fields. In [29], the authors report that 30% of ICT graduates immigrate annually to EU countries for better employment opportunities.

The EU4Digital programme has introduced training initiatives that promote digital literacy and cross-border mobility [9]. These efforts aim to harmonise skills across the

Western Balkans and integrate them into EU labour markets. In [32], the authors highlight that targeted reskilling in AI and automation could transform Albania's workforce into a regional digital talent hub.

E. Technological Factors

Technological readiness in Albania has improved markedly in recent years, although it remains below that of regional technological frontrunners [21]. Available indicators show that broadband coverage reached approximately 94% in 2024, with pilot 5G deployments operational in major urban centres, reflecting progress in core digital infrastructure [21]. However, comparative DESI indicators suggest that Albania exhibits lower performance in innovation capacity and advanced digital connectivity relative to Bulgaria and Romania, indicating persistent gaps in higher-order digital capabilities [9].

At the firm level, artificial intelligence adoption among Albanian BPO providers is estimated at around 35%, compared with higher adoption rates observed in Romania, Bulgaria, and Serbia [16]. This disparity highlights constraints related not only to technological availability but also to institutional and regulatory factors. In particular, the absence of comprehensive AI ethics guidelines and fully developed cybersecurity frameworks limits the depth of AI integration within enterprise operations [11].

Notwithstanding these constraints, emerging public–private partnerships within the Western Balkans Digital Initiative are contributing to the gradual reduction of technological gaps through shared cloud infrastructure, cross-border digital services, and the development of regional data centres [29]. These initiatives suggest that regional cooperation may play an important enabling role in accelerating technological upgrading and supporting the diffusion of advanced digital solutions within Albania's BPO sector.

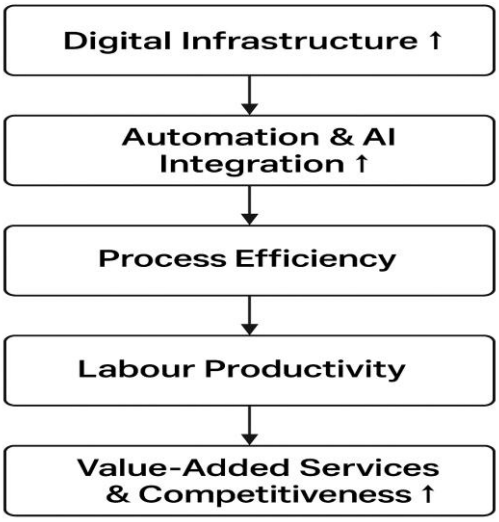


Fig. 3. Digitalisation impact on BPO growth in Albania. Source: author's conceptual model [2] [15].

F. Regional Comparison: Albania and its Peers

To assess Albania's relative position within the regional BPO landscape, a comparative evaluation was conducted across six neighbouring and peer economies: Kosovo, North Macedonia, Montenegro, Serbia, Bulgaria, and Romania. Table IV summarises key performance indicators related to labour costs, digital skills, foreign direct investment in BPO, and artificial intelligence adoption, providing a multidimensional perspective on regional competitiveness. A comparative overview of labour costs, digital skills, foreign direct investment, and AI adoption across Albania and selected regional economies is presented in Table IV.

TABLE IV. COMPARATIVE BPO PERFORMANCE INDICATORS: ALBANIA AND REGIONAL ECONOMIES (2024)

Indicator	Albania	Bulgaria	Romania	Serbia	Kosovo	North Macedonia	Montenegro	Source
Labour Cost Index	100	135	160	140	110	120	130	[21]
Digital Skills Index	68	74	77	70	63	65	67	[8]
FDI in BPO (USD m)	210	460	530	340	120	180	150	[30]
AI Adoption (%)	35	42	48	38	28	31	33	[16]

Source: [21] [30] [16] [8].

The comparative evidence indicates that Albania maintains a relative labour cost advantage compared to Bulgaria, Romania, and Serbia, reinforcing its attractiveness for cost-sensitive outsourcing activities [21]. However, this advantage is accompanied by moderate levels of digital skills and AI adoption, positioning Albania below the region's more technologically advanced BPO markets [16]. These findings suggest that cost competitiveness alone is insufficient to ensure long-term upgrading in digital BPO services.

Romania and Bulgaria demonstrate relatively higher levels of digital skills development and AI adoption compared to other economies in the region, supported by higher levels of foreign direct investment in the BPO sector [16] [29]. This combination reflects a more advanced transition toward value-added and knowledge-intensive outsourcing activities, consistent with later stages of digital transformation [21]. Serbia and North Macedonia occupy an intermediate position, combining moderate labour costs with improving digital skills and investment levels, indicating a gradual shift from cost-based to capability-driven BPO models [18] [26].

By contrast, Kosovo and Montenegro, despite maintaining comparatively lower labour costs, exhibit weaker performance in digital skills and AI adoption. This pattern highlights the limitations of cost-based competitiveness in the absence of sufficient technological capabilities and human capital development [30] [31]. The regional comparison therefore, reveals a structural trade-off: economies relying primarily on low labour costs face constraints in achieving sustainable BPO

competitiveness without parallel investments in digital infrastructure, skills formation, and innovation capacity [21] [5].

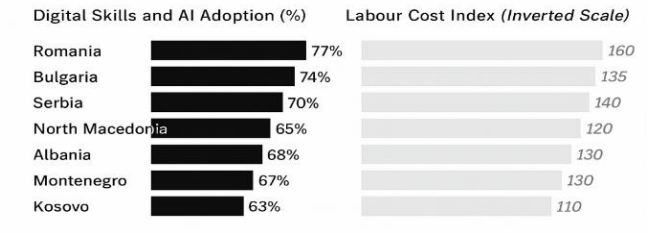


Fig. 4. Comparative digital readiness and cost competitiveness in the Western Balkans and Eastern Europe (2024). Source: [21] [30] [16] [8].

Fig. 4 complements the tabular analysis by illustrating the relationship between digital readiness and labour cost positioning across the region. The figure shows that economies with higher digital skills and AI adoption tend to be associated with higher labour costs, while lower-cost economies generally lag in advanced digital capabilities [21] [16]. Albania occupies a balanced but constrained position within this spectrum, with digital readiness exceeding that of Kosovo and Montenegro while remaining below Eastern European frontrunners [21] [29].

This intermediate positioning suggests that Albania has the potential to function as a regional bridge between cost-oriented Western Balkan economies and digitally advanced Eastern European outsourcing hubs, provided that sustained investments in human capital development, institutional coordination, and digital infrastructure are pursued [31] [26]. Overall, the regional evidence reinforces the argument that long-term BPO competitiveness increasingly depends on the alignment of institutional conditions, digital readiness, and firm-level capabilities rather than on cost advantages alone [21] [30]. These comparative insights feed directly into the conceptual framework presented in Fig. 5, which links institutional reform, digital investment, and human capital development to sustainable BPO growth.

G. Conceptual Integration

Fig. 5 synthesises the empirical findings and theoretical arguments of this study into an integrated conceptual framework that explains how digital BPO competitiveness emerges in an emerging economy context. The framework depicts a sequential and interdependent relationship between institutional alignment, digital infrastructure and innovation investment, artificial intelligence adoption in BPO operations, and human capital development, culminating in sustainable and value-added BPO competitiveness. By explicitly linking macro-level institutional conditions with micro-level firm capabilities, the model operationalizes the interaction between Institutional Theory and the Resource-Based View [9] [21] [5].

From an institutional perspective, political and regulatory alignment, particularly with EU digital governance frameworks, functions as an enabling condition that reduces uncertainty, strengthens enforcement capacity, and improves the predictability of the business environment [9] [21]. These institutional conditions influence firms' strategic decisions to invest in digital infrastructure and advanced technologies, including AI-enabled automation and data-driven service delivery [16]. In line with the Resource-Based View, such technological investments only translate into sustained competitive advantage when they are internalised as firm-specific capabilities, supported by organisational learning and skilled human capital [5] [31].



Fig. 5. Conceptual framework for the integration of business process outsourcing, artificial intelligence, and digital transformation. Source: Author's elaboration based on [21] [2] [15].

The framework further highlights the mediating role of human capital development in the digital transformation process. Investments in AI and digital infrastructure generate productivity gains and service upgrading only when firms possess the absorptive capacity to integrate these technologies into core business processes [31] [21]. This insight reinforces the argument that digital competitiveness is not driven by technology adoption alone, but by the interaction between institutional conditions and firm-level resource development [26].

Importantly, the conceptual framework moves beyond a descriptive representation by specifying directional and causal relationships that can be empirically examined. Institutional alignment is modelled as an exogenous enabling variable, digital infrastructure and AI adoption as intermediate mechanisms, and firm-level capabilities and BPO competitiveness as outcome variables. These relationships provide a clear basis for operationalization and hypothesis testing in future quantitative or mixed-methods research, for example, by examining the impact of regulatory alignment on AI adoption rates or the mediating effect of human capital between digital investment and BPO productivity [21] [30].

Finally, the conceptual relationships illustrated in Fig. 5 are fully aligned with the research propositions (P1–P3) developed in Section II(F). Together, the framework and propositions offer a transferable analytical lens for analysing digital BPO upgrading in other Western Balkan and emerging economies, while also providing practical guidance for policymakers and practitioners seeking to align institutional reforms, skills development, and technological investment in support of sustainable BPO growth [21] [26].

H. Discussion Summary

The integrated application of the PEST framework with the Resource-Based View and Institutional Theory reveals well-

defined causal mechanisms underpinning digital BPO competitiveness. From an institutional perspective, political alignment with EU digital governance frameworks reduces regulatory uncertainty and enhances enforcement capacity, thereby lowering barriers to the adoption of advanced digital technologies such as artificial intelligence and cloud-based systems [9] [21]. This institutional stability enables firms to commit resources to digital infrastructure and to transform technological inputs into firm-specific strategic assets, consistent with the logic of the Resource-Based View [21] [5].

From an economic standpoint, the findings demonstrate that although low labour costs continue to attract outsourcing activities, they do not constitute a sustainable source of competitive advantage when considered in isolation [21]. Instead, institutional reforms and targeted fiscal incentives interact with technological conditions by shaping firms' incentives and capacity to invest in automation and AI adoption [4] [16]. Social factors—particularly the availability of skilled human capital and advanced digital competencies—play a mediating role in this process by determining whether technological investments can be internalised as organisational capabilities rather than remaining operational tools [17] [19] [31].

A central insight emerging from the analysis is the structural trade-off between maintaining cost competitiveness and investing in high-skilled, and therefore more expensive, digital and AI-related human capital [5] [21]. While cost advantages facilitate entry and short-term expansion within global outsourcing markets, long-term digital upgrading increasingly depends on firms' ability to absorb higher labour costs associated with advanced skills, organisational learning, and innovation capacity [16] [31]. This tension underscores the limitations of a purely cost-based outsourcing model and highlights the need for a strategic transition toward capability-driven growth supported by institutional alignment and sustained human capital investment [9] [26] [30].

Importantly, technological factors do not emerge as independent drivers of competitiveness, but rather as outcomes of interactions between institutional conditions and firm-level resource development [21]. Political and regulatory reforms (PEST–Political) create the conditions for firms to accumulate digital and AI-related capabilities (RBV–Technological), while economic and social factors influence the speed and depth of this transformation [5] [26]. This interaction explains why economies with broadly similar cost structures can experience markedly different digital transformation trajectories within the BPO sector [21] [30].

From a theoretical standpoint, the Albanian case provides evidence that institutional alignment alone is insufficient to generate sustainable competitive advantage in the absence of firm-level absorptive capacity. This finding refines the Resource-Based View by emphasising the mediating role of institutions in shaping the value and deployability of firm-specific resources in emerging economies. Simultaneously, it extends Institutional Theory by demonstrating how governance frameworks interact with firm-level heterogeneity to produce divergent digital upgrading outcomes, even under comparable regulatory conditions [21] [5] [30].

V. Conclusion

A. Summary of Findings

The findings of this study offer important theoretical implications for understanding digital transformation in the BPO sector of emerging and transitional economies. By integrating the Resource-Based View and Institutional Theory, the analysis demonstrates that sustainable competitive advantage does not arise from cost efficiency alone, but from the interaction between institutional alignment and firm-level capability development. From a Resource-Based View perspective, advanced digital skills, organisational learning, and innovation capacity emerge as critical intangible resources that determine firms' ability to upgrade toward higher value-added BPO services [21]. However, the Albanian case shows that these resources cannot be developed or leveraged effectively in the absence of supportive institutional frameworks.

Institutional Theory further explains how regulatory alignment with EU digital governance frameworks, policy coherence, and enforcement capacity shape firms' incentives and absorptive capacity for adopting artificial intelligence and automation technologies [5] [9]. The evidence from Albania refines existing theoretical debates by illustrating that institutional reforms function primarily as enabling mechanisms rather than direct sources of competitiveness. In digitally transforming emerging economies, institutions condition the extent to which firms can convert technological investments into strategic resources, thereby mediating the outcomes predicted by the Resource-Based View [21] [29].

From a practical and policy perspective, the study provides actionable insights for policymakers and practitioners seeking to foster sustainable BPO development. The results indicate that reliance on low labour costs and fiscal incentives, while effective in attracting initial outsourcing activity, is insufficient for long-term competitiveness without parallel investments in digital skills, innovation ecosystems, and governance capacity [29]. Strengthening vocational and higher education programmes in AI, data analytics, and cybersecurity, alongside improving institutional coordination, is therefore essential for enabling firms to move up the BPO value chain [17] [32].

Moreover, the comparative regional analysis highlights the importance of positioning Albania within a broader Western Balkan digital ecosystem. As an intermediate economy between cost-oriented peers and digitally advanced Eastern European markets, Albania has the potential to act as a regional bridge if national digital strategies are aligned with regional integration initiatives such as EU4Digital and the Regional Economic Area [9] [29]. The conceptual model proposed in this study (see Fig. 5) offers a transferable framework for other Western Balkan economies, providing guidance on how institutional reforms, human capital development, and technological investment can be jointly leveraged to support value-added BPO growth and regional convergence [21] [26].

B. Strategic Directions

Based on the analysis, six strategic directions are recommended to advance Albania's BPO and digital transformation agenda:

1) Enhance digital infrastructure and regional connectivity: Accelerate broadband and 5G deployment beyond Tirana through public–private partnerships, focusing on regional cities and cross-border ICT projects [29].

2) Institutionalise digital governance: Establish a central Digital Transformation Authority to coordinate policy implementation and monitor progress under EU-aligned digital frameworks [21].

3) Develop and retain human capital: Integrate AI, data analytics, and cybersecurity into university curricula. Strengthen vocational training programmes and provide fiscal incentives for companies investing in workforce upskilling [9].

4) Promote Research and Innovation: Create Digital Innovation Hubs in cooperation with Horizon Europe and regional universities to foster applied research, start-up growth, and knowledge transfer [18].

5) Foster regional collaboration: Expand cooperation with neighbouring Western Balkan economies (Kosovo, North Macedonia, Montenegro, and Serbia) through joint AI hubs, shared cybersecurity networks, and regional outsourcing consortia [26].

6) Align BPO development with sustainability and ESG standards: Introduce green outsourcing incentives and include sustainability metrics in national digital strategies. Aligning with the EU Green Deal will ensure environmentally responsible and socially inclusive BPO growth [11].

C. Theoretical and Practical Implications

The integrated application of the *Resource-Based View and Institutional Theory* provides a coherent analytical lens for interpreting Albania's digital transformation in the BPO sector. From a Resource-Based View perspective, sustainable competitive advantage is derived from the accumulation and effective deployment of intangible firm-level resources, including advanced digital skills, organisational knowledge, and innovation capabilities [21]. Institutional Theory complements this view by explaining how governance structures, regulatory alignment, and normative frameworks condition firms' ability to develop and leverage such resources, thereby facilitating or constraining digital adoption and upgrading processes [5].

From a practical and policy-oriented perspective, the findings demonstrate that digital transformation can function as a catalyst for socio-economic development in transitional economies when institutional alignment and human capital development progress in tandem. The conceptual model proposed in this study (see Fig. 5) offers a transferable analytical framework that can be applied across the Western Balkans to guide policymakers and practitioners in designing strategies that align national digital agendas with regional integration initiatives. By linking institutional reforms to firm-level capability development, the model provides actionable insights for fostering value-added BPO services and strengthening regional digital competitiveness.

D. Limitations and Future Research

While the qualitative research design provides rich analytical insights, the exclusive reliance on secondary data constrains empirical validation at the firm level. Future research could adopt mixed methods approaches by incorporating surveys and semi-structured interviews with BPO managers, policymakers, and industry stakeholders to test and refine the proposed conceptual relationships. In addition, longitudinal analyses extending beyond 2025 would enable systematic assessment of post-transformation dynamics, including the evolution of AI adoption, productivity gains, and organisational capability development [29].

Further research could also expand the social dimension of digital BPO transformation by examining issues of gender inclusion, workforce diversity, and job quality in digitally enabled service sectors. Existing evidence suggests that inclusive digitalisation enhances innovation capacity and supports more equitable labour market participation [26]. Finally, comparative studies involving EU candidate and Western Balkan economies could provide deeper insights into how regional cooperation, regulatory convergence, and shared digital initiatives influence competitiveness and economic convergence across emerging markets [26] [30].

E. Concluding Remarks

Albania's BPO sector stands at a strategic crossroads. While political alignment with EU frameworks, cost competitiveness, and a growing digital ecosystem provide a solid foundation for development, the sustainability of this trajectory depends on decisive investment in education, advanced digital skills, and effective governance structures [9] [21]. Without such coordinated action, the sector risks remaining locked into low-value outsourcing activities despite favourable macroeconomic conditions [5] [30].

The findings confirm that digital transformation in the BPO sector is not a purely technological process, but a structural evolution shaped by the interaction between institutional alignment, human capital development, and firm-level capabilities [21] [5]. By fostering innovation-oriented policies, strengthening regional partnerships, and prioritising skills upgrading, Albania can transition from a cost-based outsourcing destination toward a digitally integrated, value-added BPO hub, contributing to long-term national competitiveness and regional economic resilience [26] [30].

REFERENCES

[1] Accenture, "Reinventing BPO through automation and cloud integration," Accenture Research, Dublin, 2023.

[2] Accenture, "The future of intelligent BPO: Cloud, AI, and automation," Accenture Research, Dublin, 2024.

[3] S. Alice and N. Khan, "AI-driven process optimisation in European outsourcing industries," J. Bus. Technol. Res., vol. 19, no. 3, pp. 211–229, 2024.

[4] Deloitte, "AI-driven outsourcing models: Europe and emerging markets," Deloitte Insights, London, 2024.

[5] Deloitte, "Technology-driven outsourcing in emerging Europe," Deloitte Research, London, 2025.

[6] Digital Minds BPO, "Key outsourcing trends for 2025: The future of outsourcing in 2025," Aug. 6, 2025. [Online]. Available: https://digitalmindsbpo.com/blog/key-outsourcing-trends/

[7] European Commission, "Albania progress report on digital integration," Brussels, 2023.

[8] European Commission, "Digital Economy and Society Index (DESI) 2024: Albania report," Brussels, 2024.

[9] European Commission, "EU4Digital Western Balkans Initiative: Regional cooperation for digital transformation," Directorate-General for Neighbourhood and Enlargement Negotiations, Brussels, 2024.

[10] EY, "Outsourcing and sustainability in the digital economy," EY Global, London, 2024.

[11] EY, "Global outsourcing survey 2025: Sustainability and innovation," EY Insights, London, 2025.

[12] F. Fornari et al., "Digital twins of business processes: A research manifesto," arXiv preprint arXiv:2410.08219, 2024.

[13] Gartner, "Trends in robotic process automation and AI-based BPO," Gartner Research, Stamford, 2024.

[14] Harvard Business Review, "Rethinking outsourcing for the digital era," Harv. Bus. Rev., vol. 102, no. 4, pp. 88–97, 2024.

[15] IBM, "The AI-augmented workforce: Future-ready automation strategies," IBM Global Report, 2023.

[16] IBM, "AI adoption in global BPO industries," IBM Research Report, 2024.

[17] INSTAT, "Labour market and ICT skills report for Albania," Institute of Statistics, Tirana, 2024.

[18] KPMG, "Digital outsourcing trends in the Balkans: Regional competitiveness," KPMG Central Europe, Vienna, 2024.

[19] OECD, "AI skills and the future workforce in emerging Europe," OECD Publishing, Paris, 2023.

[20] OECD, "Global skills report 2024: Competitiveness in the digital age," OECD Publishing, Paris, 2024.

[21] OECD, "Digital transformation outlook for emerging economies," OECD Publishing, Paris, 2025.

[22] S. Proietti and R. Magnani, "Assessing AI adoption and digitalisation in SMEs: A framework for implementation," arXiv preprint arXiv:2501.08184, 2025.

[23] PwC, "BPO in Central and Eastern Europe: Competitive landscape and future scenarios," PwC Poland, Warsaw, 2023.

[24] UNCTAD, "AI and global value chains: Opportunities for emerging economies," United Nations, Geneva, 2023.

[25] UNCTAD, "Digital economy report 2024: Artificial intelligence and development," United Nations, Geneva, 2024.

[26] UNCTAD, "World investment report 2025: Services and nearshoring trends," United Nations, Geneva, 2025.

[27] World Bank, "Innovation and employment in the Western Balkans," World Bank, Washington, DC, 2023.

[28] World Bank, "Digital economy assessment for the Western Balkans," World Bank, Washington, DC, 2024.

[29] World Bank, "Albania economic update 2025: Technology and human capital," World Bank, Washington, DC, 2025.

[30] World Bank, "Western Balkans regional economic report 2025: Competitiveness and convergence," World Bank, Washington, DC, 2025.

[31] World Economic Forum, "Future of jobs report 2024: Digital skills and automation," WEF, Geneva, 2024.

[32] XMC BPO, "Why digital skill development is key for BPO employees in 2024," Nov. 13, 2024. [Online]. Available: https://xmcbpm.com/why-digital-skill-development-is-key-for-bpo-employees-in-2024/.

Framework for Ethical Acquisition of User-Data to Improve Recommendation Models' Accuracy in Digital Systems

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***Abstract*—The modern digital ecosystem has evolved into a pervasive, opaque system where platforms collect and infer personal data through nearly every online action, search queries, email content, browsing history, and app usage, without transparency. Justified as a means to deliver "relevant" content and ads, this approach undermines user privacy, introduces bias, and normalizes surveillance. Through a comprehensive literature review, this study sought to: critically analyze the current landscape of user tracking, profiling, and privacy violations in online platforms and to evaluate the impact of existing legal, technical, and platform-driven mechanisms like GDPR, CCPA, ATT, and Privacy Sandbox in protecting user autonomy. It was learned that the current frameworks fall short by mostly being policy-based and having hard-to-access user controls. And a major flaw in existing systems is the assumption that all digital behavior reflects actual user preference, overlooking shared devices, accidental clicks, and non-user actions. To validate these insights, a survey of 572 privacy-aware participants was conducted, where nearly 71% preferring a proactive solution over passive regulatory frameworks and hard-to-navigate privacy menus/dashboards. Building on these findings, this study proposes a framework: a digital platform where individuals actively create and manage modular preference profiles, categorized by app type or content domain, which can be selectively and consensually shared with platforms in a standardized format. This concept facilitates high-quality, context-rich datasets for algorithms, enhancing personalization and recommendation models' accuracy and performance. By shifting from forced surveillance to invited participation, this approach advances ethical data-sourcing, enhances algorithmic accuracy, and aligns with SDG 9 and SDG 16 by prioritizing responsible digital solutions, process innovation, and safeguarding user autonomy.**

Keywords*—Data handling; data privacy; online tracking; data collection; user profiling; model accuracy; ethical AdTech; open standards; user autonomy; SDG 9; SDG 16; process innovation

I. Introduction

Today's online environment is mostly about surveillance advertising. You can wish for something, watch a video, or just get news somewhere on the internet, and in either scenario, there is a greater likelihood that you will have your activity monitored, not only on that website, but on the entire internet environment. This mass cyber surveillance is traditionally described as a means to provide users with "more relevant Content". This justification is no longer accepted by privacy experts, Data Protection Regulators, and increasingly by everyday users.

Regulations like the EU's General Data Protection Regulation (GDPR), America's California Consumer Privacy Act (CCPA), Apple's App Tracking Transparency (ATT), and Google's Privacy Sandbox have taken steps to curb invasive data collection. While such efforts have made some progress on the transparency and control fronts, they largely shy away from ending the underlying machinery of surveillance capitalism. Instead, they've merely shifted how tracking is accomplished rather than whether it is accomplished. For example, ATT prevents third-party tracking on Apple devices but continues to allow Apple to build behavioral profiles in-house. In a similar manner, Privacy Sandbox prevents cross-site tracking while still allowing ad targeting systems based on aggregated user information.

The contemporary online advertising economy is based on users consenting, at least implicitly, to being monitored by virtue of accessing digital services. This consent is typically buried in unreadable terms of use or covered by manipulative interface design (a "dark pattern"). The result is that users are progressively profiled on the basis of search history, device use, app use, online and offline interpersonal interaction, geolocation, and even email content with little or no awareness or control. User's personal data is no more personal due to this excessive nonconsensual data collection.

These have effects greater than nuisance. Incorrect or misattributed profiling will warp the user experience, e.g., a Beach Holiday ad having inappropriate images displayed in a game application that is being played on a kid's device, or a shared device's search history leading to irrelevant or even inappropriate ad suggestions. Moreover, users' interests are usually deduced from noisy data, misplaced clicks, one-time browse for an alternative, or passing interest, thus constructing a tilted digital profile of the user different from their actual interest.

Despite data protection laws and consent mechanisms, most tracking is technically sophisticated and legally evasive. Companies get to play by the rule book without playing by its spirit. Fingerprinting, real-time bidding (RTB), and server-side tracking tend to get round even very stringent consent mechanisms. Law is either too slow to keep up, or too vague to effectively implement. And most importantly, they rarely ever give users a real choice: opting out typically means denying a service or receiving generic content and advertising. This is an extremely worrying scenario, not only in terms of privacy, but

also on a system design level. It is based on nonconsensual data inference and on imbalanced power dynamics between users and platforms.

It is important to clarify the scope and intent of this work. This study does not propose a new recommendation algorithm, personalization pipeline, or machine learning architecture, nor does it seek to benchmark predictive performance against existing models. Instead, the contribution lies at an earlier and often overlooked stage of the personalization lifecycle: the ethical and technical acquisition of preference data itself. While existing consent dashboards, preference managers, and data portability tools focus primarily on regulatory compliance or post-hoc control, it continues to rely on behaviorally inferred, noisy, and platform-owned data. In contrast, the framework proposed here introduces a user-authored, platform-agnostic preference declaration mechanism designed to replace inference with explicit intent. The central claim is not algorithmic novelty, but that recommendation and analytical models, regardless of their internal design, benefit structurally from cleaner, context-aware, and voluntarily provided accurate preference data.

This study pursues five core objectives:

- To critically analyze the current landscape of user tracking, profiling, and privacy violations in online platforms and advertising ecosystems.
- To evaluate the strengths and limitations of existing legal, technical, and platform-driven mechanisms like GDPR, CCPA, ATT, and Privacy Sandbox in protecting user autonomy through literature review.
- To conduct a survey to get real responses from people that have knowledge of the different Data Protection Acts, Online Data Privacy, and modern Advertising industry.
- To propose a user-centric conceptual framework for preference data sharing system that is consensual, transparent, secure, and technically feasible. This approach not only respects control by users, but it also has the potential to yield more accurate data and truly personalized relevance.
- To design a simple Technical Demo of the proposed solution. The solution is to be kept simple and easy to implement. So, it can be created by any organization or developer. Standardized downloadable format for easy integration.

Building on these objectives, this study contributes a conceptual and technical framework for ethical, user-governed preference data acquisition that addresses both privacy and system-performance limitations of contemporary personalization infrastructures. In place of being passively tracked for data with an effort to guess what they would like, users would explicitly state what their interests are in a structured and shareable form. For building a social profile, users may have multiple interest profiles, customized for specific contexts like shopping, social, video content, or games, and apply them selectively to apps or sites. By enabling individuals to explicitly construct, manage, and selectively share structured preference profiles, the framework reduces reliance on inferred behavioral signals that are frequently noisy, contextually misleading, or generated without meaningful consent. The proposed approach has implications beyond privacy protection alone: it offers a practical pathway toward higher-quality datasets for recommendation and data analysis models, reduces preprocessing overhead associated with behavioral noise, and supports interoperability through standardized, platform-independent data formats. From a broader perspective, the framework advances responsible digital system design by aligning personalization mechanisms with user autonomy, informed consent, and ethical data sourcing principles.

The remainder of the study is organized as follows: Section II reviews existing literature on behavioral tracking, privacy regulation, and personalization systems, highlighting conceptual and technical gaps. Section III describes the research methodology and survey design used to gather real users' views. Section IV presents results and discussion of empirical findings. Section V presents the proposed user-governed preference framework, its design principles, and integration patterns. It also presents a simple website for demonstrating the framework's workings. Section VI discusses the challenges and limitations of such a framework. Section VII suggests implementation roadmap and recommendations for future work. Finally, Section VIII concludes the study.

II. Literature Review

There has been considerable effort on how modern digital advertising platforms use machine learning and behavioral data for targeting, with inherent trade-offs to systemic inefficiency and with privacy. In [1], the authors built a twin-framework consisting of an auction mechanism and machine learning to examine in-app advertising on mobile devices in Asia. Surprisingly, while improving click-through rates by over 66.80% when compared to a baseline, [1] discovered that optimal ad-network revenues may not always go with optimal behavioral targeting regime. This is a phenomenon reflecting a market misalignment where privacy-preserving strategies may, paradoxically, better match with greater interest of users as well as long-term platform stability than with high-dimensional personalization systems.

On the social media front, [2] examined how strong consumer–brand relationship can overcome subjective risks in personalized advertising. Such an experiment confirmed high levels of affiliation countering concerns over privacy, while poor connections drive resistance, with indiscriminate targeting likely to backfire on fragmented audiences. In support, [3] also provided evidence that personalized advertising has a positive effect on value perceived and purchase intention, but only with low concerns over privacy. The risk is that intrusive targeting will destroy campaigns, and in particular when communicated covertly or in an unsuitable manner. Political advertising based on personality was examined by [4], with matching users' psychographic profiles showing a measurable effect on persuasion. These results also attest to escalating sophistication in targeting conduct, as well as raising ethical concerns, when conducted covertly and without users' consent.

Even as platforms try in the direction of transparency, tools prove to be inadequate. Apple's Privacy labels, intended to make data more transparent, have been found by [5] to be poorly readable by users. Participants in that research were baffled by jargon and structural inconsistencies between app permissions and data disclosures, cutting off its day-to-day usefulness. This is representative of larger concerns addressed in [6], where post-GDPR web ecosystem continues to reveal glaring shortcomings. Although formal transparency was increased by that regulation, real usability and accessibility of data rights remain absent, at times even actively disenabled by "dark patterns".

More structural analysis is offered by [7], with personal information introduced not as a commodity in and by itself, but as a source for valuation regimes for Big Tech. As explained, "Techcraft" is how these companies force engagement toward predictive values on an economic level, eliminating concerns with consent or ownership altogether. This deeper structural development is behind this argument for redesigning value extraction from users' data, in aid of alternative systems such as those offered here. Attempts at syntheses and coordination on research in online behavioral advertising's distributed landscape are offered by [8]. These synthesize nearly two decades' worth of research and suggest a shortfall of integrative direction, and issue a call for integrative strategies and enhanced theory-based foundations. In contrast, [9] offers a behemoth, curated database of over a million privacy policies and reveals how these have progressively become more impenetrable over recent years. Despite policy measures like the GDPR, underlying disclosures continue to remain absent or obfuscated, suggesting a gap between practice and policy.

In [10], Protection Motivation Theory (PMT) was employed to study privacy practice and concluded that even when users perceive threats as serious, they perceive themselves to be powerless when addressing them. The powerlessness, combined with low actual-world sensitive data protection effort (e.g., cookie deleting) exhibits one deficit in empowerment as much as system design. The framework here in this study addresses this very question posed by [10]. Strategically, [11] analyzed how firms diverge with data strategy, showing how competition involving regulatory constraint and consumer mistrust produces different organizational responses, anything from aggressive monetization to defensive data sharing. Work here notes that concern with the privacy-performance trade-off is not one-size-fits-all and that company strategy has to take both ethical design as much as technical innovation into consideration. Computational research on predicting users' responses was summarized by [12], where the authors reported on pervasiveness in the environment by ML models. Technically, as impressive as this research is, it omits explorations on transparency or on augmenting user control, and thus exhibits that while algorithmic efficiency improves, that on trust, as much as compliance with regulations, lags behind.

The state of tracking in the post-cookie era was investigated in detail by [13], with an outcome such that tracker methods have migrated towards stateless ones like fingerprinting, ID leakage, and ID synchronization. Most disconcertingly, over 75% is taking place before users have even had a choice to use a cookie, or while opting-out actively. This helps to firmly substantiate this research's first hypothesis, that consent mechanisms are ineffective, and tracking has migrated towards more long-term and invisible methods. This study provided key empirical evidence for this theory that consent banners, as presently implemented, are symbolic rather than real. On the other hand, [14] took a human-focused approach, analyzing how users use privacy-enhancing technologies (PETs) and finding a broad disconnect between what sites are offering and what users use. Based on the survey by [14], it was concluded that most users are becoming educated on privacy features through unofficial sources (friends, relatives, etc.), suggesting a systemic failure with current systems to empower users. The study provides an added insightful perspective for this research in that it helps to illustrate the futility of current PET integrations, once again supporting a shift towards more open and consensual data sharing systems.

The behavioral impacts of personalized advertising are examined by [15] and show persuasive possibilities as well as the dangers of online behavioral advertising (OBA). Using SEM methodology allows systematic observation involving the double effect: personalization maximizes engagement, but ad avoidance is strongly implicated with concern about privacy. Despite its consumer-behavior orientation, it helps to identify how data exploitation strategies influence user trust as well as behavior, again affirming ethical redesigning preference data-sharing systems as a necessity.

On the development front, [16] they consider how ad networks target app developers with UI framing and nudging. Developers preferred less intrusive types of adverts when subjected to more transparent effects on privacy. This introduces an influential stakeholder, the developer, to the world of privacy. It is germane because current systems do not even provide for how backend decisions by developers shift users' data exposure. This discovery highlights how much ethical nudging by developers at a holistic level is critical. The authors concluded their findings by saying that "the developers need transparent options". And that is exactly what this proposed framework is. It does gives control in the users' hands and provides the developers and all other entities involved here with accurate data directly from the users themselves.

On the other hand, [17] takes a macroeconomic view of GDPR and argues that it has de facto concentrated monopolists like Google and Facebook. The paper attributes regulatory efforts to competition concerns, hypothesizing that current data protection laws, for all they benefit privacy, have enabled data power to shift towards accumulating in its hands. This is a sober reminder: unless novel models disrupting data collection monopolies are introduced, regulation alone may solidify the very mechanisms it aims to regulate. By contrast, [18] conduct a technical analysis of Apple's ATT and Privacy Nutrition Labels and report partial success. While tracking by IDFA has diminished, fingerprinting and cohort-based tracking remain unabated. Some apps even use backend logic or server-side code to circumvent limitations. These developments highlight the need for more transparent, enforceable, and attestable privacy mechanisms. Furthermore, the unclear nature of some disclosures also presents a case for a system-enforced, user-transparent privacy mechanism.

Adding more evidence to these claims, [19] also illustrates that Android apps largely engage in third-party tracking without consent, in violation of GDPR and UK privacy laws. Tracking libraries offload the burden on developers with little support or compliance frameworks. This is a systemic fault, everyone is guilty, no one is in charge, further supporting this study's approach of compliance by design frameworks. An online survey was conducted by [20] to examine how users perceive algorithmic profiling in Facebook. The findings illustrate users often do not appreciate or mistrust categories inferred to profile them, and there is a lack of transparency and an emotional disaffection with profiling systems. The description "algorithmic disillusionment" provided by [20] is particularly insightful; without users' comprehension or trust in algorithmic systems, consent is invalid. The overall message from [20] is the problem addressed by this study, which is that the users are tracked through their usage of the platform, in order to profile them, which inevitably results to inaccurate profiles. Then, [21] provide an exploration into the legality behind Real-Time Bidding (RTB), finding it by its very nature inconsistent with GDPR because of its inability to secure a legal basis for data processing, inability to meet transparency requirements, and inherent insecurity. A direct source of validation for a fundamental argument made by this research, by their legal analysis, is that AdTech infrastructure is, by its nature, incompatible with legal and ethical standards. Therefore, the regulations are not enough to secure a user's data.

On analyzing mobile and online environments' privacy dynamics, several studies have offered critical observations regarding digital platforms' management of users' information and its impact on the protection of privacy.

The research in [22] leverages Android and iOS apps' comparative privacy capabilities and reveals unsettling behaviors on both platforms. Third-party tracking, as well as sharing unique identifiers, were both prevalent, even among apps designed for children. While there was less advertising-based tracking on iOS apps, they were discovered to have more frequent access to kids' devices' locations than Android apps. This renders simplistic assumptions about the superiority of one platform's way over that of its competitor, and addresses the challenges that both platforms have compliance with privacy legislation such as GDPR. The evidence and analysis provided by [22] align with this study's underlying concerns, as pervasive disrespect for privacy legislation addresses the pressing necessity for a better privacy solution based on transparency and consent.

Likewise, [23] investigation on how users' opt-out of tracking cookies is impacted by legal and technical competence in terms of data collection highlights how enabling legal competence has encouraged consumers to actively opt out from data collection actions. Especially in recent years with such legislation as GDPR aimed at enabling consumers to exert greater control over personal data, the studies highlight that consumers are more likely to act (for their own online safety) when they have information about what legal ramifications follow data collection, and this serves to further highlight how better education for users is needed in conjunction with implementing privacy legislation. This aligns with the goal of creating systems that not only adhere to legal requirements but also empower users with greater choice and understanding. On a technical note, [24] demonstrates how conclusions are drawn differently when popular automatic crawlers are utilized compared to more realistic configurations for making measurements on the web in terms of privacy. The researchers argue that existing measuring tools are not able to adequately mimic actual users' experiences, and partial or incomplete conclusions form as a result. The research highlights that unless tools are adapted to actual users' action, seminal threats to privacy can be overlooked. This highlights a glaring shortfall in how research on privacy is conducted and aligns with the need for better, more accurate, and people-oriented methodologies for measuring privacy, an area on which this research aims to contribute forward-looking responses.

The use by online advertising of cookies is analyzed by [25] in considerable detail, by laying out how cookies form an extensive digital market infrastructure. The employment as a building element for online marketing and tracking by cookies is challenged here, with doubts over such systems' viability, particularly in this day when increased regulatory scrutiny exists. This consideration on "datafication" on human action is an important one in balancing trade-offs over commercialization of data and privacy. This research lends weight to concerns over having to rebuild ethics and operating procedures for tracking data and calls for innovative paradigms to move forward beyond an established cookie paradigm. Another critical analysis on how adoption has been impacted by GDPR is provided by [26], with e-commerce revenues and pageviews down by 12% when implemented. This economic analysis demonstrates that privacy regulations, while crucial for consumer protection, also carry real consequences for website performance and revenue. The findings here are key as these reflect more subtle consideration for trade-offs over protection for people's financial performance as well as people's privacy, an issue at the core of this research. By looking at techniques that minimize intrusions on people's privacy without sacrificing functionality, this research tries better to balance people's needs for protection of information with usability.

For further evidence supporting the whole regulatory framework, [27] study the impact of GDPR's opt-in principle, and conclude that it reduced consumers by 12.5%, with the remaining consumers becoming more traceable and therefore more valued by advertisers. The impact is a demonstration of the perverse effect of privacy legislation, whereby users of privacy influence others' actions, to advertisers' benefit. It is representative of the need for more sophisticated models for users' consent, that are able to exclude such privacy spillovers while maintaining control by users over information. One such design area for privacy features was proposed by [28], with particular consideration for the point that users struggle with getting around privacy features on the Internet of Things (IoT). This theoretical framework [28] proposed on building effective privacy features can also apply to other platforms, as an inspiration to building systems offering users more control over information regarding them. The idea behind this user-centered design is at the heart of the proposed research in that it is trying to build a system that not only complies with protocols on privacy but also enhances the user experience with open and

informed choice-making that users themselves take and communicate to platforms on voluntary grounds.

The dynamics behind cookie consent under GDPR compliance have been studied intensively by [29] and [30]. In [29], the researchers were interested in how cookie banners fail to provide users with adequate and accurate information to ensure consent, with an enormous 89% of banners in breach of legislation. This research frankly challenges the validity of current consent mechanisms on grounds of a presumed deficit in transparency and linguistic abuse as key barriers to users' comprehension. Conversely, [30] provides an engineering-based answer in the form of the CookieBlock add-on, grouping cookies automatically and imposing GDPR compliance. The research presents an implementable answer to concerns raised by research such as that by [29], taking into consideration how much scope there exists for tools to automatically assist users' privacy regardless of website cooperation.

On a slightly different subject, [31] investigated online student and parent cyberbullying behavior with an extension of the Theory of Planned Behavior (TPB) with a new construct, cyber parenting, to better explain online conduct. Its findings indicate a growing need for healthy digital conduct and surveillance, particularly by and on behalf of younger users and parents. This behavioral aspect has special relevance to the modern debate over digital marketing conduct now, where users' conduct, all too often removed from context or misinterpreted, fuels sneaky preference profiles. Just like how research by [31] demands worth from precise, conduct-informed data-gathering with regard to productive insight, this current concept proposes an alternative paradigm where users explicitly articulate ad/content interest themselves. Digital literacy and clear policies are necessary in this era. The proposed framework here avoids such artifacts like device-shared misguided presumptions or misclicks and reinstates users' agency, in line with the overall goal of ethical digital practice.

The comprehensive 2023 survey of [32] on American views of data privacy reveals a widespread erosion of public trust and a deep sense of powerlessness among users in the face of large-scale data collection practices. With 81% of respondents expressing concern over how companies use their data and 73% admitting they feel little to no control over that data, the findings highlight a pressing contradiction between user expectations of autonomy and the opaque, algorithm-driven surveillance ecosystems currently in place. Even more striking is the nearly universal concern over data practices affecting children, 89% worry about social platforms holding personal information on minors, and 85% object to advertisers using behavioral data to target young users. As platforms increasingly integrate AI to personalize content, nearly half (48%) of Americans find such applications unacceptable, yet remain trapped in systems where opting out is either obscured or functionally impossible.

Lastly, [33] offers a better perspective into the current global perception and operational stance on digital privacy, reinforcing the urgency and credibility of user-centric data governance models. With over 2,600 respondents across 12 countries, the study identifies strong global support for privacy legislation, 86% of organizations now view such regulations positively, marking a noticeable year-over-year increase. This reinforces that companies are not just legally compelled but also strategically motivated to respect user privacy. At the same time, nearly all participants (96%) asserted that privacy investments yield greater benefits than costs, underscoring a growing recognition that responsible data practices are not a trade-off but a competitive advantage. The study's findings validate the broader shift in enterprise thinking, which gives strong credence to the need for a transparent, structured, and user-authored preference platform as both a privacy measure and an ethical data-sharing personalization solution.

A comparative analysis of existing personalization, privacy, and tracking mitigation approaches versus the proposed user-governed preference framework is summarized in Table I below. Collectively, the reviewed literature demonstrates that contemporary personalization and advertising systems are constrained by a shared structural dependency on inferred behavioral data. Across regulatory, technical, economic, and human-centered perspectives, existing approaches attempt to mitigate harm through transparency tools, consent mechanisms, anonymization techniques, or post-collection controls. However, these interventions operate downstream of the core design assumption that user preferences must be *observed*, *predicted*, or *approximated* from activity traces. This assumption persists even when tracking is partially restricted, anonymized, or made less identifiable, resulting in persistent noise, contextual misinterpretation, and diminished user trust. The literature, therefore, converges on a common limitation: current systems focus on controlling or obscuring data collection practices rather than rethinking the origin and authorship of preference data itself.

Moreover, while several tools and extensions aim to block, reduce, or anonymize tracking, they remain platform-specific, require continuous maintenance by developers or organizations, and frequently shift the burden of privacy protection onto users without offering a constructive alternative. Anonymization-based approaches, while reducing identifiability, often degrade content relevance and recommendation quality, particularly in contexts involving shared devices or younger users, where contextual sensitivity is critical. Notably absent from the literature is a system-level framework that replaces behavioral inference with explicit, user-authored preference declaration in a standardized and portable format. This gap motivates the present work, which reframes ethical personalization not as a problem of limiting surveillance, but as one of redesigning how preference data is generated, owned, and shared at the source.

The following sections, namely subsection “A” and subsection “B” are extended explanations for the conclusive data in Table I.

TABLE I. COMPARATIVE ANALYSIS OF EXISTING PERSONALIZATION, PRIVACY, AND TRACKING MITIGATION APPROACHES VERSUS THE PROPOSED USER-GOVERNED PREFERENCE FRAMEWORK

Dimension	Behavioral Tracking–Based Personalization	Regulatory & Consent-Based Mechanisms	Privacy Tools & Tracking Blockers	Anonymization & Aggregation Approaches	Proposed User-Governed Preference Framework
Primary Data Source	Implicit behavioral signals (clicks, views, dwell time, device data)	Same as tracking systems, with legal constraints	Same as tracking systems, partially suppressed	Behavioral data after de-identification	**Explicit, user-authored preference declarations**
Mode of Data Acquisition	Passive, continuous surveillance	Passive collection with formal consent	Passive collection with selective blocking	Passive collection with identity masking	**Active, voluntary user input**
User Awareness	Low to none	Limited, often symbolic	Moderate, tool-dependent	Low	**High and intentional**
User Control Granularity	None	Coarse (opt-in / opt-out)	Binary (block / allow)	None	**Fine-grained, category- and context-level**
Reliance on Behavioral Inference	Core dependency	Core dependency	Core dependency	Core dependency	**None**
Data Noise & Misattribution	High (misclicks, shared devices, incidental actions)	High	High	High	**Low (self-declared intent)**
Context Sensitivity	Poor	Poor	Poor	Poor	**Explicitly contextual via multiple profiles**
Impact on Recommendation Accuracy	Variable, often inflated by noise	Unchanged	Often degraded	Often degraded	**Improved via cleaner input data**
Effect on User Experience	Intrusive, opaque	Fatiguing, confusing	Disruptive or incomplete	Often less relevant	**Transparent and intention-aligned**
Suitability for Children / Shared Devices	Poor	Poor	Poor	Poor	**High (explicit profiles avoid misattribution)**
Platform Dependency	High (platform-owned data)	High	High	High	**Platform-agnostic**
Interoperability Across Platforms	None	None	None	None	**Designed for cross-platform use**
Maintenance Burden	Platform-side	Platform-side	User and developer dependent	Platform-side	**Minimal once profile is created**
Scalability Across Ecosystems	High (centralized)	High	Limited	High	**High via standardization**
Compliance with Privacy-by-Design	Weak	Partial	Partial	Partial	**Intrinsic**
Ethical Alignment	Low	Moderate	Moderate	Moderate	**High**
Transparency of Data Semantics	Opaque	Opaque	Opaque	Opaque	**Explicit and inspectable**
Data Ownership	Platform-controlled	Platform-controlled	Platform-controlled	Platform-controlled	**User-owned**
Long-Term Sustainability	Increasingly contested	Regulatory-dependent	Fragile	Fragile	**Systemically sustainable**
Primary Limitation	Systemically sustainable	Symbolic control	Fragmentation and relevance loss	Accuracy degradation	**Adoption and standardization effort**

A. Current System and Efforts Made to Overcome These Issues

User tracking is an omnipresent, albeit contentious, element of online advertising and targeted content in modern online society. A variety of sophisticated methods are used by websites, apps, and online services to collect great volumes of information on what users do, typically without users' conscious or active consent. The tracking is executed by a variety of tracking technologies, such as cookies, pixels, device fingerprinting, and device identifiers, by means of which companies are able to build very rich profiles on users based on how they use a range of different sites and services.

1) How the Users are Tracked (for Ads and Content Preferences)?

Tracking is also a multi-faceted practice that is carried out at virtually every phase of online activity. These businesses want to create a profile about users that will allow them to provide highly targeted, personalized advertising, optimizing digital promotion campaigns. Among the most critical means that are leveraged to track users are:

- Cookies and Tracking Pixels: These are little pieces of information stored on users' devices that track what users do on websites. Cookies allow advertisers to track users' activity data on different websites and connect it with individual users' profiles.
- Device and advertising identifiers (AdID, IDFA): Google's AdID and Apple's IDFA are two device identifiers marketers use to identify users across apps and services. These identifiers are associated with unique profiles belonging to users, making it possible for marketers to target users with personalized advertising based on their app-based activities.
- Browser Fingerprinting: It uses unique characteristics of the device of the user (like screen resolution, fonts, and operating system) to create a fingerprint for tracking users from website to website, even without cookies.
- Behavioral Analytics: Sites observe how long a consumer stays on a page, what they click on, and how they interact with a piece of content. From this, they deduce what a consumer prefers, even when a preference point has not been explicitly stated by them.

Despite its blatant encroachment, companies will most often justify this nonconsensual data collection or tracking by calling on the value in delivering users targeted advertising. The underlying idea is that, by tracking users, companies are better able to customize the experience and are thus better able to target advertising and content at users, making it more relevant and, as such, more valuable to users. This argument, however, is most often employed as a pretense to cover over a darker reality: invasion of privacy.

2) Advertising Relevance as a Scapegoat for Privacy Infringement

The term "relevant content/ads" is widely marketed as a quid pro quo for loss of privacy. Consumers believe that it is an acceptable trade-off to provide information to online sites in exchange for targeted advertising. The most frequent justification offered by the major tech organizations is that the fundamental motivation for tracking is to improve the consumer's user experience by showing them more targeted advertising and relevant content. However, this presupposes that users willingly agree to the tracking, a premise that is often questionable at best.

In reality, most users have no idea on what magnitude they are having data mining carried out on them, nor do they have an idea of long-term effects of such data becoming an input to algorithms for perpetual behavioral prediction. Additionally, ubiquity of tracking mechanisms leaves little or no choice for users to opt out, while "relevance" boasted by such mechanisms is overpowered by exploitation of users' personal data. The ad is shown not only on users' interests but also on inferred behavioral propensities without users' notice. This has created serious concerns regarding data ownership, consent, as well as manipulation of users' actions.

3) Platform-Based Efforts

There are several systems that are used to manage tracking and privacy in online marketing, and these systems have been heavily criticized as failing to keep users' information safe or offering adequate control over what is delivered. The most common are:

- AdID and IDFA: The two dominant identifiers for mobile device-based cross-app and cross-platform tracking are Google's AdID and Apple's IDFA. These two identifiers allow advertisers to monitor users' actions within applications and assign actions such as purchases or advertising interaction data to a specific user profile. While there have been efforts by Google and Apple to limit how such identifiers can be utilized (e.g., Apple's App Tracking Transparency (ATT) policy), the process remains to support tracking at mass levels based on inferred behavior rather than direct user consent.
- App Tracking Transparency (ATT): Apple introduced the App Tracking Transparency framework with its shift towards curtailing invasive tracking. The ATT framework requests apps to obtain consumers' permission before they can track consumers' actions on other apps and sites. While this was hailed as a consumer privacy victory, it has not solved the problem entirely. The majority of users, even when provided with an opportunity to opt out, are not aware of what this implies or do not have sufficient technical expertise to make an educated choice. The ATT mechanism also relies on an inferred user interests model, with users having no real control over where and how their data is used and shared.
- Privacy Sandbox: Google's Privacy Sandbox is an initiative to create alternatives to third-party cookies to preserve user privacy. The system is intended to provide advertisers with the tools to target users without making personal information directly available to advertisers. However, the system involves in-app activity-based profiling and attempts at deducing the desires or interests of users, an activity most detractors say still eliminates consumer control over personal information.

These efforts, as much as they are attempts at confronting privacy concerns, still don't provide users with full control over how they use their data. Despite efforts like ATT and Privacy Sandbox, users remain profiled outside of their direct, conscious consent, and companies still have considerable control over what data they collect and how they use it.

4) Data Protection Acts and Policies in Place

After increased online privacy concerns, several data protection acts have been enforced globally to safeguard users' personal information. Among them are two key laws:

- General Data Protection Regulation (GDPR): Implemented by the European Union in 2018, GDPR grants users robust data protection rights. It compels organizations to obtain users' consent first when gathering and processing their personal data. It also grants users the right to review, modify, and delete their information, among other rights. Enforcement has been spotty even with its strengthening, and businesses have kept finding loopholes in these regulations.
- California Consumer Privacy Act (CCPA): The CCPA, enacted by California in 2020, gives California users the right to know what information is gathered on them, gives them a right to access it, and gives them a right to have it removed. While more open than previously, it still does not address at its root the problem with tracking consent. It does not require companies to stop tracking at all, only provide an opportunity for users to opt out of having their personal information sold.

Although such legislation provides protection for users to some degree, it does not fully address consent to tracking, nor is its enforcement a success. Besides, they concentrate on collection and processing as opposed to tracking activities and users' lack of control over their online identities.

The current tracking system, with its target advertising and content tailoring, by its very nature disrespects users' trust. Even with measures such as Privacy Sandbox and ATT, they don't even come anywhere near making users have full control over their data, and most users aren't even aware of how much tracking is going on, as we learned through the literature. Regulations such as GDPR and CCPA are there for some protection, but they don't address the core issue of getting users' consent when it comes to tracking. The models currently in use, by inferred interest and data profiles, are by nature, defective and do not allow such ideals as transparency, autonomy, and privacy that users should have.

B. Weaknesses and Improvement Gaps in the Current System and Efforts

Despite statutory data protection and transparency legislation, current online advertising and recommendation mechanisms are technically flawed. The technical flaws are not so much legal or ethical, but rather a design flaw intrinsic in how users' data is collected, inferred, and utilized. The mechanism based on pervasive surveillance and covert profiles cannot simultaneously grant real control to users and reduce advertising and content targeting quality.

1) The Limited Role of GDPR, CCPA, and Other Data Regulations

Regulations like the General Data Protection Regulation (GDPR) and California Consumer Privacy Act (CCPA) have been introduced to give users greater control over information about them. While these regimes provide legal protection, they are deficient in several key areas:

- Consent fatigue: Consumers are fatigued with cookie notices and consent banners that try to confuse or push users toward compliance. The majority click "Accept All" without reading and understanding what it means.
- Gross unenforceability: Despite GDPR mandating minimization and use limitation, its enforcement is aimed at pursuing large-scale blatant abuse and ignoring day-to-day misuse of inferred information and tracking loopholes.
- Vague "legitimate interest" clauses: Companies justify data collection in terms of "legitimate interests," with grey areas where profiling continues even when users try to opt out.

Lastly, laws such as these do not ensure ethical practice. The spirit of such legislation is always evaded by way of vagueness and exploitation by users.

2) Inferred Interests: The Core Technical Fallacy

At its heart, it is a risky presumption, one that machines are able to successfully infer users' interests from behavioral data.

- It uses passive data such as search history, clicks, scrolling, watch time, and hover actions to train algorithms to construct a profile of "what the user wants."
- Context is overlooked: The consumer may only want "baby strollers" due to an isolated reason, or on behalf of someone, or perhaps out of interest. The system is assuming this is an interest at the top and is showering them with baby advertising for months.
- Temporal interest fading is poorly implemented. Interest profiles are infrequently time-limited, and dated conclusions will continue long past when they should be applicable.

These systems are essentially flawed; they sacrifice accuracy for automation and are making assumptions where there should not even be any. This results in poor user experience as well as poor targeting.

3) False Positives and Shared Device Challenges

Dependence on device or browser-based behavior leads to an exceedingly high rate of false positives:

- Shared devices (e.g., schools, families, or cyber cafes) lead to different behaviors being correlated with a single profile.
  - One innocent action by a child will initiate travel high-ends advertising.

- A roommate's impulsive late-night shopping spree may also result in product suggestions that are not appealing to the original user.

- Disproportionate effect of single actions: A misclick, unintentional click, or experimental search may significantly skew ad/content suggestion for days or weeks.

This lack of disambiguation leads to data pollution, where extraneous interests get confused with real preferences, affecting advertiser ROI and user experience.

4) Non-Consensual and Opaque Profiling

Modern systems don't ask for preferences, they deduce them with no input from users:

- Users are rarely informed about how their data profiles are built.
- Inference models are not open-source, and most platforms don't allow users to review or verify what has been recorded about them.
- Profiling persists across devices and apps even when users erase identifiers or opt out, and it is most often carried out with browser fingerprinting, shadow profiles, and SDK data collection across apps.

Fundamentally, users are profiled by systems they don't understand, based on signals they didn't agree to provide, for purposes over which they have no control.

5) Clunky and Deceptive Preference Management

While there are some sites (Google, Facebook, Apple) that do have ad preference controls, they are plagued with usability problems:

- Hidden in menus: Choices are hidden behind several layers of menus with unclear labels.
- Auto-enabled interests: Platforms pre-define interest categories based on historical tracking and force users to opt-out.
- Inadequate granularity: Options are abstract (e.g., "Sports," "Travel") with no way to state sub-preferences or rule out presumed ones.
- No true opt-out: Even when interests have been opted out, there remains background behavioral tracking, and there is still targeting on other inferred information.

These are not intended for real control, rather to seem compliant while still being trackable.

6) Defective Opt-Out Mechanisms

Choosing not to participate in personalized advertising now is an illusion:

- Ad identifiers (e.g., Google's AdID or Apple's IDFA) may get cleared, but tracking is resumed shortly thereafter under a fresh identifier.
- Mechanisms such as opt-out cookies or Do Not Track (DNT) are not commonly honored or are erased when cookies are cleared.
- App-level opt-outs, such as ATT on iOS, only stop certain types of cross-app tracking while enabling server-side code tracking and profiling to still continue.

In essence, users are struggling with a hydra, severed from one tracking source, and two others from less obvious sources.

7) Technical and Ethical Failures in Real-World Scenarios

Consider these case studies and examples uncovering the serious shortcomings in current profiling systems:

- YouTube's feedback loop: Someone accidentally watches a video about a conspiracy theory. The site overloads them with related videos for weeks, propagating fringe viewpoints, a documented phenomenon called "algorithmic rabbit-holing".
- Amazon's Purchase Memory: One purchase of a vacuum cleaner leads to months of promotions for vacuum cleaners, something that the buyer won't need again for years.
- Political Ad Micro-Targeting: People are subjected to emotionally manipulative political messages during elections that are tailored to inferred personality attributes (e.g., fearfulness or extroversion) from past clicks and social media activity, and this is ethically objectionable when it impacts democracy and consent.
- Instagram Shopping Feeds: Your device is used by your friend to search for fashion goods, and your feed is filled with clothes from this domain, irrespective of it not aligning with your interests.

These instances depict how tracking often fails, and users are harmed because of poor inference.

8) The Systematic Problem: Tracking is the Default

We now have an online space where tracking is the rule and opting out is an exception. "If you're not paying, you're the product" has become a truism, though little is mentioned about how this business model is harming users and advertisers:

- Users lose control and confidence in the technology.
- Advertisers waste money targeting people with irrelevant ads/content based on noisy, inaccurate, or outdated preference profiles.
- Developers incorporate SDKs and third-party libraries that expose users' data without adequate transparency.
- Other platforms are also in the spotlight, as shown by recent events and consumer-led revolts (e.g., against Instagram and Facebook).

Not only is this model unviable, but it is also technically defective and ethically deficient.

III. METHODOLOGY

After critical analysis of the literature on Data Integrity and Privacy issues, it seems necessary to obtain a broad knowledge base regarding actual users' views on digital tracking, data privacy measures, and alternative advertising models' perceived acceptability, a quantitative approach was utilized.

A. Target Audience

A carefully designed questionnaire was shared among several online forums and communities focused on data privacy matters. These sites included boards and groups, where users typically have a more advanced understanding of digital rights, data handling practices, and implications of tracking technologies. This selection was intentional because individuals having a core understanding about data privacy provide richer answers, something indispensable to ideas like preference systems and user-consensual data sharing platforms. It was agreed that if this survey is distributed to normal public, then the results would be quite inaccurate, because, as it was learned through the literature review that the normal public usually doesn't have knowledge on technology being utilized to get their data and the Data Protection Acts in place that try to stop such Tracking.

B. Survey Structure

The questionnaire included a set of Likert-scale, multiple-choice, and open-ended questions aimed at gauging participants' opinions about mandatory behavioral profiling, current data privacy regulations, the level of clarity regarding data use, and the feasibility of creating user-defined preference profiles. General themes examined included the perceived effectiveness of legislation like the GDPR and CCPA, the level of satisfaction with current opt-out features (such as App Tracking Transparency and the Privacy Sandbox), and attitudes toward the use of personal data to allow for better content personalization using artificial intelligence.

To protect the target audience's privacy expectations, the survey avoided collecting personally identifiable data, like age, gender, or geo-location. Rather, it focused on collecting relevant information pertaining to privacy expectations, trust in digital platforms, and potential participation in a new, permission-based model for advertising and content preferences data sharing platform. The tone of the questions was kept at a friendly level in order to let users select the best option, which reflects not only their opinion, but also their feelings. The survey was shared across privacy-oriented subreddits, encrypted messaging apps, and federated platforms, thus ensuring collected data was a true representation of users concerned with privacy. These responses were anonymized, and participants gave informed consent to participate in this study, along with explicit disclaimers provided informing participants about the non-commercial nature of the work. The design of this approach was not intended to provide generalizability to a wider populace, but merely to measure whether a well-informed audience would see value in this proposed framework in comparison to invasive tracking.

IV. RESULTS AND DISCUSSION

A total of 572 valid responses were collected from privacy-aware online communities. The results provide empirical grounding for evaluating whether a user-authored, consent-driven preference framework is socially acceptable, practically viable, and theoretically aligned with existing privacy research. Microsoft Excel was used to create figures and charts for easy evaluation. Each subsection below discusses one thematic result and situates it within prior findings.

A. User Sentiment on Tracking and Data Collection

As illustrated in Fig. 1, a dominant majority of respondents (62.59%) regarded behavioral tracking as inherently violating privacy and rejected it outright. An additional 30.77% indicated conditional acceptance of personalization, but only when preferences are explicitly provided by users themselves, rather than inferred through passive surveillance. By contrast, only 2.10% were comfortable with tracking in exchange for free services.

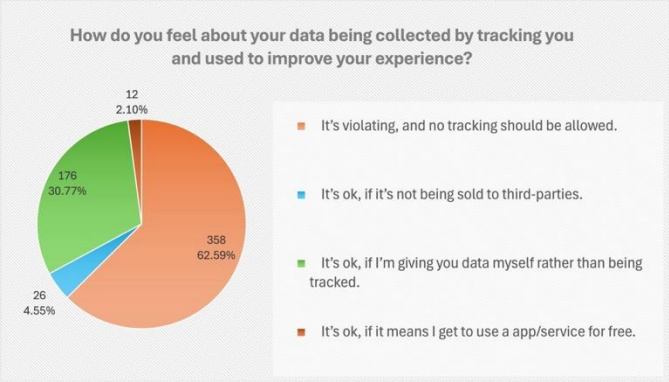


Fig. 1. User sentiment on tracking and data collection.

This finding directly reinforces prior work demonstrating that method of data acquisition, rather than personalization itself, is the primary driver of user discomfort [2], [3], [15]. It also empirically supports observations in [20] that users distrust inferred profiles and experience what has been described as algorithmic disillusionment. The strong preference for voluntary data provision further aligns with Protection Motivation Theory findings in [10], where perceived lack of agency suppresses protective behavior even among informed users. Collectively, these results validate the study's premise that user-declared intent is more socially acceptable than algorithmic inference, even when outcomes (e.g., personalization) appear similar.

B. Attitudes Toward Existing Data Protection Mechanisms

Fig. 2 demonstrates widespread dissatisfaction with current regulatory approaches. Only 2.27% of respondents considered existing data protection laws sufficient, while 70.98% explicitly stated that a functional solution is needed rather than additional rules.

This sentiment closely mirrors empirical critiques of GDPR effectiveness found in [6], [13], and [29], where compliance mechanisms such as consent banners were shown to be largely symbolic. The results also echo macro-level analyses in [17] and [27], which argue that regulation alone can unintentionally consolidate data power instead of redistributing it. Respondents' desire for actionable tools aligns with findings in [14] and [23], where users expressed frustration at being formally empowered yet practically constrained. These results strengthen the

argument that compliance-by-design systems, rather than policy-only approaches, are required to operationalize privacy rights.

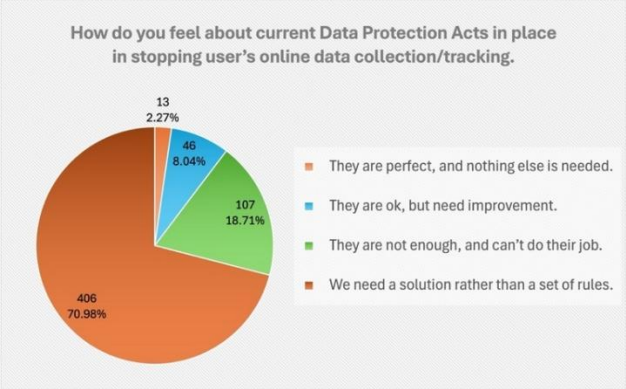


Fig. 2. Attitudes toward existing data protection mechanisms.

C. Preferred Type of Solution

Responses in Fig. 3 reveal a nuanced, but decisive preference landscape. While 83.22% favored stopping data collection entirely, reflecting deep-rooted distrust, substantial support was also observed for voluntary preference sharing (77.80%), prohibiting third-party data sales (72.90%), and data anonymization (56.47%).

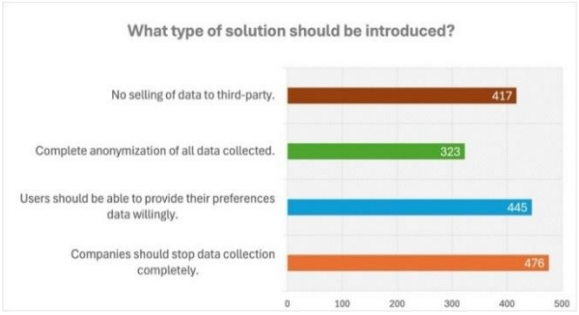


Fig. 3. Preferred type of solution.

This apparent tension between idealistic rejection and pragmatic compromise is consistent with prior findings in [15] and [26], which highlight trade-offs between privacy protection and system functionality. Importantly, the strong endorsement of voluntary preference sharing provides empirical validation for alternative paradigms proposed in [7], [8], and [28], where value extraction is decoupled from covert surveillance. Unlike anonymization-only approaches, which can degrade content relevance and raise concerns for vulnerable users such as children [22], [32], user-authored profiles preserve contextual accuracy while respecting consent. The findings thus support a middle-ground model that balances personalization utility with ethical data governance.

D. Willingness to Use a User-Controlled Preference Platform

As shown in Fig. 4, willingness to adopt the proposed model was notably high. A combined 86.19% indicated they would use such a platform either unconditionally (9.97%) or provided it remained simple to manage (76.22%). Only 7.34% rejected the need entirely.

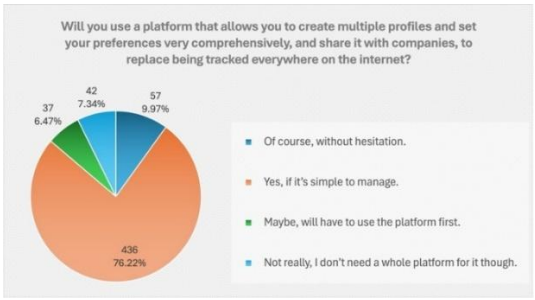


Fig. 4. Willingness to use a user-controlled preference platform.

These results reinforce usability-focused findings in [5], [14], and [28], where complexity and opacity were identified as primary barriers to meaningful privacy engagement. The emphasis on simplicity also corroborates observations in [10] that perceived effort reduces protective action. From a systems-design perspective, this underscores that technical feasibility alone is insufficient; adoption depends on intuitive interfaces and low cognitive overhead. The results further suggest that multi-profile support, allowing users to contextualize preferences, may address shortcomings of one-size-fits-all consent mechanisms.

E. Trust in Who Should Build and Maintain the System

Trust attribution results in Fig. 5, reveal a pronounced institutional divide. Privacy-focused organizations (90.20%), open-source communities (73.60%), and non-profits (52.80%) were overwhelmingly preferred, while Big Tech (9.97%) and governments (28.50%) ranked lowest.

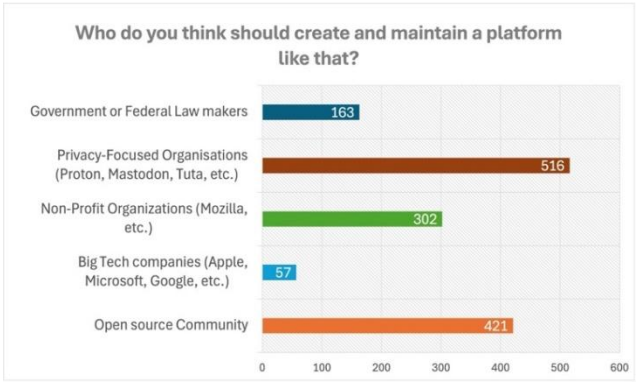


Fig. 5. Trust in who should build and maintain the system.

These findings are consistent with broader trust erosion documented in [32] and [33], as well as structural critiques of Big Tech's data governance in [7] and [17]. The strong preference for open and privacy-native stewardship aligns with research advocating transparency, auditability, and decentralization as trust-building mechanisms [18], [21]. This suggests that for the proposed framework to be credible, governance structure is as critical as technical design, favoring open standards, inspectable codebases, and non-commercial custodianship.

F. Discussion and Implications

To conclude, the results demonstrate a clear mismatch between current data collection practices and user expectations. While prior research has extensively documented the harms and

inefficiencies of behavioral tracking [1], [13], [21], this study contributes empirical evidence that even privacy-literate users favor constructive alternatives rather than absolute disengagement. The findings support a paradigm shift from inferred behavioral profiling toward explicit, user-authored preference signaling, addressing long-standing concerns about consent validity, trust, and ethical personalization raised in [8] and [20].

Importantly, the results do not contradict existing literature, but rather operationalize its conclusions: users want personalization without surveillance, control without complexity, and privacy without sacrificing functionality. The proposed framework responds directly to these conditions by enabling consent to become an active, expressive process rather than a defensive reaction. In doing so, it aligns regulatory intent with technical implementation and user agency, offering a viable path beyond the limitations of both tracking-centric and regulation-only models.

V. Proposed Model: A User-Governed Data Sharing Platform and Standard

A. Overview of the Concept

The current ad environment is built on an interest-inference information system based on passive tracking. Companies track users through apps, sites, devices, and off-line activity and build hidden profiles by unknown means. Based on this inferred interest profile, supposedly "relevant" advertising and material is served. Its justification has always been: "you get relevant ads/content". Never once along the chain is anything asked of users: what they are interested in watching or how they want to get profiled. The system is by its nature defective.

The innovation here is a move from hidden tracking to open, user-consented preference sharing. Rather than getting tracked everywhere, users would have control over actively building and sharing interests on one platform. The platform described here can enable users to create their own Preference Profiles, to be linked to apps or sites in an easy, privacy-preserving way. Think of it as creating a social media account, but rather than uploading photos and updates, users select what they want to see: advertising, kinds of content, topics of interest, and more.

This is not an ad business model, but a technological solution to restoring control of data and trust by users in online environments. It is a simple solution, though one with pressing practical application as people's frustration over loss of control, over personal data tracking and its use in training AIs escalates.

B. Core Features

User Accounts like Social Media: The initial point is a user account, identical to what you would have on a social media website. The difference here is that there is no messaging, posting, or networking aspect to this account. It is only used for storing preference and interest, only for passing on to apps or companies that people will be interacting with. Sharing is opt-in and under users' control.

User-Generated Interest Profiles with Individualized Preference Profile IDs: Any given user can create multiple Interest Profiles in their account. Each can have a unique alphanumeric Preference Profile ID as its "username" or API key. These IDs or direct downloads of JSON format of profiles may then be shared with sites that request advertising or content preferences from the user. This will enable users to use different profiles for different purposes without disclosing personal data or correlating all activity with one single identity.

Multi-Profile Support for ADs, Interests, Content Preferences: Users are not homogeneous, and their interests vary based on context. An individual might want new productivity applications' ads in a working environment and entertainment content during leisure time. Hence, this model supports multiple profiles per user account, which enables users to define various sets of interests for:

- Ads (e.g., job offers, tech products)
- Content (e.g., comedy, music genres, educational videos)
- General interests (e.g., travel, fitness, finance)

This system avoids having ad engines guess and instead relies on declarative data provided by users.

App-Specific Profile Preferences: There can be profiles created specifically for a particular platform. For example:

- A video application profile like a YouTube or TikTok profile, for instance, "ContentProfile_YT" with interests like "Tech Reviews, Music, No Politics, Comedy, Memes, Pranks".
- Another for professional networks like LinkedIn (e.g., "CareerAds_LI" with interests like "Project Management, Startups, Recruitment").

Apps only request a Preference Profile ID or a direct JSON file, and the user will provide them with one of their preference IDs or files. This avoids over-personalization with unwanted information and promotes context relevance. It is an ethical way of sharing your interest data for online content/ads, rather than being tracked everywhere online.

C. Functionality

User Experience Design: The system must have optimal usability. Within each profile, the users should have the ability to select interests from pre-designed template options, search by categories, and build profiles through a guided, intuitive interface. The users should have a sense of empowerment rather than frustration with the process. Selecting pre-designed default template options (e.g., "Gaming Profile," "Work Profile," "Music Preferences") can provide optimal reduction in cognitive load without sacrificing fine-tuned personalization.

Linking and Sharing Mechanisms: The platforms can request Preference Profile IDs from users. This can take place through:

- Manual Entry: The users enter or paste their Preference Profile ID into an input field.
- Account Linking: As with OAuth, users can directly link their preference profile via an API handshake.
- File Upload: Directly upload the exported JSON file of that Preference Profile on the requesting platform.

- Username-based linking: Social apps already have a facility for linking via usernames, this method can emulate the same with Preference Profile IDs.

This will allow developers to have flexibility and ensure that consent is specific and accurate.

Integration with Applications and Sites: Developers can be offered an API or an SDK. This allows applications and sites to:

- Query a user's Preference Profile ID (read-only).
- Fetch updated preferences dynamically (optional).
- Respect content/advertising category exclusions (e.g., avoid political ads).

Access to all data would be governed by an open protocol without permanent identifiers or behavioral surveillance.

Open Standards, Open-Codebase: In order to foster trust and collaboration, the platform should be open-source under an open standard. This prevents vendor lock-in, and third-party auditing is feasible. Developers can propose categories, tailor template logic, and perform integrations. Open protocols also support modular implementations, and decentralized control or even self-hosting is feasible.

Decentralization and Identity Ownership: Decentralized Identity (DID) standards or principles of Web3 can expand on this model further. This gives users control over profiles with cryptographic ownership, makes the entire system tamper-resistant, and could support zero-knowledge proofs whereby users reveal preferences data without identity disclosure.

AI integration for Profile Creation: AI can easily be embedded within this platform. It can create a user's profile based on user's text input by harvesting the power of NLP techniques available in modern AI age.

Prompt style simple example:

"I need a general profile. I like all music except jazz. I hate drama movies, but I love all other movie categories, especially comedy. I love everything related to technology, but I hate marketing and SEO stuff. I love the power of AI and what it can do, but I don't like AI generated content (as in music, video, photos, etc.) as it seems lazy. I'm an outdoor person, so I have many physical hobbies, like Sports and exercising. I enjoy traveling a lot, but I'm not a luxury freak. I love almost all animals, but I'm not quite fond of dogs or pigs. And when it comes to News, I absolutely hate politics. Please generate a good profile for me and try to understand my personality to get all the preferences correct."

There're few ways it can be done, as listed below:

- Own Trained Model: This will probably be the best implementation, as the AI doesn't need to external knowledge base to be used. An AI Model can be trained on manually crafted examples and their outputs, which will allow for highly accurate User's Preference Profile creation.
- API Linking: An advanced AI Model can be used with the help of API Keys. This way when the users writes the text of what they want from the profile, the prompt can be sent to the AI Model's server using its API to get the categories list having users' likes and dislikes. This way the users have created their preference profile via an API handshake. In this, most of the Processing will be done by the outsourced server.
- Local AI model: This method is by far the toughest to get right, as the entire AI Model will have to run locally, taking up a lot of RAM and GPU power. It is quite inefficient in terms of what the overall platform looks to accomplish.

Overall, this brings us to an open, privacy-based internet with the actual user at its center. Some of these features are too advanced and out of scope to implement right now but are to be considered in future developments of the platform. In the survey conducted, the respondents emphasized simplicity of the platform, linking it to usability. The Demo web interface developed here ensures the basic requirements of the proposed system are met and showcases the simplicity of this solution's implementation.

D. Demo Website Showcasing the Workings of the Proposed Framework

To illustrate the practical feasibility and interaction flow of the proposed user-governed preference data acquisition framework, a lightweight demonstration website was developed. The purpose of this prototype is not to present a production-ready system or a novel software contribution, but to concretely demonstrate how the conceptual framework described in the previous section can operate in practice from a user and platform perspective.

The demo implementation focuses on three core aspects of the framework: 1) explicit user-authored preference declaration, 2) multi-profile and context-aware preference management, and 3) standardized, portable export of preference data for third-party use.

Accordingly, the system was intentionally kept minimal in scope and complexity, prioritizing conceptual clarity over feature completeness or optimization. The prototype serves as a reference implementation to support understanding, reproducibility, and future extension by researchers, developers, or organizations.

1) System Overview and Interaction Flow

At a high level, the demonstration platform allows individuals to create and manage one or more preference profiles, each representing a distinct context of interest (e.g., content consumption, advertising, professional use). These profiles are explicitly authored by users through direct input rather than inferred from behavior. Once created, a profile can be selectively shared with external platforms via a unique identifier or exported in a standardized machine-readable format (JSON).

The interaction flow is intentionally simple: users register, define preferences through structured categories, optionally refine or update those preferences over time, and provide the resulting profile to platforms that request preference data. This flow reflects the framework's central design principle of

replacing passive behavioral inference with explicit, user-controlled preference declaration.

2) Entry Point and Navigation

The platform entry point is a minimal landing interface that introduces the purpose of the system and provides navigation to user-facing actions such as registration and login. As shown in Fig. 6, the landing page is deliberately sparse, reflecting the framework's goal of minimizing friction and cognitive overhead during onboarding.

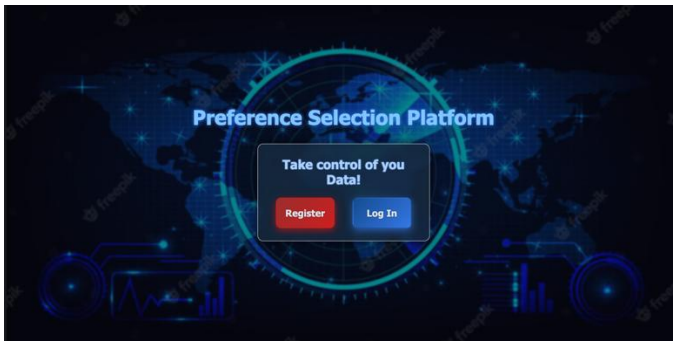


Fig. 6. Landing page.

3) User Authentication and Account Access

Users interact with the system through a basic account access that enables secure access to preference management functions. The registration and login interface, illustrated in Fig. 7, exists solely to associate multiple preference profiles with a single user.

Importantly, authentication is treated as an enabling mechanism rather than a profiling mechanism. No behavioral tracking or implicit data collection is performed during account creation or login.

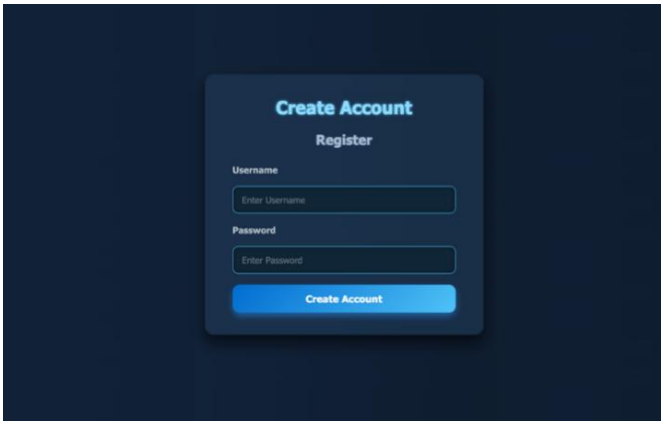


Fig. 7. Register page.

4) Preference Profile Management Dashboard

Once authenticated, users are presented with a centralized dashboard that lists all preference profiles associated with their account. As shown in Fig. 8, the dashboard functions as the primary control surface for managing preference contexts.

Each profile is treated as an independent, self-contained declaration of interests, allowing users to maintain multiple profiles for different use cases without cross-contamination. This design directly addresses issues identified in the literature related to shared devices, mixed contexts, and misattributed behavioral signals.

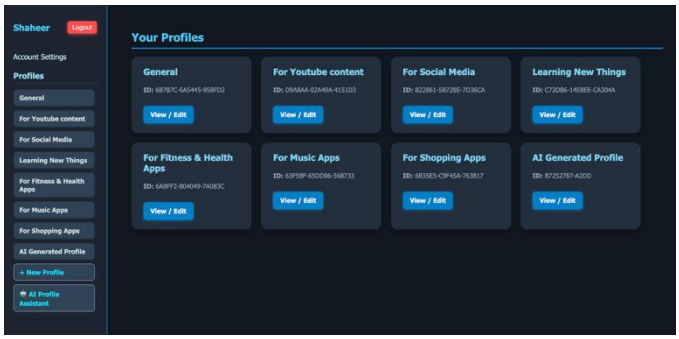


Fig. 8. Dashboard page.

5) Account-Level Controls

In addition to profile-level management, the demo includes a basic account settings interface, shown in Fig. 9, enabling users to update credentials or remove their account entirely. This functionality is included to demonstrate user autonomy and data lifecycle control, consistent with privacy-by-design principles.

Account deletion removes all associated profiles, reinforcing the notion that preference data remains user-owned and revocable rather than persistently retained by the system.

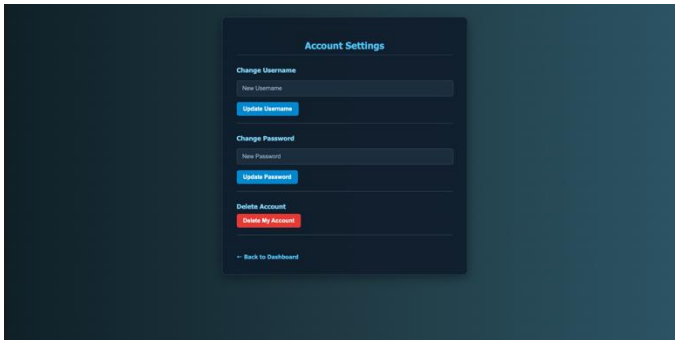


Fig. 9. Account settings page.

6) Explicit Preference Profile Creation

The creation of a new preference profile is the core interaction through which the framework's principles are operationalized. As illustrated in Fig. 10, users define preferences through a structured category hierarchy, explicitly indicating positive (Like), negative (Dislike), or neutral interest (Not Decided) states. Categories can be very comprehensive.

This explicit declaration mechanism replaces behavioral inference entirely. No assumptions are made based on past activity, accidental interactions, or temporal proximity. The hierarchical structure supports both coarse-grained and fine-grained preference expression while remaining interpretable to both users and consuming platforms.

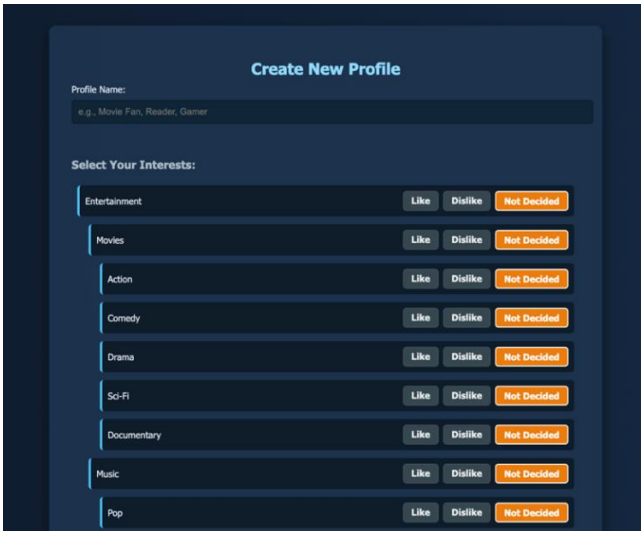


Fig. 10. New profile creation page.

7) Profile Review, Modification, and Export

Once created, preference profiles can be reviewed, modified, or deleted through a dedicated profile management interface, shown in Fig. 11. Preferences are not static; users may revise them as interests evolve or contexts change.

Crucially, profiles can be exported in a standardized JSON format that preserves the full preference structure and semantics. This export functionality demonstrates how platforms can consume high-quality preference data without engaging in surveillance, fingerprinting, or behavioral tracking. The JSON format is used as an example standard that can be established for this framework.

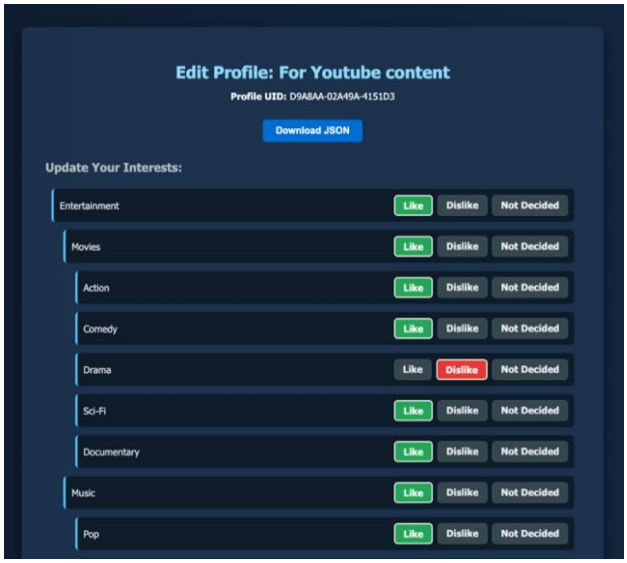


Fig. 11. Profile management page.

8) Assisted Preference Authoring via Natural Language Input

To reduce user effort and improve accessibility, the demo includes an optional AI-assisted preference authoring interface, illustrated in Fig. 12. This component allows users to describe their interests in natural language, which are then translated into structured preference categories. The performance of this depends on the AI model(s) used by either the individual or the organization, as explained in the above subsection B. Core Features.

This feature is intended as a usability enhancement rather than a replacement for user control. Users remain free to review, modify, or reject any generated preferences before saving the profile. The inclusion of this panel demonstrates how assistive technologies can support explicit preference declaration without reverting to opaque behavioral inference.

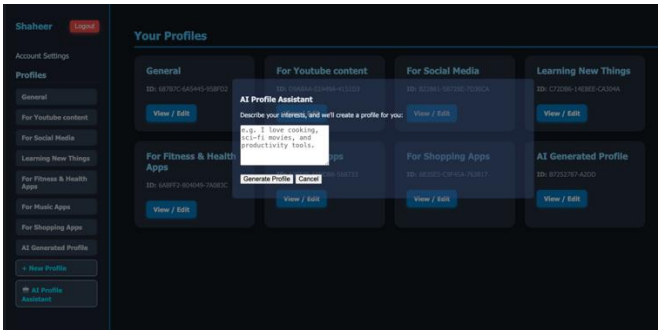


Fig. 12. AI profile creation panel.

9) Preference Sharing and Third-Party Access

Finally, the demo includes a minimal interface through which external entities can retrieve a preference profile using a user-provided identifier. As shown in Fig. 13, this interaction models how platforms may request and consume preference data without requiring user accounts, cookies, or tracking identifiers.

This mechanism highlights the framework's platform-agnostic and interoperable design, where preference data is shared deliberately and contextually rather than collected implicitly.

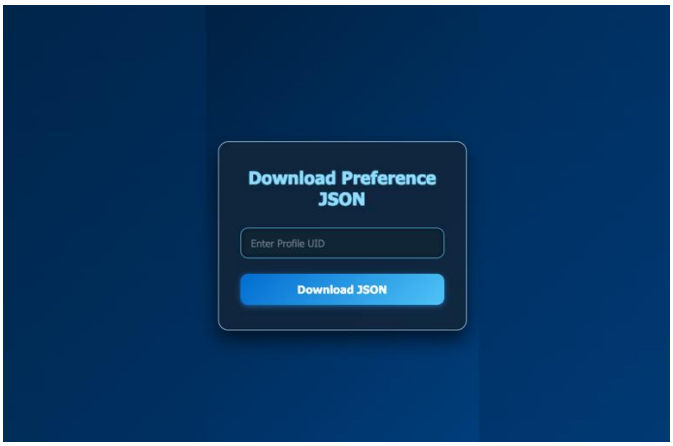


Fig. 13. Downloader page.

10) Scope and Limitations of the Demonstration

It is important to emphasize that this demo website is not intended as a complete system, performance benchmark, or commercial platform. Its role is illustrative: to demonstrate feasibility, interaction flow, and conceptual alignment with the proposed framework.

Advanced concerns such as large-scale deployment, governance models, standardization bodies, security hardening, and integration with production recommender systems are intentionally left out of scope and are identified as directions for future work.

E. Benefits of the Proposed Solution

The system proposed here, an opt-in and user-driven Ad/Content Preference Profile (data sharing) platform, introduces paradigm-shifting benefits to the entire digital environment. This is different from invasive ad-supported models that are now in existence and is privacy-preserving without sacrificing relevance. It's a real win-win for all stakeholders in digital marketing.

1) For Users: Autonomy, Privacy, and Relevance, Without Surveillance

For most people on the internet, such a platform model truly gives freedom. Rather than having to be passively followed everywhere on the entire Internet, users would have control over what types of data, information, content and advertisements they want to have displayed. It is relevant content/ads delivery with permission rather than at the sacrifice of privacy protection.

Users can create personalized profiles for different sites, such as different job interests for LinkedIn, different genres of movies and television for YouTube/Streaming platforms, or type of products for Amazon/Shopping. It's less intrusive and on purpose. The days have gone by when users get shown an ad because they typed in one stray search term or because someone was on their computer. Users decide, Users select, Users provide. It's advertising at user's consent.

2) For Businesses: Cleaner Data, More Accurate Targeting, Greater Brand Trust

This model is revolutionary when looked at from a business perspective. Current ad tech is rooted mostly on inferred data compiled predictively and inaccurately. The result is a clutter of false positives and poorly targeted postings that users actively avoid.

Having openly stated user-generated interest profiles, brands receive high-quality, precise, and volunteered data. Not only is this improved targeting, but it also rebuilds trust within an industry where consumers are becoming cynical towards Big Tech. There is no risk in taking a leap of faith on shady third-party trackers or complicated behavioral inference engines. The user data is clean, relevant, and ethically provided.

On top of this, companies can use this paradigm as a marketing theme, "We value your Data and only show you something that you want to see". This is positive branding when concern for data privacy is on the rise.

3) For Regulators: Compliance by Design

There are laws on the books to protect users, like GDPR and CCPA, but with modern tech, compliance is more about damage control than damage prevention. The proposed conceptual platform reverses that. Ethics are built-in here. No loopholes, no dark patterns, no fine print. The users themselves create their Profiles and willingly share their Interest data with the Apps, companies, and organizations.

Every ad or content displayed through this system is backed by consent on behalf of the users, explicitly given through their preference profile. There is no need for regulators to chase companies for breaches as the consumer is in charge in the first instance. It's not damage control, it's damage prevention.

4) For Developers: Simplicity, Flexibility, and Future-Proof Design

Today developers must deal with complicated SDKs, notice banners for privacy, cookie banners, and third-party data providers. This Model answers it as one open standard. Create a preference profile, add preferred categories, share the ID of that profile, and finally get shown accurate content, no background tracking or hidden algorithms required.

This concept makes it easier to create ethically sound, lightweight, and privacy-oriented apps and still allows for monetization through advertising or personalization. As an open-source platform, developers can contribute, adapt, and expand on the platform as required by use cases.

5) For Data Scientists: Cleaner Data, Minimum Preprocessing, and Consent-based

The proposed framework offers data scientists a clean, structured, and consent-driven source of user preference data, removing much of the noise, ambiguity, and ethical burden associated with current tracking-based methods. Unlike opaque behavioral inference systems, where interests are derived from cluttered signals like accidental/incidental clicks or shared devices, this approach provides explicit, user-declared profiles that can significantly improve model accuracy and personalization outcomes. It eliminates guesswork in distinguishing actual intent from outliers, allowing data teams to work with high-integrity datasets that are legally and ethically sound. This not only enhances recommendation engine quality and ad targeting algorithm quality, but also facilitates better governance and auditing for data sets.

For machine learning pipelines, it means faster training cycles, reduced labeling overhead, and clearer feedback loops, while avoiding the risks associated with overfitting on biased or improperly collected data. By switching from invasive data mining to consensual data sharing, this framework creates a more sustainable and transparent data ecosystem where scientific rigor and user autonomy can coexist.

6) Overall Novelty and Conceptual Leap

The most significant aspect of this proposal is that none of the existing research or practice has attempted to address this issue from this angle. The most common proposed remedies and conversations are damage control, minimizing harm inflicted by existing tracking methods, or implementing opt-out functionality afterwards. This proposal is proactive rather than reactive.

Instead of trying to fix the broken system of surveillance capitalism, it offers an alternative: decentralized, consent-based, user-governed, and future-enabled system. It doesn't just

minimize harm; it renders tracking obsolete. This is the true innovation that can be enhanced through further research.

F. Conclusive Comparison Between Current System and Proposed Solution

1) Current System: Invasive by Default

Today's online economy rests on an idea that has become hardened: when you're getting it for no charge, you are the product. Sites and apps are scooping up everything, what you search, click, watch, stream, and even mouse-hover. The users didn't give any permission to get tracked everywhere online. Most don't even know what's being monitored or are too busy to stop it.

Even GDPR and CCPA, as excellent as they are, have been disadvantageous in certain situation as concluded through the literature review. The cookie notices are drafted to mislead, rather than reveal, privacy settings are buried behind a chain of multiple menus, and consent is implied rather than actual. Compliance is on study and not in spirit.

To make things worse, profiling is inaccurate. A parent using their child's iPad or a one-time Google search can skew their entire digital identity data. Ad relevance often feels like guesswork, and users feel more intruded upon than ever.

2) Proposed System: Consent-Driven by Design

By contrast, the platform suggested here eliminates surveillance. People create interest profiles for themselves, directly and by conscious choice. Users decide what every app learns about them and can toggle or shift tastes at will. There is no guessing. There is no spying. There is no tracking across unrelated platforms.

One may have a variety of preferences for different activities such as work, entertainment, shopping, etc. and map them with the respective apps with a simple identifier like a username. This preference profile will only become shareable when desired by the user.

3) No tracking. No third-party cookies. No behavioral inference.

This approach solves many of the core issues with current user data exploitation systems:

- No more unwanted advertising or irrelevant ads.
- No more misattributed activity from shared devices or one-time search data.
- No more hidden profiling or silent consent.
- No more complex legal back-and-forth.

4) Privacy Becomes the Default, Not the Afterthought

Where other systems ask for forgiveness or hide behind technobabble (incomprehensible technical jargon), the solution presented here asks for permission. It makes an online community where privacy is not just kept intact, it is engraved as an unbreakable ideal.

Companies still get data, but better data, and that data will voluntarily come from users who know what they are sharing with the Company or app. Ads and content are still personalized, at real user intent rather than usual tracking or guesswork. And users can still use services for free, without having that uneasy feeling of being watched.

This framework is not an extension to what already exists, but a rethink on how relevance and privacy might best be aligned.

VI. Challenges and Limitations

For all its potential to revolutionize consumer and online advertising privacy, mandating a preference-governed, consumer-led Preference Data sharing system is not without its hurdles. As with every shift away from established systems, it must overcome a multi-faceted environment of opposition, logistics obstacles, as well as an education shortfall. The significant hurdles to mention are as follows:

Resistance by Big Tech Giants: The largest obstacle is entrenched interest by the Giants. They now monetize information accumulated with invasive surveillance methods. The entire business model is based on behind-the-scenes profiling and data collection instead of having users provide data on an opt-in arrangement. A move toward a consent-based framework would entail some loss of profit and control. So, Google, Meta, and Amazon businesses would not welcome this with open arms naturally. It is not just tech, they would need to rethink their data stack, ad framework, and platform dynamics. This is a big order.

Risk of Abuse - Spoof or Manipulated Profile: Granting users control over what they are interested in presents one loophole risk: malicious players will game the system. Companies or spammers may also create spoof Preference Profiles to poison ad targeting or reap benefits assigned to designated segments. In order for a system to successfully function, it would require verification tools or behavioral checks without reviving intrusive tracking, a tricky thing indeed.

Monetization and Incentivization Strategy: When advertising is served based on users defined criteria, advertisers will naturally ask: Where's the optimization? Currently, machine learning optimizes ad delivery in real-time on inferred behavior. With a system based on user-defined profiles, there is some loss of granularity. This is a bigger question, how do platforms monetize such a system, and how do advertisers measure performance? There will have to be new cost-per-interest models, new measures of efficiency of conversion, and perhaps even incentivization by users, paying users to opt-in to have preferences refreshed or to answer honestly.

The two decades and billions invested in the surveillance-based data collection and tracking economy have no click-of-a-switch expectation of a flash transition to an alternative system. Such systems are built on top of heavyweight APIs, SDKs, real-time bidding systems, and price-per-data-point selling by third-party data brokers, all delicately tuned to behavioral targeting. Transitioning from there to consent-based would have gradual, perhaps even agonizing transition. Hybrid models will have a temporary relief, but these can become backdoors for inserting covert tracking unless regulated hard.

Failure to Educate General Users: In the real-world situation, most users don't even have a clue about what's spying on them online, let alone how to manage Preferences Profiles. Assuming all users will develop rich preference profiles is an expectation of a sort of digital literacy that no one possesses. In order for this to take off as a success, there needs to exist a robust layer of user education, tutorials, onboarding tours, perhaps even gamified experiences to help users manage interests. If it's difficult or an enormous effort, users will revert back to "what works" and return control to tracking systems.

Interoperability and Standardization: In order for such a system to achieve size, it cannot possibly operate on a single app or platform only. It must be made into an open standard, something that any app, game, or website can integrate with seamlessly. To make that happen will require open protocols, interoperability arrangements, and likely regulatory promotion. Without standards, the idea risks becoming fragmented, one platform implementing it and one that doesn't, and users would have to navigate several systems. Standardization may also drive healthy competition and ad tech innovation that is respectful to users' privacy.

While there is immense potential in having a preference-based economy, it will not be a cakewalk. It goes against the way business is now carried out online, and it's not going to come with open arms. But that's precisely what makes it worth trying. Privacy shouldn't have to be the price you pay for convenience. The entire industry has an honest opportunity now to reimagine online relevant content delivery and advertising, not as a method by which to sell more, but as an operating framework based on respect, on consent, and on true relevance. Cooperation, transparency, and most fundamentally, an agreement to get off the road to least resistance will take it.

VII. Implementation Roadmap, Recommendations, and Future Work

As learned from the literature review and the survey taken, making an open, opt-in ad economy is not a vision, it's a mandate. The people are actively looking for a solution rather than waiting for Big Tech to comply with Data Protection Acts and regulations. In the previous sections, this research's perspective of such a platform was presented which can successfully fulfil the users' requirements and not cause an issue for the companies. Stating again, it's a win-win solution for all digital entities involved. The users get the control over their data whereas the companies get the data by peacefully asking for it from the user. This section maps out a pragmatic way back to restoring control for users without shattering the "data tracking" supported web.

A. Cross-Industry Alliance for Ethical Advertising

No single actor can compel this shift. What one needs is an inter-industry group comprising stakeholders with a genuine interest in building trust on the digital space, privacy-oriented developers, ethical start-ups, digital liberties groups, open-source groups, as well as progressive advertisers. These players, as a group, can:

- Set transparent ethical standards for consent-driven data sharing and personalization.
- Advocate for privacy-by-design principles.
- Promote adoption of open standards and APIs for sharing content/ads preferences data.

Such a platform should have no linkage with Big Tech and rather should be funded by neutral nonprofits, open-source devices, and local platforms committed to users' autonomy.

B. MVP Idea: Open-Source Website to Build Interest Profiles

Phase one is an MVP: A fundamental open-source website on which users may create and manage ad and content preference profiles. The key features can include:

- Easy-to-use UI for selecting and categorizing interests.
- Multiple profile creation (e.g., Shopping, Music, Gaming, Social Media).
- Option to generate a unique alphanumeric Profile ID for each profile.
- Support to refresh interests at any time with real-time syncing features.

This MVP is an operational utility as well as a proof-of-concept. By open-sourcing the platform/app, there is transparency, as well as promotion of collaboration with the global developer and Privacy community.

C. API Standard for App Integration

For this to scale, an open, standardized API is required on which apps, sites, and platforms can ask this profile for users' preferences instead of making their own in secret by tracking behind users' backs. The most fundamental functionality offered by the API must be:

- Requesting a specific profile by ID (with consent).
- Syncing updated interests securely for linked profile.
- Allowing apps to offer category-specific personalization (e.g., only show Music and Comedy categories from the user profile).
- Full revocation of access from the user's end at any time.

This provides people with control and encourages platforms to not collect data without reason.

D. Partnerships: Start Small, Grow Gradually

Though Big Tech might not sign up on day one, smaller developers and privacy-oriented companies are great partners upon whom to test and prove out the system. They include:

- Indie game developers (who currently rely on ad SDKs that disrespect user privacy).
- Ethical data privacy friendly platforms such as Proton, Mastodon, or Lemmy.
- Music or podcast applications with interest in community-based personalization.
- Content filtering tools or browser extensions that want to build in clean advertising alternatives.

Such partners would provide aid in credibility building, interoperability verification, and proving real-world applicability of preference-based personalization without surveillance.

E. Governance: User-Led, Not Company-Controlled

To avoid it becoming "just another platform," its governing framework should have collective accountability, transparency, and control at its core. One possibility is a user-led or consortium, cooperative where users, contributors, and even occasional users participate in voting on:

- New features and categories.
- API access rules.
- Third-party app partnerships.
- Security protocols and breach responses.

The idea is not to become locked into control by a few individuals, but to create a decentralized, organized system where the interest of the user is not an afterthought, but the priority.

VIII. Conclusion: A Future Beyond Tracking

The conclusion drawn from literature review was that the current practices in the Data Integrity and Privacy space are trying their best to protect and equip Users with some control, yet they have certain definite flaws that cannot be solved by making more policies. As seen in the survey results, the users were willing to adapt a new solution rather than depending on policies. No doubt, Data Protection Acts are doing their best, but it's just not enough, as companies can find loopholes and workarounds every time. This creates privacy issues for users and their personal data as discussed extensively in this study.

Imagine a world where you only see what you truly value, with none of what you're doing online tracked and recorded. That's the vision here: Relevance without surveillance. This is not just another idea. It is a shift in mindset. Instead of having businesses follow users from app to website to collect their data in the name of providing "relevant" content, what if users had a choice and were able to communicate to companies what they truly want to see?

At its essence is a basic, yet powerful principle: have users develop ad and content preference profiles like they create social media profiles. Instead of shrouded by veil-of-uncertainty algorithms, users would tell different platforms (or share their data) explicitly and openly about what kind of ads or what kind of content interests them. Companies would not have to track anything. No more guessing, no more eavesdropping, no more false data, no more embarrassing advertising for something your friend checked out on your device. Just preferences, by choice.

This is not only an ethical principle, it's pragmatic. It's a win-win. Businesses still get data to sell advertising and keep services free. But they get clean data, direct feedback rather than piecing together conclusions through intrusive tracking. Consumers, on the other hand, have privacy and have more control over what they watch, write, buy, etc. Both consumers and businesses are better off.

Of course, this is just a simple framework. But it's a solution to such a problem that hasn't had any so far. A platform like this can easily be built. The technology is there. It can start as an open-source online platform/application. It can become an open protocol, an open standard. Just like demo website in this study, it is the simple website but has the ability to share users preference data with any organization. Developers, companies, and people can get behind such a thing. But it would require people, researchers, designers, coders, policymakers to mold it. The framework introduced in this research will certainly get data scientists, privacy researchers, and tech companies to one table. Although, it might look like a simple solution, but that is the purpose. It won't be beneficial to make an overly complex solution that users hesitate to use, as proven by the Survey Results. The simplicity itself will get everyone onboard.

Let's reimagine how we do relevance online. Let's create systems that honor users rather than take advantage of them. Instead of teaching algorithms to guess what users want, let users simply tell them. If we can get organized, do some additional research, and start prototyping this vision on a bigger scale than what this work presents in the previous sections, people may be able to guide the internet in a path that serves all of us ethically.

References

[1] O. Rafieian and H. Yoganarasimhan, "Targeting and Privacy in Mobile Advertising," Marketing Science, vol. 40, no. 2, Dec. 2020, doi: https://doi.org/10.1287/mksc.2020.1235.

[2] J. L. Hayes, N. H. Brinson, G. J. Bott, and C. M. Moeller, "The Influence of Consumer–Brand Relationship on the Personalized Advertising Privacy Calculus in Social Media," Journal of Interactive Marketing, vol. 55, no. 1, pp. 16–30, Aug. 2021.

[3] L. F. Lina and A. Setiyanto, "Privacy Concerns in Personalized Advertising Effectiveness on Social Media," SRIWIJAYA INTERNATIONAL JOURNAL OF DYNAMIC ECONOMICS AND BUSINESS, vol. 5, no. 2, pp. 147–156, Aug. 2021, doi: https://doi.org/10.29259/sijdeb.v1i2.147-156.

[4] B. Zarouali, T. Dobber, G. De Pauw, and C. de Vreese, "Using a Personality-Profiling Algorithm to Investigate Political Microtargeting: Assessing the Persuasion Effects of Personality-Tailored Ads on Social Media," Communication Research, vol. 49, no. 8, p. 009365022096196, Oct. 2020, doi: https://doi.org/10.1177/0093650220961965.

[5] S. Zhang, Y. Feng, Y. Yao, L. F. Cranor, and N. Sadeh, "How Usable Are iOS App Privacy Labels?," Proceedings on Privacy Enhancing Technologies, vol. 2022, no. 4, pp. 204–228, Oct. 2022, doi: https://doi.org/10.56553/popets-2022-0106.

[6] M. Kretschmer, J. Pennekamp, and K. Wehrle, "Cookie Banners and Privacy Policies: Measuring the Impact of the GDPR on the Web," ACM Transactions on the Web, vol. 15, no. 4, pp. 1–42, Jul. 2021, doi: https://doi.org/10.1145/3466722.

[7] K. Birch, D. Cochrane, and C. Ward, "Data as asset? The measurement, governance, and valuation of digital personal data by Big Tech," Big Data & Society, vol. 8, no. 1, p. 205395172110173, Jan. 2021, doi: https://doi.org/10.1177/20539517211017308.

[8] K. Varnali, "Online behavioral advertising: An integrative review," Journal of Marketing Communications, vol. 27, no. 1, pp. 1–22, Jun. 2019, doi: https://doi.org/10.1080/13527266.2019.1630664.

[9] R. Amos, G. Acar, E. Lucherini, M. Kshirsagar, A. Narayanan, and J. Mayer, "Privacy Policies over Time: Curation and Analysis of a Million-Document Dataset," Proceedings of the Web Conference 2021, pp. 2165–2176, Apr. 2021, doi: https://doi.org/10.1145/3442381.3450048.

[10] S. C. Boerman, S. Kruikemeier, and F. J. Zuiderveen Borgesius, "Exploring Motivations for Online Privacy Protection Behavior: Insights From Panel Data," Communication Research, vol. 48, no. 7, p.

009365021880091, Oct. 2018, doi: https://doi.org/10.1177/0093650218800915.

[11] S. Quach, P. Thaichon, K. D. Martin, S. Weaven, and R. W. Palmatier, "Digital technologies: Tensions in Privacy and Data," Journal of the Academy of Marketing Science, vol. 50, no. 1, pp. 1299–1323, 2022, doi: https://doi.org/10.1007/s11747-022-00845-y.

[12] Z. Gharibshah and X. Zhu, "User Response Prediction in Online Advertising," ACM Computing Surveys, vol. 54, no. 3, pp. 1–43, Jun. 2021, doi: https://doi.org/10.1145/3446662.

[13] E. Papadogiannakis, P. Papadopoulos, N. Kourtellis, and E. P. Markatos, "User Tracking in the Post-cookie Era: How Websites Bypass GDPR Consent to Track Users," arXiv:2102.08779 [cs], Feb. 2021, doi: https://doi.org/10.1145/3442381.3450056.

[14] M. Mehrnezhad, K. Coopamootoo, and E. Toreini, "How Can and Would People Protect From Online Tracking?," Proceedings on Privacy Enhancing Technologies, vol. 2022, no. 1, pp. 105–125, Nov. 2021, doi: https://doi.org/10.2478/popets-2022-0006.

[15] S. Aiolfi, S. Bellini, and D. Pellegrini, "Data-driven digital advertising: benefits and risks of online behavioral advertising," International Journal of Retail & Distribution Management, vol. 49, no. 7, pp. 1089–1110, May 2021, doi: https://doi.org/10.1108/ijrdm-10-2020-0410.

[16] M. Tahaei, A. Frik, and K. Vaniea, "Deciding on Personalized Ads: Nudging Developers About User Privacy," Symposium On Usable Privacy and Security, pp. 573–596, May 2021, doi: https://doi.org/10.7488/ds/3045.

[17] D. Geradin, T. Karanikioti, and D. Katsifis, "GDPR Myopia: how a well-intended regulation ended up favouring large online platforms - the case of ad tech," European Competition Journal, vol. 17, no. 1, pp. 1–46, Dec. 2020, doi: https://doi.org/10.1080/17441056.2020.1848059.

[18] K. Kollnig, A. Shuba, M. Van Kleek, R. Binns, and N. Shadbolt, "Goodbye Tracking? Impact of iOS App Tracking Transparency and Privacy Labels," arXiv:2204.03556 [cs], May 2022, doi: https://doi.org/10.1145/3531146.3533116.

[19] K. Kollnig et al., "A Fait Accompli? An Empirical Study into the Absence of Consent to Third-Party Tracking in Android Apps," arXiv (Cornell University), Jun. 2021, doi: https://doi.org/10.48550/arxiv.2106.09407.

[20] M. Büchi, E. Fosch-Villaronga, C. Lutz, A. Tamò-Larrieux, and S. Velidi, "Making sense of algorithmic profiling: user perceptions on Facebook," Information, Communication & Society, vol. 26, no. 4, pp. 1–17, Oct. 2021, doi: https://doi.org/10.1080/1369118x.2021.1989011.

[21] M. Veale and F. Zuiderveen Borgesius, "Adtech and Real-Time Bidding under European Data Protection Law," German Law Journal, vol. 23, no. 2, pp. 226–256, Mar. 2022, doi: https://doi.org/10.1017/glj.2022.18.

[22] Konrad Kollnig, A. Shuba, R. Binns, M. V. Kleek, and N. Shadbolt, "Are iPhones Really Better for Privacy? Comparative Study of iOS and Android Apps.," Privacy Enhancing Technologies, Sep. 2021.

[23] Dr. J. Strycharz, Dr. E. Smit, Dr. N. Helberger, and Dr. Guda van Noort, "No to cookies: Empowering impact of technical and legal knowledge on rejecting tracking cookies," Computers in Human Behavior, vol. 120, p. 106750, Feb. 2021, doi: https://doi.org/10.1016/j.chb.2021.106750.

[24] J. Jueckstock et al., "Towards Realistic and ReproducibleWeb Crawl Measurements," pp. 80–91, Apr. 2021, doi: https://doi.org/10.1145/3442381.3450050.

[25] K. Mellet and T. Beauvisage, "Cookie monsters. Anatomy of a digital market infrastructure," Routledge eBooks, pp. 14–33, Apr. 2021, doi: https://doi.org/10.4324/9781003130154-2.

[26] S. G. Goldberg, G. A. Johnson, and S. K. Shriver, "Regulating Privacy Online: An Economic Evaluation of the GDPR," American Economic Journal: Economic Policy, vol. 16, no. 1, pp. 325–358, Feb. 2024, doi: https://doi.org/10.1257/pol.20210309.

[27] G. Aridor, Y.-K. Che, and T. Salz, "The Effect of Privacy Regulation on the Data Industry," Proceedings of the 22nd ACM Conference on Economics and Computation, Jul. 2021, doi: https://doi.org/10.1145/3465456.3467543.

[28] Y. Feng, Y. Yao, and N. Sadeh, "A Design Space for Privacy Choices: Towards Meaningful Privacy Control in the Internet of Things," Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems, May 2021, doi: https://doi.org/10.1145/3411764.3445148.

[29] C. Santos, A. Rossi, L. S. Chamorro, K. Bongard-Blanchy, and Ruba Abu-Salma, "Cookie Banners, What's the Purpose?: Analyzing Cookie Banner Text Through a Legal Lens," Workshop on Privacy in the Electronic Society, pp. 187–194, Nov. 2021.

[30] Bollinger, D., Kubicek, K., Cotrini, C., & Basin, D. (2022). Automating cookie consent and {GDPR} violation detection. In 31st USENIX Security Symposium (USENIX Security 22) (pp. 2893-2910).

[31] Ke Xin Ch'ng, A. Y. Lee, Wou Onn Choo, and Pei Boon Ooi, "Students' and Parents' Online Behavior and Exposure towards Cyberbullying," Oct. 2021, doi: https://doi.org/10.1109/icriis53035.2021.9617112.

[32] C. Mcclain, M. Faverio, M. Anderson, and E. Park, "How Americans View Data Privacy The role of technology companies, AI and regulation -plus personal experiences with data breaches, passwords, cybersecurity and privacy policies FOR MEDIA OR OTHER INQUIRIES," vol. 18, p. 2023, Available: https://www.pewresearch.org/wp-content/uploads/sites/20/2023/10/PI_2023.10.18_Data-Privacy_FINAL.pdf

[33] "The Privacy Advantage: Building Trust in a Digital World." Available: https://www.cisco.com/c/dam/en_us/about/doing_business/trust-center/docs/cisco-privacy-benchmark-study-2025.pdf

Towards Quantum-Accelerated Urban Systems: Integrating Quantum Computing into Saudi Smart City Megaprojects

Architecting Quantum-Smart Infrastructure for Deployment in Vision 2030 Initiatives

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***Abstract*—Quantum Computing (QC), rooted in the principles of superposition and entanglement, enables transformative computational capabilities that surpass classical systems, particularly in solving NP-hard combinatorial optimization, simulation, and machine learning problems. These capabilities are increasingly vital for smart cities, which depend on real-time data from the Internet of Things (IoT) devices, Artificial Intelligence (AI), and Urban Digital Twins (UDTs) to orchestrate complex urban systems such as traffic, energy, logistics, and public safety. As global urbanization accelerates, the demand for hyper-efficient, secure, and adaptive infrastructure exceeds the limits of classical computation. This study employs a multi-pronged methodology that combines literature synthesis, algorithmic mapping, and strategic roadmap design. This study investigates the strategic alignment between QC and the computational demands of next-generation urban environments, with a specific focus on Saudi Arabia's greenfield megaprojects, including NEOM, The Line, and the Red Sea Project, within the Saudi Vision 2030 framework. The analysis systematically maps urban computational challenges to applicable quantum algorithm families—Quantum Approximate Optimization Algorithm (QAOA), Variational Quantum Eigensolver (VQE), and Quantum Machine Learning (QML)—and synthesizes the technical, organizational, financial, ethical, and regulatory prerequisites for national deployment. The core contribution is the development of a conceptual Hybrid Quantum-Classical Architecture (HQCA) and a methodologically grounded three-phase deployment roadmap, tailored to the Saudi context, mapping quantum technical readiness to policy and infrastructure milestones in Saudi Arabia. This framework positions Saudi Arabia to pioneer quantum-accelerated urban systems, enabling resilient infrastructure, sovereign digital capabilities, and global leadership in the emerging Quantum City paradigm.**

Keywords*—Quantum Computing (QC); Hybrid Quantum-Classical Architecture (HQCA); quantum security; smart cities; NEOM; Saudi Vision 2030; combinatorial optimization; Urban Digital Twin (UDT); Quantum Machine Learning (QML); roadmap

I. Introduction

The development of Smart Cities (SC) represents a global strategic shift toward sustainable, hyper-efficient, and digitally integrated urban living environments. These ecosystems rely on the real-time processing of massive data streams generated by the Internet of Things (IoT), sophisticated Artificial Intelligence (AI) models, and comprehensive Urban Digital Twins (UDTs) to manage everything from water distribution to public security [1], [2], [3]. Designed to be adaptive and data-driven, smart cities promise enhanced citizen well-being, resource optimization, and resilient governance.

As smart cities evolve, they generate massive, complex, and real-time datasets from millions of interconnected sensors and systems. The management of these data requires advanced computational methods capable of handling dynamic multivariate environments. Many of the most pressing urban management tasks, such as global traffic synchronization, real-time energy grid balancing, and large-scale logistical coordination, are classified as combinatorial optimization problems. The computational complexity of these challenges increases exponentially with scale, often rendering them intractable, even for the most powerful classical supercomputers [4], [5].

Although classical High-Performance Computing (HPC) has facilitated the first generation of smart cities, the exponential scaling of computational demands now presents a critical bottleneck. Core operational problems in these hyperscale environments, such as dynamic traffic and logistics routing (Vehicle Routing Problem), complex energy grid load balancing (QUBO), and full-fidelity UDT simulation, require solutions that go beyond heuristic approximations, which often lead to systemic inefficiencies and instability in critical infrastructure.

Quantum Computing (QC), grounded in the principles of superposition and entanglement, unlocks new capabilities for a paradigm shift in computational capability. Quantum algorithms, including the Quantum Approximate Optimization Algorithm (QAOA), Variational Quantum Eigensolver (VQE), Quantum Annealing (QA), and Quantum Machine Learning (QML), are particularly well-suited to address the bottlenecks inherent in smart city operations [6], [7], [8]. Their integration into smart city platforms and UDTs enables high-fidelity simulations, predictive modeling of climate and energy dynamics, and real-time decision support for autonomous agents [9], [10].

This opportunity is especially salient in the Kingdom of Saudi Arabia, where Vision 2030 is driving the creation of greenfield urban megaprojects such as NEOM, The Line, and the Red Sea Project, which are designed to be zero-carbon, high-speed, and sovereign in terms of digital infrastructure [11], [12]. These developments require computational solutions that exceed the current urban planning standards. Embedding

quantum capabilities from inception offers Saudi Arabia a unique opportunity to leapfrog legacy constraints and pioneer the Quantum City paradigm.

Despite its compelling technical potential, a significant research and policy gap remains: the absence of a concrete, nation-specific, and phased architectural blueprint for QC adoption in urban transformation initiatives. Most existing studies focus on theoretical algorithmic advantages without addressing the Hybrid Quantum-Classical Architecture (HQCA) required for integration or the strategic framework involving hardware investment, talent development, and regulatory governance required for national deployment.

This study addresses this gap through two key contributions: 1) Architectural Blueprint: Development of the conceptual Hybrid Quantum-Classical Architecture (HQCA) for managing and executing quantum-tractable subproblems in complex smart city operations, providing the necessary technical foundation for integration. 2) Strategic Deployment Roadmap: A methodologically grounded, three-phase roadmap tailored to Saudi Arabia's Vision 2030, guiding policymakers and technical teams from foundational infrastructure readiness to operational quantum advantage, linking technical requirements to strategic policy milestones.

The remainder of this study is structured as follows: Section II provides a comprehensive review of the quantum computing landscape and current smart city architectures, identifying the key research gap this work addresses. Section III details the multi-pronged methodology, including the systematic approach for algorithmic mapping and strategic roadmap development, providing the necessary methodological rigor requested by reviewers. Section IV introduces the foundational Hybrid Quantum-Classical Architecture (HQCA) for smart urban systems and clarifies the distinction between genuine quantum and quantum-inspired methods. Section V presents the strategic three-phase roadmap for integrating QC into Saudi megaprojects, outlining specific use cases and readiness levels. Finally, Section VI concludes the study and discusses future research directions and policy implications.

II. Literature Review

This section critically examines the intersection of quantum computing and smart city development and establishes the theoretical and practical foundations of the proposed framework. It begins by outlining the core principles and architectural models of quantum computing, emphasizing their relevance to urban optimization challenges. This review explores the computational demands of smart cities, highlighting the limitations of classical systems and the strategic imperative for quantum integration. Building on this, the synergy between quantum technologies and smart city platforms is analyzed, with particular attention paid to urban digital twins and autonomous systems. Finally, the literature converges on the context of Saudi Arabia's Vision 2030, presenting an integrated architecture that aligns Smart City layers with quantum capabilities. This progression identifies key research gaps and sets the stage for the technical and strategic contributions of this study to address them.

A. Quantum Computing: Fundamentals and Architecture for Urban Optimization

Quantum Computing (QC) represents a transformative shift in computational paradigms, leveraging quantum-mechanical principles such as superposition, entanglement, and interference to process information in fundamentally different ways from classical von Neumann architectures [8]. Unlike classical bits, which encode data as either 0 or 1, quantum bits (qubits) can exist in multiple states simultaneously. This property enables quantum systems to explore exponentially larger solution spaces in parallel, offering powerful capabilities for solving complex urban challenges [4].

These principles underpin several algorithmic families that are relevant to smart city applications. Quantum optimization algorithms, such as the Quantum Approximate Optimization Algorithm (QAOA) and quantum annealing, have shown promise in solving traffic routing, resource allocation, and scheduling problems [6], [14]. Quantum Machine Learning (QML) enhances predictive modeling in domains such as mobility, infrastructure, and public services [15], whereas quantum simulation enables high-fidelity modeling of physical systems such as climate, energy, and water networks [16]. Additionally, quantum-safe cryptographic protocols, including Post-Quantum Cryptography (PQC) and Quantum Key Distribution (QKD), are essential for securing municipal data and IoT infrastructure [17], [18].

Although the potential of Quantum Computing (QC) is vast, its current realization is characterized by the Noisy Intermediate-Scale Quantum (NISQ) era [4]. This designation describes today's hardware, which features a limited number of physical qubits (typically 50 to a few hundred) and critically lacks robust quantum error correction (QEC). The inherent noise and limited qubit connectivity in NISQ devices impose severe practical constraints on the complexity and runtime of quantum algorithms, causing quantum states to decohere and computational errors to accumulate rapidly.

For smart city applications, this reality mandates the use of Hybrid Quantum-Classical Architectures (HQCAs), particularly in algorithms such as the QAOA and VQE. In these models, quantum processors handle computationally intensive kernels (e.g., optimization components), whereas classical supercomputers manage most data handling and iterative loop control [19]. Furthermore, research efforts are intensely focused on error mitigation techniques—methods that use existing noisy hardware to produce statistically meaningful results by carefully managing and analyzing error signatures rather than relying on full-scale QEC, which remains years away. This pragmatic hybrid approach is critical for the phased adoption outlined in this study, ensuring that early-stage quantum pilots in megaprojects are grounded in achievable computational gains, rather than idealized future performance.

Quantum computing architectures are typically categorized into gate-based systems and quantum annealers. Gate-based architectures support universal quantum algorithms and are programmable and scalable, making them suitable for long-term Smart City applications, such as urban simulation and autonomous system coordination [7]. Quantum annealers, on the other hand, are specialized for solving combinatorial

optimization problems formulated as Quadratic Unconstrained Binary Optimization (QUBO), which are common in traffic signal coordination, smart grid balancing, and logistics routing [14], and [10]. Fig. 1 illustrates the foundational structure of the integrated Smart City framework, emphasizing the role of the computational core in processing vast amounts of urban data.

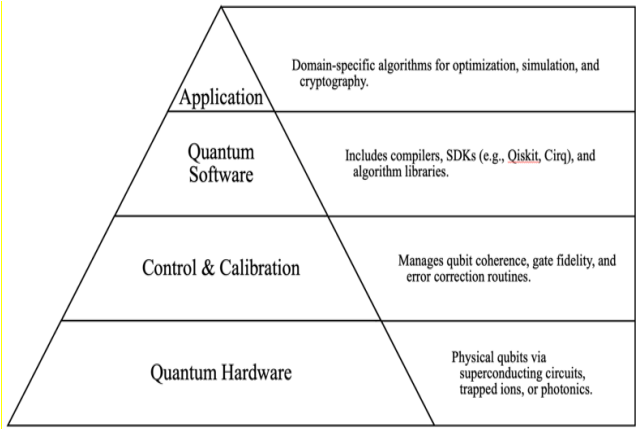


Fig. 1. Architectural layers of quantum computing.

To interface with smart city platforms, quantum architectures must be extended using hybrid quantum-classical systems, middleware abstraction layers, and quantum-safe security modules. Hybrid Quantum-Classical Architectures (HQCA) combine quantum solvers with classical infrastructure to enable real-time decision support in Urban Digital Twins (UDTs), traffic systems, and energy grids [11]. Middleware translators convert Smart City variables into QUBO or Hamiltonian formats for quantum processing [20], whereas quantum-safe security modules embed PQC and QKD into IoT and blockchain layers to ensure resilience against future quantum threats [17], [18].

Although fault-tolerant quantum advantage is still a medium-term objective, quantum-inspired algorithms and hybrid workflows are already delivering near-term value. These approaches enhance performance in targeted domains, such as smart grid balancing and traffic optimization. Moreover, the rise of QC necessitates immediate preparation for quantum threats to current encryption standards, as algorithms such as RSA and ECC are vulnerable to quantum attacks.

B. Smart Cities and the Computational Imperative for Quantum Integration

Smart cities are dynamic ecosystems that integrate advanced technologies to enhance urban life, optimize resource utilization, and ensure sustainability. They represent the convergence of physical infrastructure, digital intelligence, and human-centric governance, orchestrated through interconnected systems [1], [2]. At their core, smart cities rely on Information and Communication Technologies (ICT), Internet of Things (IoT) devices, Urban Digital Twins (UDTs), automated control systems, and real-time analytics to deliver responsive, efficient, and equitable services [3], [10].

The architecture of a smart city comprises multiple interdependent layers, as shown in Fig. 2, including physical infrastructure, sensor networks, connectivity, data management, service orchestration, and governance. These layers support strategic pillars, such as smart governance, smart mobility, smart environments, and smart living. Each pillar involves solving complex optimization problems, multivariate simulations, and secure communications. For example, smart governance demands the predictive modeling of policy outcomes and secure data sharing [9], whereas smart mobility demands real-time route planning and congestion prediction [14]. Smart environments involve dynamic energy balancing and climate resilience modeling [16], whereas smart living depends on the orchestration of intelligent services and secure communications [7].

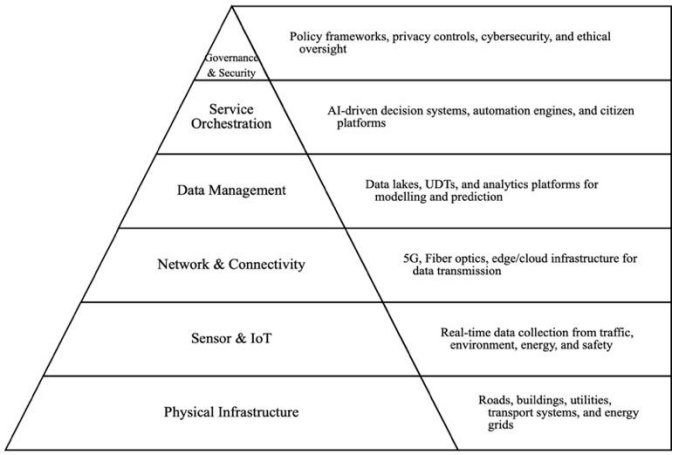


Fig. 2. Architecture layers of smart cities.

The computational demands of these systems, particularly for real-time optimization and high-fidelity simulations, are rapidly outpacing the capabilities of classical computing. Many of the most critical smart city tasks are NP-hard, meaning that the time required to determine optimal solutions increases exponentially with system complexity [4], [8]. Quantum computing provides a novel approach for strategically addressing these bottlenecks. Algorithms such as the QAOA and quantum annealing solve routing and scheduling problems more efficiently [5], [6], while QML enhances predictive modeling, and quantum simulation supports infrastructure planning and resilience [15], [16]. Quantum-safe cryptography ensures long-term data integrity and privacy across Smart City layers [17], [18].

Saudi Arabia's Vision 2030 presents a unique opportunity to embed quantum technologies from inception into greenfield megaprojects, such as NEOM, The Line, and the Red Sea Project [21], [22]. These developments demand computational solutions that exceed the current urban planning standards, particularly in achieving zero-carbon, high-speed, and adaptive operations.

C. Quantum Technologies and Smart City Synergy

The convergence of quantum technologies with smart city systems marks a pivotal evolution in urban innovation. As cities become increasingly complex and data-driven, classical computational architectures struggle to meet the demands of real-time optimization, predictive modeling, and secure communication [4], [8]. The Quantum City paradigm introduces a new computational model that leverages quantum physics to

unlock hyper-efficiency, resilience, and intelligence in urban domains [10].

Conventional smart city technologies—including IoT, AI, blockchain, and cloud computing—operate within deterministic, binary frameworks. Although these systems have enabled significant advancements in urban management, they are inherently limited in solving large-scale combinatorial problems and securing data against emerging threats [1], [2]. Quantum computing bridges this gap by accelerating complex calculations using superpositions and entanglements. Quantum annealing is ideal for solving QUBO problems, such as traffic coordination and energy grid balancing [14], whereas gate-based quantum computing supports universal algorithms, such as QML, for predictive modeling [6], [15].

Quantum communication technology further enhances the resilience of smart cities. Quantum Key Distribution (QKD) provides provably secure encryption, and Post-Quantum Cryptography (PQC) protects urban systems from future quantum attacks (Mosca, 2018; Barletta et al., 2023). These capabilities are especially critical for safeguarding IoT networks, blockchain platforms, and cloud-based services.

Urban Digital Twins (UDTs) are among the most promising applications of quantum technologies. Quantum-enhanced UDTs enable accelerated simulations of traffic systems, climate impacts, and energy demand (Georgescu et al., 2014). Quantum Reinforcement Learning (QRL) trains autonomous agents, such as traffic controllers and energy regulators, within UDT environments, allowing them to adapt in real time and improve system-wide performance [7]. By embedding quantum capabilities into UDTs, Saudi Arabia can achieve predictive, resilient, and intelligent urban systems that scale with complexity and adapt to uncertainties.

D. Integrated Smart City Architecture with Quantum Computing

To operationalize the convergence of smart city systems and quantum technologies, this study presents an integrated architectural framework that aligns urban infrastructure layers with the corresponding quantum computing capabilities of the latter. As cities evolve into complex, data-intensive ecosystems, the limitations of classical computing are becoming increasingly apparent, particularly in domains that require real-time optimization, high-dimensional simulation, and secure communication.

The proposed framework reflects the layered nature of smart cities, as structured in Table I, beginning with the foundational physical infrastructure and progressing through sensor networks, connectivity, data management, service orchestration, and governance. Each layer is mapped to a quantum counterpart, illustrating how quantum hardware, algorithms, simulation engines, and cryptographic protocols can be embedded in the urban stack. For example, quantum hardware environments support infrastructure-level integration, whereas quantum sensors enhance data collection precision. Quantum communication channels, such as QKD-secure network layers and quantum simulation engines, enhance the data management systems. The QAOA, QML, and QRL enhance service orchestration, whereas the PQC and ethical quantum governance modules reinforce governance and security [10], [11], [18].

To bridge classical and quantum systems, the architecture includes integration middleware components, such as a Hybrid Execution Manager, which routes tasks to either classical or quantum processors based on complexity. The Quantum API Gateway provides a unified interface for accessing Quantum-as-a-Service (QaaS) platforms such as IBM and Pasqal, whereas the Semantic Translator converts smart city variables, such as traffic flows, energy loads, or policy constraints, into quantum-compatible formats such as QUBO or Hamiltonians.

TABLE I. LAYERED ARCHITECTURE: CLASSICAL–QUANTUM ALIGNMENT

Layer	Smart City Components (Classical)	Quantum Integration (Enhancement)
Governance & Security	Policy frameworks, privacy controls, cybersecurity, ethical oversight	Post-Quantum Cryptography (PQC), Quantum-safe Protocols, Ethical Governance Modules
Service Orchestration	Automated control systems, intelligent service delivery, multi-agency coordination	Quantum Algorithms (QAOA, QML, QRL) for optimization, learning, and autonomy
Data Management	Urban Digital Twins (UDTs), data lakes, AI-driven analytics platforms	Quantum Simulation Engines and Quantum-Enhanced Data Processing
Network & Connectivity	5G, fiber optics, and edge/cloud infrastructure for data transmission	Quantum Communication Channels (QKD, Entanglement-based Networks)
Sensor & IoT	Real-time data collection from traffic, environment, energy, and public safety	Quantum sensors for ultra-precise measurements (e.g., magnetic fields, temperature)
Physical Infrastructure	Roads, buildings, transport systems, energy grids, and utilities	Quantum Hardware Environments (Cryogenic Systems, Superconducting Circuits, Photonics)

Fig. 3 illustrates the vertical alignment between the conventional five-layer Smart City stack and the specific Quantum Computing (QC) technologies designed to accelerate, optimize, and secure each layer. The model highlights the use of Post-Quantum Cryptography (PQC) and Quantum Key Distribution (QKD) for foundational security, while Quantum Machine Learning (QML) and optimization algorithms (QAOA, VQE) provide the necessary computational speedup to manage NP-hard problems in real-time city operations.

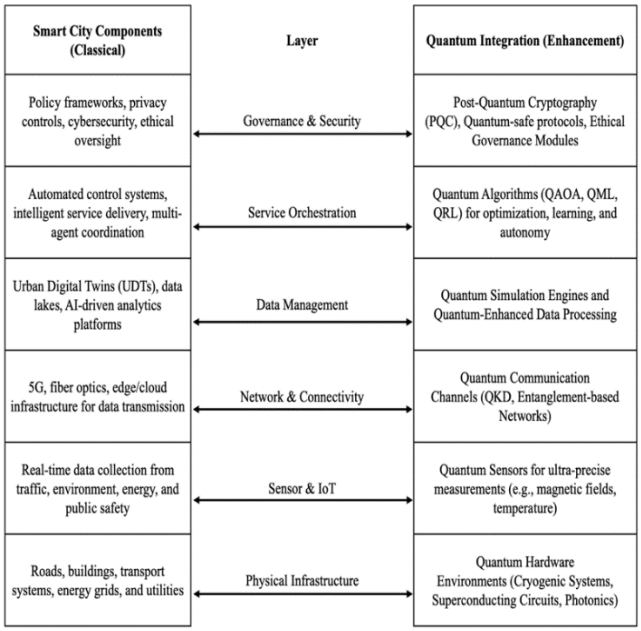


Fig. 3. Hybrid Quantum-Classical Architectures (HQCA) for urban systems.

E. Saudi Arabia: Quantum Computing Technologies and Smart Cities Context

Saudi Arabia's Vision 2030 positions the Kingdom as a global leader in digital transformation and urban innovation. Greenfield megaprojects, such as NEOM, The Line, and the Red Sea Project, are designed to be zero-carbon, high-speed, and digitally sovereign, making them ideal testbeds for quantum integration [11], [12]. The strategic imperative is clear: classical systems cannot meet the computational demands of hyperscale environments.

Although Saudi Arabia has invested in AI, 5G, and IoT infrastructure, quantum computing is an emerging frontier. There is limited national literature on phased QC adoption, talent development, and regulatory alignment. This gap underscores the need for a tailored Strategic Adoption Framework that maps quantum capabilities to Saudi Arabia's urban transformation goals to ensure operational readiness and sovereign-technology leadership.

III. Methodology

A. Overview of Methodological Framework

This study adopts a multi-layered methodological framework to guide the strategic integration of quantum computing (QC) into Saudi Arabia's emerging smart city ecosystem. The approach begins with a systematic literature review synthesizing global advancements in quantum technologies across urban domains. Peer-reviewed publications, government reports, and pilot project documentation were analyzed to benchmark the technical feasibility and deployment patterns. This review was complemented by a thematic synthesis of Saudi Arabia's digital transformation agenda, particularly Vision 2030 and the National Strategy for Data and AI, to contextualize quantum integration within the national priorities.

Building on this foundation, this study conducts a comparative contextual analysis that juxtaposes international quantum-smart city use cases with the unique characteristics of Saudi greenfield megaprojects, such as NEOM, The Line, and Qiddiya. These developments, unconstrained by legacy infrastructure, present distinct requirements for low-carbon efficiency, secure communications, and real-time urban intelligence. From this analysis, three high-impact domains were systematically selected:

- Traffic signal coordination, mapped to QAOA and quantum annealing for optimization.
- Smart grid balancing, mapped to VQE for complex simulation and optimization.
- Infrastructure simulation via Urban Digital Twins (UDTs), mapped to QML and QRL for predictive modeling and autonomous decision-making.

Hybrid quantum-classical workflows were designed using platforms such as IBM Qiskit and D-Wave Leap, with problem formulations translated into quantum-compatible formats like QUBO and Hamiltonians.

The final phase of the methodology involved strategic synthesis and roadmap design processes. Insights from the literature and algorithmic mapping were consolidated into a three-phase national roadmap—exploration, pilot deployment, and scaled integration—each of which is aligned with technical, organizational, and financial milestones. Key Performance Indicators (KPIs) were defined to measure progress in infrastructure readiness, talent development, regulatory alignment, and cross-sector adoption. To validate the framework, evaluation criteria were applied across four dimensions: computational efficiency, scalability, integration feasibility, and strategic alignment with Saudi Vision 2030. This iterative process ensures that the proposed roadmap remains adaptable to the evolving quantum capabilities and urban planning priorities. Fig. 4 illustrates the overall iterative methodology used in this study.

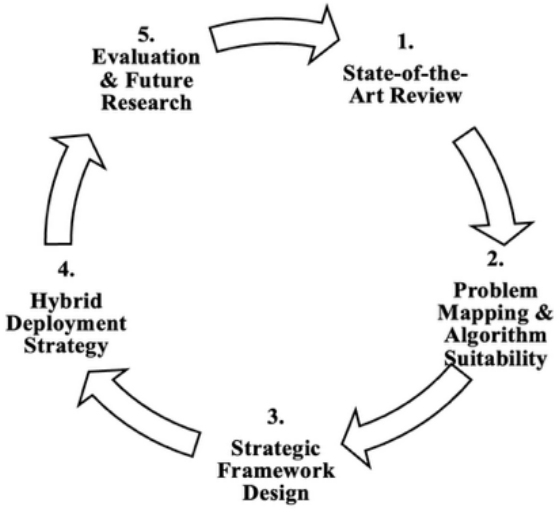


Fig. 4. Overall methodology.

B. Methodological Grounding of Algorithmic Mapping and Roadmap Design

This study adopts a systematic algorithmic mapping and strategic foresight analysis approach to address the need for greater methodological transparency and rigor in the mapping and strategic design processes. This study adopts an approach of systematic algorithmic mapping and strategic foresight analysis. The criteria for use case selection, mapping scope, and roadmap phasing were explicitly defined as follows.

First, the criteria for Use Case Selection and prioritization were based on three synergistic factors that justify the strategic investment in quantum resources. These factors are Strategic Relevance, where cases were chosen based on their direct alignment with the high-impact, technologically ambitious goals of Saudi Vision 2030 megaprojects (e.g., NEOM's cognitive systems, high-speed logistics, and sustainable resource management); Classical Bottleneck Justification, which explicitly placed focus on problems identified as NP-hard (e.g., complex combinatorial optimization, large-scale traffic modeling, resource allocation) where current state-of-the-art classical High-Performance Computing (HPC) or AI solutions face known computational limitations, thereby justifying the search for quantum acceleration; and Theoretical Quantum Applicability, where use cases were confirmed against existing, peer-reviewed literature demonstrating a theoretical fit with known quantum algorithm families (e.g., the QUBO formulation required by QAOA or the linear algebra necessary for HHL).

Second, the Algorithmic Mapping and Technical Scope section clarifies that the mapping presented is a conceptual architectural blueprint rather than a formal complexity proof. It links the class of urban problems to the class of suitable quantum algorithms. This is explicitly a strategic mapping intended to both identify where potential quantum advantage could be realized and inform the design of the Hybrid Quantum-Classical Architecture (HQCA) discussed in Section IV. Formal complexity analysis and empirical performance comparisons against classical HPC are acknowledged as critical future work, dependent on the scaling and maturity of fault-tolerant quantum hardware. Therefore, this study provides the necessary conceptual foundation for those future comparisons.

Third, the Roadmap Phasing and Readiness Assessment explains that the three-phase roadmap adapts the conventional Technology Readiness Level (TRL) framework to a Quantum Readiness Level (QRL) relevant for strategic urban systems deployment. The phasing is benchmarked against three factors: QPU Scaling, which considers anticipated global timelines for NISQ device maturity (e.g., 50+ effective qubits) and the development of rudimentary fault-tolerant QPUs; Infrastructure Maturity, encompassing the projected development schedule and foundational readiness of the specific Saudi megaprojects; and Goal Orientation, where each phase (Readiness, Pilot, and Deployment) is structured to progressively move from foundational research/quantum-inspired techniques to full integration of true QPU acceleration, providing a clear path from current capabilities to future quantum advantage.

IV. Results

This section presents the analytical results and strategic insights derived from the proposed methodology. It begins by examining the international use cases of quantum computing in smart cities and offers comparative benchmarks and insights. The discussion then shifts to the Saudi Arabian context, evaluating its current readiness and identifying the key requirements for quantum integration. Based on this foundation, a three-phase strategic roadmap is proposed to guide adoption across national megaprojects. This section elaborates on a holistic technical integration strategy and hybrid quantum-classical software architecture designed to support scalable, secure, and intelligent urban systems. Finally, this study critically assesses the benefits and challenges of quantum adoption, offering a balanced perspective on its feasibility, impact, and future direction.

A. Use Cases from Around the World for Quantum Computing Adoption in Smart Cities

Global pilot projects and proof-of-concept deployments have demonstrated that quantum computing (QC) offers tangible near-term value for smart cities, not by replacing classical systems, but by augmenting them using hybrid algorithms, simulation-based proofs, and targeted hardware trials. These initiatives span a wide spectrum of domains, including traffic optimization, energy grid management, logistics, environmental sensing, cybersecurity, healthcare, education, and digital governance. These pilots offer strategic foresight for Saudi Arabia's megaprojects, such as NEOM, Qiddiya, and the Red Sea Project, especially in areas where classical computational limits are likely to be reached owing to the scale, complexity, and sustainability ambitions of these developments.

In traffic and mobility optimization, quantum annealing and quantum-inspired algorithms have been applied to complex routing and scheduling problems, such as the Traveling Salesperson Problem (TSP), enabling real-time traffic light sequencing and congestion reduction. In energy grid management, hybrid quantum-classical algorithms accelerate unit commitment and battery placement, enhancing grid balance in renewable-heavy microgrids. Urban logistics and supply chain routing have benefited from quantum formulations for last-mile delivery and dynamic routing, thereby improving freight efficiency in densely populated city environments.

In environmental modeling and sensing, quantum-enhanced sensors and quantum machine learning (QML) enable high-fidelity anomaly detection and climate-resilience forecasting. Cybersecurity pilots have deployed Quantum Key Distribution (QKD) and post-quantum cryptography (PQC) to secure municipal infrastructure and citizen data. Smart healthcare modeling leverages quantum graph analytics and probabilistic modeling to simulate disease spread and optimize hospital logistics, thereby supporting national preparedness and NEOM's health systems.

Emerging domains are gaining popularity. Smart waste management uses quantum optimization for dynamic bin scheduling and route planning, aligning with circular economy goals in cities such as Medina. In education, quantum-enhanced

clustering and recommendation systems enable personalized learning paths and adaptive curricula, supporting NEOM's digital education platforms. Digital twin simulation integrates quantum-enhanced multi-agent modeling for real-time urban planning and resilience forecasting. Finally, smart tourism applications use quantum algorithms to optimize visitor flows and enhance cultural site management, which is critical for destinations such as Alula, Diriyah, and Hajj logistics.

Table II summarizes these global pilot projects, highlighting their focus areas, enabling technologies, demonstrated outcomes, and strategic relevance to Saudi Arabia's Smart City initiatives.

TABLE II. GLOBAL QUANTUM COMPUTING PILOT PROJECTS FOR SMART CITIES

Focus Area	Technology & Mechanism	Outcome	Saudi Applicability	Technical Enhancement	Ref.
Traffic Signal Optimization	Quantum Annealing (QUBO formulation)	Adaptive signal control, reduced congestion	NEOM and Riyadh traffic systems	Quantum-assisted learning automata for dynamic timing	[23] [24] [25]
Port Logistics & Routing	Quantum-Inspired Optimization (Digital Annealer)	Lower truck travel time, reduced CO_2 emissions	Jeddah and Dammam logistics hubs	Hybrid QUBO for multi-modal freight routing	[26] [27]
Grid Battery Placement	Hybrid Quantum-Classical Algorithms	Optimized voltage control and battery siting	Saudi smart grid expansion	Quantum-enhanced simulation for energy resource planning	[28], [29], [30]
Urban Mobility Forecasting	Quantum Machine Learning (QML) on traffic sensor data	Improved traffic prediction accuracy	Riyadh and NEOM AI mobility platforms	Quantum-enhanced time series forecasting	[31], [32], [33]
Emergency Response Optimization	Quantum annealing for multi-agent dispatch	Faster resource allocation and coordination	NEOM autonomous emergency systems	Quantum scheduling for emergency logistics	[34], [35]
Infrastructure Optimization	Quantum-Inspired Evolutionary Algorithms	Multi-variable optimization for traffic and energy	NEOM and Qiddiya infrastructure planning	QiEA restarts and swarm intelligence	[36], [37], [38]
Energy & Water Management	Quantum simulation for desalination and grid modeling	Improved modeling of water-energy nexus	Red Sea Project and NEOM water-energy systems	Quantum-enhanced digital twin for resource optimization	[39], [40], [41]
Cybersecurity Infrastructure	Quantum Key Distribution (QKD) and Post-Quantum Cryptography (PQC)	Secured municipal data links	PQC rollout across Saudi smart city platforms	Integration of QKD with blockchain-based services	[42], [43]
Urban Governance Simulation	Quantum-enhanced agent-based modeling	Simulated policy outcomes across complex urban systems	NEOM governance and Vision 2030 policy planning	Quantum scenario simulation for zoning, taxation, and incentives	[13]
Climate Resilience Forecasting	Quantum simulation for climate and disaster modeling	High-resolution prediction of floods and heatwaves	Coastal and desert urban adaptation	Quantum-enhanced microclimate and extreme event modeling	[39], [41]
Smart Healthcare Modeling	Quantum graph analytics and probabilistic modeling	Disease spread modeling, hospital logistics optimization	NEOM health infrastructure and national preparedness	Quantum-enhanced epidemiological simulation	[44], [45], [46], [47]
Digital Identity & Citizen Services	Quantum-secure identity verification and blockchain integration	Secure e-government, voting, and citizen data platforms	National digital identity and civic platforms	PQC-based authentication and encrypted citizen services	[42], [48], [49], [50]
Smart Waste Management	Quantum optimization for route planning and bin prediction	Dynamic scheduling, reduced fuel and overflow	NEOM circular economy, Medina municipal services	Quantum-enhanced logistics for sanitation networks	[51], [52]
Smart Education & Learning Analytics	Quantum-enhanced clustering and recommendation systems	Personalized learning paths, curriculum optimization	NEOM education platforms, national e-learning	Quantum machine learning for adaptive education	[53], [54]
Digital Twin & Urban Simulation	Quantum simulation for multi-agent urban modeling	Real-time city-scale digital twins	NEOM, Qiddiya, Red Sea infrastructure	Quantum-enhanced planning and resilience modeling	[55], [56]
Smart Tourism & Cultural Heritage	Quantum-enhanced recommendation and crowd flow modeling	Optimized visitor experience, congestion prediction	AlUla, Diriyah, Hajj logistics	Quantum algorithms for cultural site management	[57], [58]

These benchmarks inform the technical and strategic directions for quantum adoption in Saudi Arabia. The following subsections explore three representative use cases in greater depth, illustrating how quantum algorithms address specific Smart City challenges and how these solutions translate into measurable impacts within the Saudi context.

1) Energy grid load balancing and optimization: An excellent example of a combinatorial-optimization problem is managing scattered urban energy systems heavily reliant on renewable sources. In smart cities, such as NEOM, where energy systems are built around 100% renewable sources, a considerable amount of computer power is required to balance the real-time energy flow, predict how demand will change, and schedule battery storage among thousands of dynamic nodes. Quadratic Unconstrained Binary Optimization (QUBO) models typically address these issues. Classical solvers use heuristics

to solve them; however, these heuristics become less accurate and slower as the system becomes more complex.

Quantum computing is an intriguing alternative to classical computing methods. The Quantum Approximate Optimization Algorithm (QAOA) and Variational Quantum Eigensolver (VQE) are two examples of algorithms that can solve QUBO problems by converting them into quantum circuits. These circuits examine extensive solution spaces in superposition and identify near-optimal configurations for load distribution and storage scheduling. The VQE and QAOA can determine the optimal times to charge and discharge a quantum system by lowering its energy state. This reduces energy loss and maximizes the use of renewable sources.

In Saudi Arabia, this ability immediately helps the Line and other megaprojects achieve their goal of carbon neutrality. Recalibrating the grid in real time makes operations more reliable, reduces energy waste, and makes the system more sustainable in the long run. Improvements in computing efficiency can lead to significant reductions in costs and emissions, demonstrating the importance of quantum integration in national energy planning.

2) Dynamic traffic and logistics routing: In hyper-connected cities, urban logistics and mobility systems require route optimization that is always on and can predict the next event. As Saudi Arabia moves toward fleets of self-driving cars and public transit networks that function together, managing real-time traffic flow and supply chains becomes increasingly difficult. These problems are usually modeled as different versions of the Vehicle Routing Problem (VRP) or the Traveling Salesperson Problem (TSP). Both problems are NP-hard and scale poorly in classical computations.

Quantum Annealing (QA) is a powerful way to solve these kinds of problems. QA enables a quantum system to anneal toward its lowest-energy state by introducing routing constraints and objectives in the energy landscape. This is the most efficient method for setting up routes. This approach offers significant speed-ups over classical heuristics, such as simulated annealing, particularly in high-dimensional and time-sensitive scenarios.

Quantum-enhanced routing can guarantee zero-latency mobility and logistics in smart cities in Saudi Arabia. This is a basic prerequisite for NEOM's autonomous infrastructure. Efficient routing reduces fuel consumption, minimizes battery drainage, and lowers the environmental emissions. Moreover, quantum scheduling can support multi-agent coordination across emergency response systems, freight hubs, and public transit, making both operations more efficient and improving the experience of citizens.

3) Urban digital twin (UDT) simulation and forecasting: Urban Digital Twins (UDTs) are central to predictive governance in smart cities, enabling planners to simulate and evaluate infrastructure, environmental, and social systems before implementation. Planners can test and assess infrastructure, environmental, and social systems using UDTs prior to construction. However, for UDTs to work well, they must simulate complicated, interconnected tasks, such as fluid dynamics, air quality, population mobility, and material behavior. These tasks involve solving large systems of equations and modeling high-dimensional physical processes, which often exceed the capabilities of classical computing.

Quantum Simulation and Quantum Machine Learning (QML) are two methods that work well together to solve problems. Quantum simulation uses quantum mechanics to represent physical systems at an exponential speed, making it ideal for simulating chemical reactions and designing materials. In contrast, QML excels at extracting patterns from noisy sensor data, enabling accurate forecasting and predictive maintenance of urban infrastructure.

Quantum-enhanced UDTs can transform static planning tools into dynamic engines for resilience and foresight in Saudi Arabia. For example, they can be used to forecast water demand under stress conditions, simulate the structural integrity of new materials, and predict the spread of airborne pollutants. These capabilities aid in proactive governance, smart capital planning, and the long-term success of urban transformation initiatives, especially in areas susceptible to climate change, such as the Red Sea Coast and NEOM.

B. Quantum Computing Adoption for Smart Cities in Saudi Arabia

Saudi Arabia is undergoing a profound transformation under the Vision 2030 framework, with smart city development as the national cornerstone. The Kingdom desires to build smart, zero-carbon, and hyper-efficient cities using advanced technologies such as Artificial Intelligence (AI), the Internet of Things (IoT), and quantum computing (QC). NEOM, The Line, Riyadh Smart City, and the Red Sea Project are some of the most important projects that demonstrate this goal in Saudi Arabia.

These projects differ because of their massive size and "greenfield" design, which allows quantum-readiness to be embedded into the infrastructure and data architecture from the start. This strategic advantage enables Saudi cities to bypass outdated integration challenges and utilize the most advanced computational models from the beginning. In this case, three imperatives drive the adoption of QC. First, the absence of legacy systems allows the native integration of quantum technologies, thereby avoiding costly retrofitting. Second, the optimization-critical nature of energy, water, and mobility systems requires computational capabilities that exceed the classical limits. Third, the Kingdom's ability to invest and its long-term commitment to Vision 2030 make it possible to continue investing in quantum infrastructure, talent development, and ecosystem creation.

Quantum computing is particularly important for Saudi Arabia's initiatives. NEOM is a $500 billion cognitive megacity designed to integrate AI, quantum technologies, and self-driving systems to improve sustainability and operational efficiencies. The Line is a 170-kilometer-long city in NEOM that aims to have no cars and no carbon emissions, which means it needs real-time smart systems to manage different types of transportation. The Red Sea Project and Qiddiya are large-scale tourism and entertainment hubs that require smart infrastructure for logistics, resource management, and the provision of tailored services. Owing to their size and

complexity, these projects are likely to reach classical computational limits sooner than retrofitted cities. Therefore, quantum computing is not a luxury upgrade but a strategic necessity for real-time multimodal optimization across the energy, water, mobility, and security domains.

Saudi Arabia has initiated the development of a local quantum ecosystem to facilitate such changes. The Quantum Valley Initiative is a partnership between the King Abdulaziz City for Science and Technology (KACST), the Saudi Data and AI Authority (SDAIA), IBM, and Pasqal. Its goal is to create a national center for quantum research, hardware hosting, and application development. Early-stage quantum security pilots in NEOM are working on quantum-secured IoT and blockchain frameworks to ensure city resilience and maintain data integrity. There are national talent programs underway to teach more than 50 graduate students in Quantum Information Science (QIS) and provide more than 200 IT professionals with certificates in quantum computing and post-quantum cryptography (PQC). In addition, hybrid pilots are used in the energy, logistics, and water sectors to test quantum-classical operations and help shape regulatory frameworks.

Saudi smart cities are in a unique position to profit from quantum computing because they utilize Urban Digital Twins (UDTs), maintain expansive IoT networks, and implement blockchain-based infrastructure. UDTs require real-time simulation and optimization of multimodal systems, whereas the rapid growth of sensor networks necessitates the use of PQC and QKD for secure data transmission. QC also complements blockchain platforms by enhancing data integrity and cyber resilience. In this perspective, NEOM and The Line are worthy examples of the quantum imperatives. Because they require operational complexity and demand QC for predictive modeling, resource allocation, and coordinating autonomous systems, the Kingdom's smart city future will be based on quantum computing.

C. *Requirements of Quantum Computing Adoption for Smart Cities in Saudi Arabia*

As Saudi Arabia accelerates its smart city transformation under the Vision 2030 framework, quantum computing (QC) is becoming a strategic enabler, creating urban settings that are zero-carbon, hyper-efficient, and cognitively adaptive urban environments. NEOM, The Line, and the Red Sea Project are major projects that require computing power greater than that provided by traditional methods, particularly for tasks such as real-time optimization, secure data sharing, and accurate simulation. To harness quantum technologies effectively, a multidimensional understanding of the technical, organizational, financial, legal, ethical, and regulatory requirements is essential. Saudi Arabia has a unique position for quantum integration because it offers a greenfield advantage, the ability to invest in its quantum ecosystem, and a commitment to its development.

Drawing on global governance frameworks and strategic roadmaps, including those from the World Economic Forum, Stanford Law, Cambridge University Press, and UK government publications, this section outlines the key prerequisites for QC adoption in Saudi Arabia's Smart Cities.

- Technical Requirements. Quantum adoption requires robust hybrid architecture, secure communication protocols, and middleware integration. To ensure data sovereignty, Saudi Arabia must move from quantum-as-a-service (QaaS) models to sovereign Hybrid Quantum-Classical Architectures (HQCA). It is critical to integrate QC into NEOM's digital twin and smart grid platforms, along with standardized Post-Quantum Cryptography (PQC) across IoT and blockchain systems. Mitigation strategies include investing in sovereign infrastructure, collaborating with global vendors for localized deployments, and launching a national standards body under the KACST and SDAIA.
- Social and Human Capital Requirements. Quantum-literate staff and public trust are foundational elements of quantum governance. Addressing talent shortages in Quantum Information Science (QIS), engaging citizens in data governance, and localizing QIS curricula are essential steps. Initiatives such as the Quantum Talent Initiative (QTI), public engagement campaigns, and joint academic programs with King Abdullah University of Science and Technology (KAUST), King Abdulaziz University (KAU), and other international institutions support inclusive and sustainable capacity building.
- Organizational Requirements. Effective QC adoption requires agile governance, inter-agency coordination, and collaboration. Aligning the governance structures of SDAIA, KACST, the Ministry of Education, and NEOM will make it possible to prototype and deploy quickly. Institutionalizing quantum innovation requires the establishment of a National Quantum Steering Committee, the use of regulatory sandboxes, and the hiring of Chief Quantum Officers (CQOs) within megaprojects.
- Financial Requirements. Long-term sovereign investments and private-sector incentives are vital. Leveraging the Public Investment Fund (PIF) and Vision 2030 resources, attracting Foreign Direct Investment (FDI), and modeling the Return on Investment (ROI) in hybrid deployments will ensure financial sustainability. The Quantum Innovation Fund, tax credits, and cost-benefit frameworks for pilot evaluation are recommended as mitigation strategies.
- Regulatory Requirements. Saudi Arabia must define a national quantum policy, align it with international compliance standards, and regulate quantum-enhanced services. Ensuring adherence to global PQC and QKD protocols, addressing dual-use concerns, and being consistent with Gulf Cooperation Council (GCC) and Organization for Economic Cooperation and Development (OECD) digital regulations are all important considerations. Developing a National Quantum Regulatory Framework and participating in working groups for the International Organization for Standardization/International Electrotechnical Commission (ISO/IEC) and the European Telecommunications Standards Institute (ETSI) would aid regulatory maturity.

- Ethical Requirements. Responsible innovation must lead to quantum AI deployment. Ethical risks in predictive policing, facial recognition, and behavioral modeling must be addressed in accordance with Islamic principles and Vision 2030 standards. A National Quantum Ethics Board will be established, WEF Quantum Governance Principles will be adopted, and fairness audits of quantum algorithms will be mandated to ensure transparency and cultural sensitivity.
- Legal Requirements. Legal frameworks must be adjusted to accommodate these technologies. It is important to update intellectual property laws, define liability in quantum-enhanced decision-making systems, and clarify data ownership and cross-border flows. Saudi Arabia must safeguard its sovereign rights over quantum-generated insights, oversee quantum-enhanced public services, and guarantee adherence to national data protection laws, such as the Personal Data Protection Law (PDPL). Mitigation strategies include amending cybersecurity laws, drafting hybrid AI/QC legal frameworks, and defining thresholds for quantum automation.

Table III summarizes a structured overview of the key requirements for adopting quantum computing in Saudi smart cities.

TABLE III. QUANTUM COMPUTING ADOPTION REQUIREMENTS FOR SMART CITIES IN SAUDI ARABIA

Requirement Category	Key Requirements	Specific Requirements for Saudi Arabia	Mitigation Strategy
Technical	Develop Hybrid Quantum-Classical Architectures (HQCA) Implement Post-Quantum Cryptography (PQC) standards. Build middleware for UDT–QC integration. Establish benchmarking and error mitigation protocols.	Transition from QaaS to sovereign HQCA for data sovereignty Integrate QC into NEOM's digital twin and smart grid platforms. Standardize PQC across smart city IoT and blockchain systems.	Invest in sovereign quantum infrastructure. Collaborate with global QC vendors for localized deployments. Launch a national QC standards body under KACST/SDAIA.
Social / Human Capital	Build a quantum-literate workforce. Promote public awareness and trust. Ensure inclusive access to quantum education.	Address QIS talent shortages in academia and industry. Engage citizens in smart city data governance. Localize QIS curricula in Arabic and align with Vision 2030 education reforms.	Expand the Quantum Talent Initiative (QTI). Launch public engagement campaigns. Partner with KAUST, KAU, and international institutions for joint programs.
Organizational	Establish inter-agency coordination frameworks. Create agile pilot governance models. Embed quantum innovation units in city planning bodies.	Align SDAIA, KACST, MoE, and NEOM governance structures. Enable rapid prototyping and iterative deployment in smart city zones.	Form a National Quantum Steering Committee. Use regulatory sandboxes for pilot testing. Appoint Chief Quantum Officers (CQOs) in megaprojects.
Financial	Secure long-term sovereign investment. Incentivize private sector R&D and startups. Model ROI for hybrid QC deployments.	Leverage PIF and Vision 2030 funds for infrastructure. Attract FDI in quantum ventures. Justify QC investment through energy, logistics, and security gains.	Establish a Quantum Innovation Fund. Offer tax credits and grants for QC R&D. Develop cost-benefit frameworks for pilot evaluation.
Regulatory	Define national quantum policy and standards. Align with international export controls and compliance. Regulate quantum-enhanced services and data flows.	Ensure compliance with global PQC and QKD standards. Address dual-use concerns in defense and energy sectors. Harmonize with GCC and OECD digital regulations.	Draft a National Quantum Regulatory Framework. Participate in ISO/IEC and ETSI quantum working groups. Create a regulatory sandbox for quantum pilots.
Ethical	Promote responsible innovation and transparency. Prevent misuse of quantum-enhanced surveillance. Ensure cultural and social sensitivity in deployment.	Address ethical risks in predictive policing, facial recognition, and behavioral modeling. Align with Islamic ethical principles and Vision 2030 values.	Establish a National Quantum Ethics Board. Adopt WEF Quantum Governance Principles. Require explanations and fairness audits for quantum algorithms.
Legal	Update IP laws for quantum algorithms and hardware. Define liability in quantum-enhanced decision systems. Clarify data ownership and cross-border data flows.	Protect sovereign rights over quantum-generated insights. Regulate quantum-enhanced public services (e.g., traffic, energy, and health). Ensure compliance with Saudi data protection laws (e.g., PDPL).	Amend IP and cybersecurity laws to include quantum domains. Draft legal frameworks for hybrid AI/QC systems. Define legal thresholds for quantum-enhanced automation.

D. Proposed Strategic Three-Phased Roadmap for QC Adoption in Saudi Arabia's Smart Cities

1) Proposed strategic three-phased roadmap for QC adoption: The quantum computing roadmap for Saudi Arabia's smart cities is designed to evolve from foundational capability building to full operational deployment, in alignment with the Saudi Vision 2030 mandates for human capital development, digital transformation, and sovereign technological leadership. The roadmap is divided into three strategic phases and includes key pillars, focus areas, and measurable milestones to guide the Kingdom's transition from pilot experimentation to global quantum leadership. Fig. 5 presents the proposed three-phase roadmap for QC adoption in smart cities in Saudi Arabia. The three phases are detailed as follows:

- Phase I: Foundation and Preparation (0–3 years). This initial phase focuses on establishing a foundational ecosystem required for the adoption of quantum computing. Activities include the publication of a National Quantum Strategy and the development of ethical, legal, and social implications (ELSI) frameworks to guide responsible innovations. Talent development is prioritized through the launch of the Quantum Talent Initiative, which aims to retrain IT professionals and reform university curricula to include Quantum Information Science (QIS). Early access to quantum resources is secured via quantum-as-a-service (QaaS) contracts, and pilot-scale post-quantum cryptography (PQC) is deployed on noncritical smart city subsystems to test the security protocols.
- Phase II: Pilot and Integration (3–7 years). This phase emphasizes hybrid system validation and integration with Urban Digital Twins (UDTs). Quantum-classical pilots are launched in high-impact domains, such as smart grid optimization and traffic control, leveraging algorithms such as Quantum Reinforcement Learning (QRL). A middleware is developed to abstract the UDT variables into the QUBO format, enabling compatibility with quantum solvers. Cyber resilience is enhanced by mandating post-quantum cryptography (PQC) across IoT and blockchain frameworks within pilot zones to ensure secure data flows and infrastructure integrity.
- Phase III: Deployment and Leadership (7+ years). The final phase focuses on full-scale operationalization and positioning Saudi Arabia as a global leader in quantum-smart-city innovation. Proven hybrid quantum algorithms are integrated into core operational systems in major cities. A National Quantum Hardware Center has been set up to provide local optimization tools, like quantum annealers, to enhance the country's computing power. By hosting international forums and advancing research on next-generation concepts, such as quantum digital twins, Saudi Arabia further solidifies its leadership.

Table IV summarizes the detailed milestones, duration, and strategic objectives for each phase of the quantum computing roadmap.

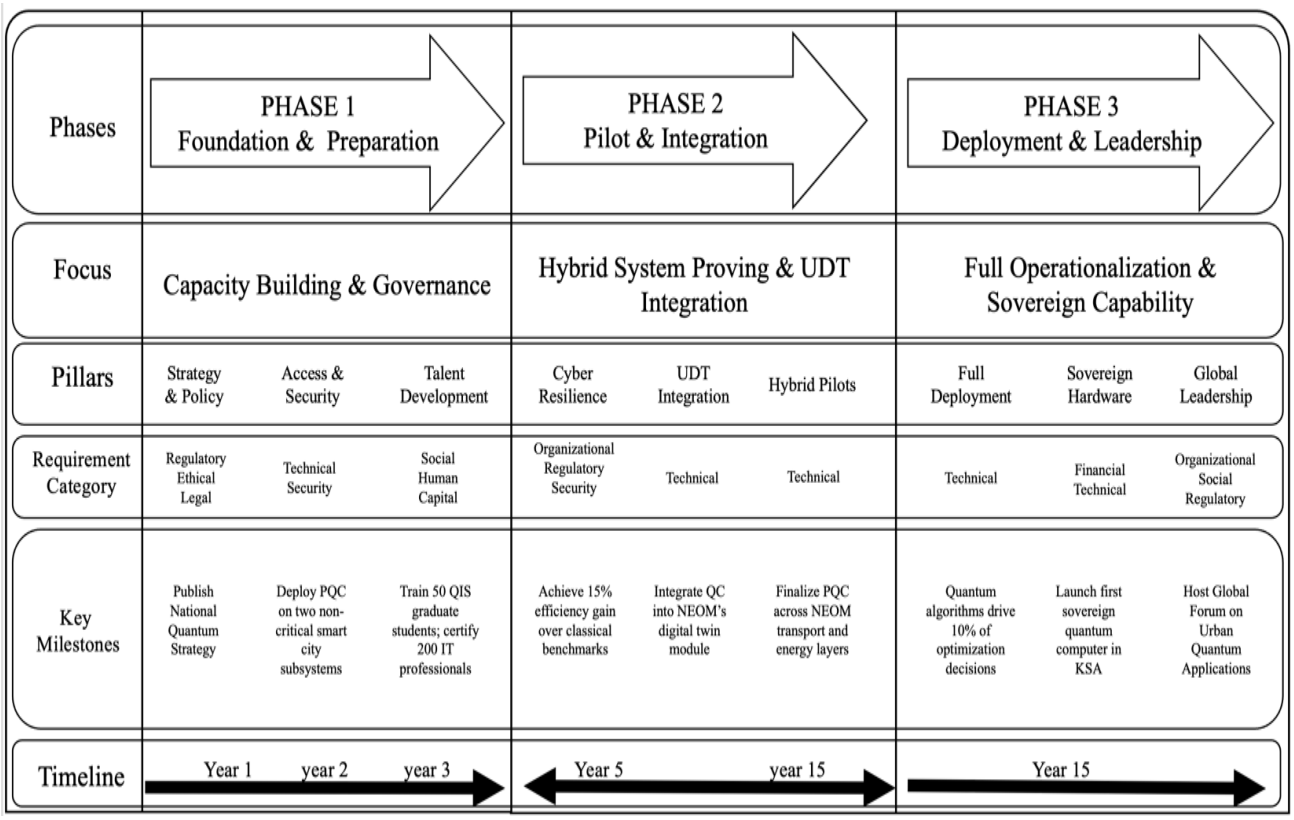


Fig. 5. A proposed strategic three-phased roadmap for QC adoption for smart cities within Saudi Arabian environments.

TABLE IV. QUANTUM COMPUTING ROADMAP FOR SAUDI SMART CITIES

Phase	Duration	Primary Focus	Key Pillars	Requirement Category	Strategic Objectives / Milestones
I. Foundation & Preparation	0–3 Years	Capacity Building & Governance	Strategy & Policy (Governance, ELSI)	Regulatory Ethical Legal	Year 1: Publish the National Quantum Strategy and ELSI framework.
			Talent Development (Human Capital)	Social Human Capital	Year 3: Train 50 QIS graduate students; certify 200 IT professionals in QC/PQC.
			Access & Security (QaaS, PQC)	Technical Security	Year 2: Deploy PQC on two non-critical smart city subsystems.
II. Pilot & Integration	3–7 Years	Hybrid System Proving & UDT Integration	Hybrid Pilots (Smart Grid, Traffic)	Technical	Year 7: Achieve a 15% efficiency gain over classical benchmarks.
			UDT Integration (QUBO Middleware)	Technical	Year 5: Integrate QC into NEOM's digital twin module.
			Cyber Resilience (PQC in IoT/Blockchain)	Organizational Regulatory Security	Year 5: Finalize PQC across NEOM transport and energy layers.
III. Deployment & Leadership	7+ Years	Full Operationalization & Sovereign Capability	Full Deployment (Citywide QC Integration)	Technical	Year 10: Quantum algorithms drive 10% of optimization decisions.
			Sovereign Hardware (National QC Center)	Financial Technical	Year 12: Launch the first sovereign quantum computer in KSA.
			Global Leadership (Research & Policy)	Organizational Social Regulatory	Year 15: Host Global Forum on Urban Quantum Applications.

E. Holistic Technical Quantum–Smart City Integration Strategy

To ensure a cohesive execution plan, a holistic integration strategy is necessary to synchronize the architectural elements of urban infrastructure with relevant quantum capabilities along the national roadmap. This section delineates a detailed structure that correlates each smart city domain with its quantum computing equivalent, situated within the strategic priorities and Greenfield advantages of Saudi Arabia.

The framework has eleven architectural levels, starting with fundamental infrastructure and progressing through data systems, decision-making platforms, and governance structures. Each layer corresponds to a distinct quantum capability and is associated with one of three roadmap phases. This matrix allows technologists, urban designers, and policymakers to visualize the incremental integration of quantum technologies into the urban framework.

The integration strategy is governed by the following phase objectives:

- Phase I (Foundational Exploration): Focuses on foundational exploration, including cloud-based quantum-as-a-service (QaaS) access, feasibility studies for localized quantum hardware, and early pilot deployments in sensing and simulation, often leveraging quantum-inspired classical methods.
- Phase II (Hybrid Integration): Emphasizes hybrid integration, deploying genuine quantum-enhanced algorithms in high-impact areas like traffic, energy, and logistics systems, and embedding middleware for Urban Digital Twin (UDT) compatibility.
- Phase III (Governance Maturity): Targets infrastructure maturity and governance, including the Post-Quantum Cryptography (PQC) rollout, quantum-secure identity systems, and the establishment of national ethics and regulatory frameworks.

Saudi Arabia's greenfield advantage enables the integration of quantum technologies without the limitations of legacy infrastructure. This strategic positioning supports the Kingdom's ambition to lead quantum-enhanced urban innovation. Table V details the holistic integration strategy, mapping specific smart city components and their corresponding quantum technologies to the strategic phases of the Saudi Adoption Roadmap, ensuring all components are properly addressed.

TABLE V. HOLISTIC INTEGRATION STRATEGY FOR QUANTUM-SMART CITY MAPPED TO THE SAUDI ADOPTION ROADMAP

Layer	Smart City Component	Quantum Computing Component	Saudi Roadmap Phase
1. Physical Infrastructure	Roads, buildings, transport systems, and energy grids.	Quantum hardware environments (cryogenics, superconducting circuits).	Phase I: QaaS access, feasibility studies.

2. Sensor & IoT Layer	Real-time data from traffic, environment, and public safety.	Quantum sensors for ultra-precise measurements.	Phase I–II: Research partnerships, pilot deployments.
3. Network & Connectivity	5G, fiber optics, and edge/cloud infrastructure.	Quantum communication channels (QKD, entanglement networks).	Phase III: Municipal QKD pilots, infrastructure planning.
4. Data Management Layer	Urban digital twins, data lakes, and analytics platforms.	Quantum simulation engines, quantum-enhanced data processing.	Phase II: Middleware integration, QDT pilots.
5. Urban AI & Decision Systems	Predictive analytics, autonomous agents.	Quantum machine learning (QML) and quantum reinforcement learning (QRL).	Phase II: Deploy QML/QRL in traffic, energy, and emergency systems.
6. Service Orchestration	Intelligent service delivery, multi-agent coordination.	Quantum algorithms (QAOA, QML, QRL) for optimization and autonomy.	Phase II: Hybrid deployments in traffic, energy, and logistics.
7. Resilience & Simulation	Climate modeling, disaster response planning.	Quantum simulation for multivariable urban systems.	Phase II–III: QDTs for resilience planning.
8. Digital Identity & Trust	Identity management, authentication, and trust frameworks.	Quantum-resistant protocols, zero-knowledge proofs.	Phase III: PQC integration, quantum trust models.
9. Governance & Security	Policy, privacy, cybersecurity, ethical oversight.	PQC, quantum-safe protocols, ethical governance.	Phase III: National policy, PQC rollout, ethics board.
10. Ethics & Regulatory Layer	Data governance, algorithmic transparency, citizen rights.	Quantum ethics frameworks, algorithmic accountability.	Phase III: Ethics board, global standards alignment.
11. Talent & Innovation Ecosystem	Education, R&D, startups, and academic partnerships.	Quantum education programs, research centers, and innovation clusters.	Phase I–III: Talent Initiative, regional innovation hubs.

Fig. 6 shows the sequential integration of quantum computing capabilities with smart city elements in Saudi Arabia's national roadmap. A specific quantum technology and deployment stage align with every urban domain, from infrastructure and IoT to governance and innovation. The central roadmap column guides the sequence from fundamental exploration (Phase I) to hybrid integration (Phase II) and governance maturity (Phase III).

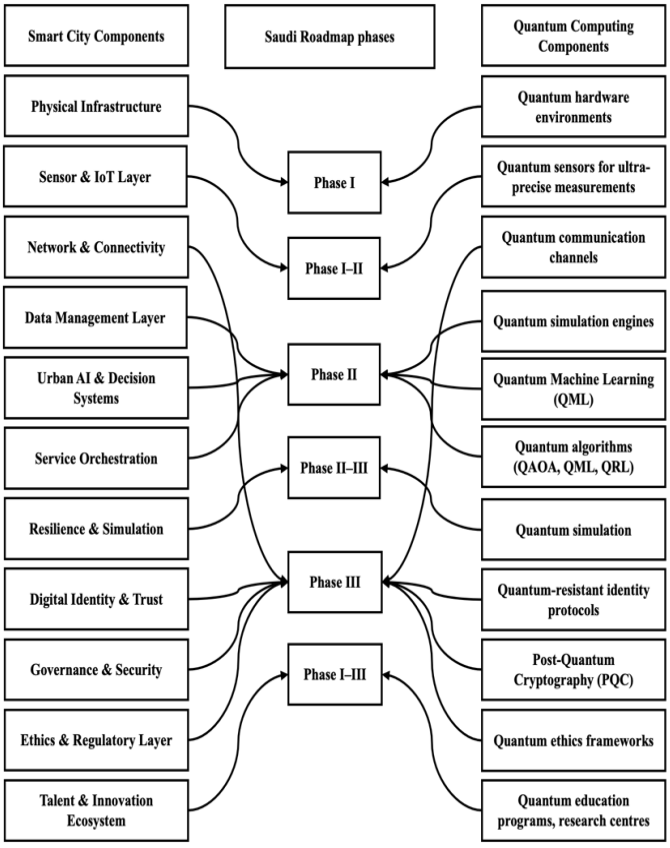


Fig. 6. Holistic integration strategy for a quantum-smart city mapped to the Saudi adoption roadmap.

F. Hybrid Quantum-Classical Software Architecture (HQCA)

The Hybrid Quantum-Classical Software Architecture (HQCA) offers a secure, closed-loop operational framework for integrating specialized quantum computing resources into the Smart City technology stack. HQCA is engineered to solve computationally intractable optimization kernels recognized by traditional modeling engines, ensuring that quantum resources are utilized judiciously—exclusively in areas where they provide a true computational benefit—whereas the classical infrastructure handles most of the sensing, modeling, and control tasks. The design is systematically organized into three interrelated zones: the Classical Smart City Stack, the Hybrid Orchestration Layer, and the Quantum Computing Stack.

1) Classical smart city stack: data ingestion and control: Based on high-performance computing (HPC) and graphics processing unit (GPU) acceleration, this zone represents the traditional software environment of smart cities. It comprises five layers:

- Layer 1: Data, Sensing, and Streaming. Stream-processing engines, such as Kafka and Spark, ingest real-time data from IoT sensors, edge gateways, and infrastructure via stream-processing engines (e.g., Kafka and Spark). Data integrity is verified using blockchain or Distributed Ledger Technologies (DLT).

- Layer 2: Context and Modeling (Urban Digital Twin). The Urban Digital Twin (UDT) maintains a high-fidelity real-time model of the city. Classical AI/ML engines perform predictive modeling and anomaly detection, supported by Explainable Artificial Intelligence (XAI) components to ensure transparency. The UDT identifies optimization kernels, such as traffic scheduling and energy balancing, which require quantum acceleration.
- Layer 3: Classical Pre-Processing. HPC/GPU resources are used to clean, normalize, and reduce problem data (e.g., via Principal Component Analysis) and prepare them for quantum translation.
- Layer 4: Classical Post-Processing. The raw quantum outputs are validated and converted into actionable, classical commands.
- Layer 5: Infrastructure Control. City control systems (e.g., SCADA, Traffic Management System (TMS), and Distribution Management System (DMS)) execute optimized commands and provide feedback to the sensing layer, completing the operational cycle.

2) Hybrid orchestration layer: The Secure, Iterative Bridge

This middleware layer enables seamless, secure, and low-latency interactions between classical and quantum domains. It includes:

- Problem Abstraction and Software Toolchain. A Quantum Software Development Kit (SDK) and compiler suite translate classical optimization problems into quantum-native formats (e.g., QUBO and Ising). A quantum kernel generator encodes classical data into quantum states for quantum machine learning (QML) tasks.
- Resource Management and Execution Control. Jobs are directed to the optimal backend, that is, quantum-as-a-service (QaaS) or sovereign QC hardware, through a low-latency interconnect. The orchestration layer manages job queues and execution scheduling and incorporates a Quantum Error Mitigation (QEM) module to enhance the result fidelity.
- Security Gateway. Post-Quantum Cryptography (PQC) secures data in transit, whereas Quantum Key Distribution (QKD) ensures ultra-secure communication across the classical-quantum interface.
- Quantum Computing Stack: Specialized Acceleration and Solution Output
- This zone functions as a dedicated accelerator that solves the optimization kernels identified by UDT. It includes:
- Execution Backend. Quantum solvers (e.g., annealers, gate-based systems) execute algorithms such as QAOA, QML, and QRL. A hardware-specific transpiler optimizes quantum circuits for physical qubit topologies.
- Physical Control Interface. Qubit control electronics and cryogenics handle basic tasks by changing logical gates into microwave pulses and laser controls.
- Solution Output and Validation. The quantum system produces an optimal bit string that represents resource assignments or scheduling variables. These results are securely transmitted back to the classical stack, where they are validated and refined through iterative feedback until convergence is achieved. The final outputs were translated into actionable infrastructure commands, closing the loop via the sensing layer.

3) HQCA operational flow: Fig. 7 presents a modular three-layer architecture designed to integrate quantum computing into smart city operations. The system comprises the following components:

- Layer 1: Classical Smart City Stack. Responsible for data ingestion, modeling, and control, this layer includes IoT-based edge processing, blockchain-secured data streams, and Urban Digital Twin (UDT) platforms powered by classical AI/ML engines. HPC/GPU accelerators handle the initial data processing, whereas post-processing modules check the results from quantum computing and convert them into useful information for smart city services, such as improving traffic flow and managing infrastructure.
- Layer 2: Hybrid Orchestration Layer. Serving as an intelligent bridge, this layer manages problem decomposition, algorithm selection (e.g., QAOA and VQE), and resource allocation across quantum and classical domains. It includes a quantum software development kit/compiler suite, real-time pre/post-processing accelerators, and a secure job submission system. The Physical Control Electronics interface directly with the quantum hardware, whereas the Security Gateway ensures encrypted communication via PQC and QKD protocols.
- Layer 3: Quantum Computing Software Stack. This layer functions as a dedicated accelerator for solving intractable computational issues. It includes quantum solvers (annealers and gate-based systems), execution-dispatch modules, and hardware-specific transpilers. The red dashed feedback loop illustrates the iterative optimization process typical of Variational Quantum Algorithms (VQAs), where quantum outputs are measured, refined, and re-executed until convergence is achieved.

Together, these layers form a secure closed-loop system capable of translating complex urban challenges into quantum-native formats, executing them on specialized hardware, and reintegrating optimized solutions into real-world Smart City operations.

4) Clarifying the quantum-classical divide and the HQCA role: To ensure technical clarity and address the potential overstatement of near-term relevance, it is crucial to explicitly distinguish between genuinely quantum-accelerated methods and quantum-inspired classical techniques within the HQCA framework:

- Genuine Quantum Acceleration: This refers exclusively to algorithms (e.g., QAOA, VQE, HHL) executed on a dedicated Quantum Processing Unit (QPU) that leverage superposition and entanglement. These methods offer the potential for exponential or polynomial speedups over the best-known classical algorithms for specific problem classes. Our long-term strategic goal (Phase III) is predicated on this capability.
- Quantum-Inspired Techniques: These are classical, hardware-accelerated optimization and simulation algorithms (e.g., Digital Annealing (DA), Simulated Annealing, and coherence-based methods) that are inspired by quantum principles but run entirely on conventional or specialized classical hardware (like FPGAs or specialized CMOS). While highly effective for near-term NP-hard optimization, they are not quantum computing. The HQCA explicitly allows for the incorporation of quantum-inspired algorithms in the initial phases (Readiness/Pilot) to build computational maturity and realize immediate-term optimization gains, thereby serving as a critical bridge and an essential component of the classical side of the hybrid architecture.

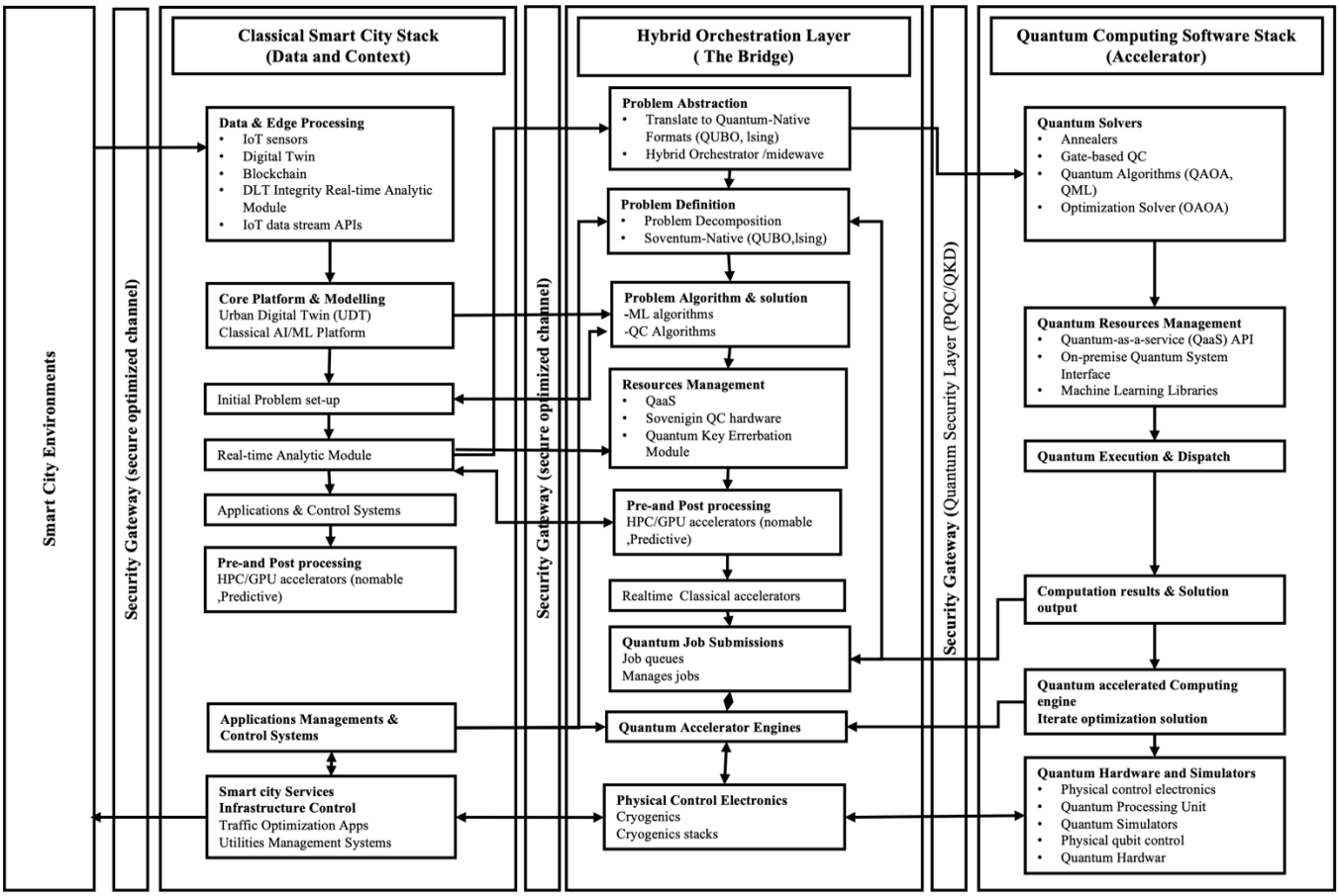


Fig. 7. Hybrid Quantum-Classical Architecture for smart city optimization.

G. Benefits and Challenges of QC Adoption in Smart Cities

Quantum computing presents a fundamentally different computational paradigm that offers significant benefits for smart cities in terms of optimization, simulation, cybersecurity, and strategic competitiveness. Its ability to address large-scale combinatorial problems facilitates exceptional performance in areas such as traffic management, logistics, and resource distribution. Quantum algorithms, particularly those tailored for near-optimal real-time decision-making, surpass conventional systems in urban mobility and energy balance, where complexity and latency are significant limitations.

In simulations, quantum methods offer high-fidelity modeling of intricate urban systems, encompassing climate dynamics, infrastructure stress testing, and materials science for sustainable construction. These capabilities boost planning accuracy and resilience, especially in megaprojects such as NEOM and The Line. Quantum technologies enhance cybersecurity. Quantum-safe cryptography and Quantum Key Distribution (QKD) provide robust protection for critical infrastructure, IoT networks, and municipal data systems, reducing their vulnerability to quantum-enabled attacks.

Quantum optimization enhances energy systems by augmenting smart grid efficiency and optimizing the incorporation of renewable sources such as solar and wind. This aligns with the sustainability objectives of Saudi Arabia outlined in Vision 2030. The strategic deployment of quantum technology has established the kingdom as a regional leader in innovation. By aligning quantum projects with national

priorities, Saudi Arabia may attract international investment, expertise, and collaborations, thereby enhancing its competitive advantage.

Despite its potential, quantum computing faces several challenges in smart-city environments. Technologically, quantum hardware functions inside the Noisy Intermediate-Scale Quantum (NISQ) era, which is defined by constrained qubit numbers and vulnerability to decoherence. Fault-tolerant systems are several years away from realization. The worldwide shortage of quantum scientists, engineers, and programmers further limits adoption, particularly in emerging ecosystems such as Saudi Arabia.

Cost and accessibility are also major hurdles. Quantum hardware is costly and is generally accessed through cloud services, which constrain experimentation and implementation. Establishing a definitive return on investment (ROI) for early-stage pilot projects remains challenging. The development of algorithms is complicated, necessitating specific knowledge to transform classical issues into quantum-native representations of the problem.

Integrating current Smart City platforms, such as Urban Digital Twins (UDTs), sensor networks, and control systems, necessitates the development of new middleware, standards, and hybrid quantum-classical architectures (HQCA). Concerns regarding governance and security continue to revolve around data privacy, regulatory frameworks, and secure communications. Financial and infrastructure costs, including chilled environments and quantum-safe channels, add further complications. Table VI summarizes the benefits and challenges of adopting quantum computing in smart cities.

TABLE VI. SUMMARY OF BENEFITS AND CHALLENGES OF QC ADOPTION IN SMART CITIES

Benefits	Challenges
• Superior optimization. • Advanced simulation fidelity. • Enhanced cybersecurity (QKD, PQC). • Smart grid energy efficiency. • Strategic competitiveness (Vision 2030). • Real-time resource allocation. • Climate and infrastructure modelling.	• Technological maturity (NISQ era). • Talent shortage in quantum fields. • High cost and limited hardware accessibility. • Algorithmic complexity and reformulation. • Integration complexity with legacy systems. • Governance, privacy, and regulatory concerns. • Financial and ROI uncertainty.

V. DISCUSSION

The shift to quantum-ready smart cities in Saudi Arabia is not simply a technology enhancement; it is a strategic cornerstone of the Kingdom's economic diversification initiative under Vision 2030. As urban systems become more intricate and data-driven, traditional computational architectures encounter constraints in addressing large-scale optimization, simulation, and security problems. Quantum computing (QC), which leverages superposition and entanglement, presents a transformative solution to these challenges [4], [5].

Saudi Arabia's most significant megaprojects, NEOM, The Line, and the Red Sea Project, offer greenfield potential for the integration of quantum capabilities from the outset. These projects are intended to function at an unprecedented scale and complexity, necessitating computing systems that surpass classic thresholds [12], [59].The aspiration to create cognitive cities characterized by real-time responsiveness and predictive intelligence immediately corresponds to the capabilities of quantum-enhanced optimization and simulation [10].

The establishment of a quantum-ready smart city is not merely a singular technology implementation but rather a whole, interconnected ecosystem propelled by strategic coherence and continuous advancement. As illustrated in Fig. 8, the central goal of achieving a quantum-ready smart city, a core pillar of the Saudi Vision 2030 megaprojects, is supported by several critical and interdependent components.

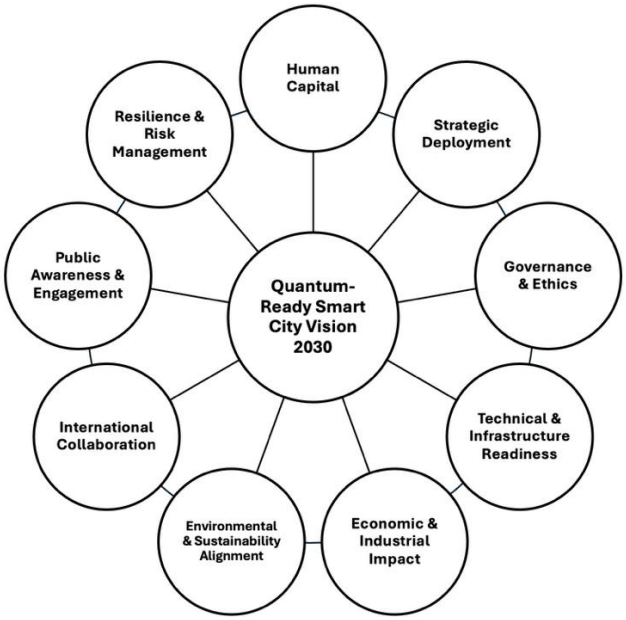


Fig. 8. Interconnected ecosystem of a quantum-ready smart city.

These range from foundational efforts, such as cultivating human capital and establishing robust technical and infrastructure readiness, to strategic oversight elements, such as governance, ethics, and international collaboration. The framework's arrows demonstrate the interconnectedness of these dimensions, establishing crucial feedback loops. Successful strategic deployment influences the economic impact, supported by continuous resilience and risk management, thereby ensuring a secure and sustainable transition that aligns with national environmental and economic objectives.

A. Human Capital as the Strategic Bottleneck

Despite substantial government investment capabilities, the foremost challenge is human capital. The acknowledged global deficiency of quantum-fluent engineers and scientists necessitates that Saudi Arabia swiftly develops a homegrown talent pool. This includes the initiation of the Quantum Talent Initiative, modification of university curricula to incorporate Quantum Information Science (QIS), and the establishment of

collaborative research centers with international quantum leaders [21]. The localization of quantum education through Arabic-language resources is crucial for guaranteeing accessibility and long-term sustainability [22].

B. Strategic Deployment and Intermediate Steps

Considering the existing limitations of quantum technology in the Noisy Intermediate-Scale Quantum (NISQ) era, Saudi Arabia should implement a gradual deployment approach. In the short term, utilizing quantum-as-a-service (QaaS) platforms through cloud access facilitates experimentation without infrastructure overheads. The Kingdom should simultaneously invest in hybrid quantum-classical algorithms designed for urban optimization challenges, middleware for Urban Digital Twin (UDT) integration, and pilot initiatives in areas where quantum advantage is anticipated [20].

Energy grid optimization is a promising area in which quantum algorithms have demonstrated efficacy in unit commitment and load balancing [60]. Quantum annealing has been employed to enhance traffic signal optimization in Sendai, Japan, and to improve port logistics in Hamburg, Germany [61], [62]. Secure communications provide a strategic opportunity, as demonstrated by the Quantum Key Distribution (QKD) pilots in [63], which serve as examples of protecting municipal networks. These fields provide quantifiable benefits and evident Return on Investment (ROI), facilitating the justification of long-term R&D commitments and infrastructure investments.

C. Governance, Ethics, and Strategic Alignment

Quantum deployment requires guidance through coordinated governance frameworks that synchronize cross-agency agendas and guarantee ethical and secure implementation. The World Economic Forum [64] emphasizes the significance of ethical governance, transparency, and stakeholder engagement in quantum innovation. Saudi Arabia should formulate a national quantum policy, create a Quantum Ethics Board, enforce PQC compliance in IoT and blockchain systems, and engage with international standards organizations such as the ISO/IEC and ETSI [18].

D. Technical and Infrastructure Readiness

The adoption of quantum computing depends on the advancement of hardware and software systems. Saudi Arabia must assess its readiness to meet various technical requirements. Initially, it is essential to develop hardware infrastructure, including cryogenic environments, quantum laboratories, and secure data centers capable of accommodating quantum processors or interfacing with cloud-based quantum-as-a-service (QaaS) platforms [60]. Second, middleware and integration layers must be created to convert smart city variables into quantum-compatible representations, including QUBO and Hamiltonians [20]. Third, interoperability with current urban platforms must be guaranteed via standardized APIs and modular architecture to facilitate easy integration with digital twins, IoT networks, and AI systems [18].

E. Economic and Industrial Impact

The adoption of quantum technology may anticipate a sectoral revolution in industries such as logistics, energy, construction, and cybersecurity, which will benefit from quantum-enhanced modeling and optimization. To facilitate this shift, Saudi Arabia should encourage quantum startups, incubators, and collaborations with international entities to expedite the development of its domestic capabilities [21]. Moreover, quantum-related roles, which vary from algorithm development to hardware engineering, facilitate the objectives of Vision 2030 concerning advanced employment and less reliance on oil [59].

F. Environmental and Sustainability Alignment

Quantum computing supports Saudi Arabia's climate initiatives and sustainability goals through various channels. Quantum algorithms can enhance smart grid operations, minimize energy waste, and facilitate the integration of renewable sources such as solar and wind [16]. High-fidelity quantum simulations facilitate predictive planning for climate resilience, water management, and infrastructure stress testing [10]. Moreover, quantum-enhanced materials science may accelerate the advancement of sustainable construction materials and energy-storage technologies, fostering low-carbon innovations.

G. Ethical, Legal, and Cultural Dimensions

In addition to governance, more profound ethical and cultural considerations require further attention. Data sovereignty is essential for ensuring that quantum data processing meets national privacy regulations and upholds citizens' rights. Cultural localization is crucial, necessitating the adaptation of quantum education, interfaces, and policy frameworks to align with Saudi cultural norms and language [22]. Saudi Arabia must engage in international quantum ethics discussions to influence the standards of transparency, accountability, and equal access [64].

H. International Collaboration and Geopolitical Positioning

Quantum technologies are becoming essential resources for global innovation and security purposes. Saudi Arabia's engagement in global quantum research collaborations, standards organizations, and bilateral partnerships may accelerate knowledge transfer and access to advanced quantum computing platforms. This position allows the Kingdom to serve as a regional leader in quantum diplomacy and reduces the risk of technological isolation by conforming to global standards and protocols [64].

I. Public Awareness and Citizen Engagement

Quantum computing is complex and is frequently misinterpreted. Public trust and comprehension are important for the successful implementation of smart cities in the GCC. Saudi Arabia should initiate public education campaigns to elucidate quantum technology and advocate citizen-oriented applications such as secure identity management and traffic optimization to showcase concrete advantages. Transparency in data utilization, particularly in quantum-enhanced surveillance or decision-making systems, will cultivate a culture of informed participation and diminish opposition to technology development.

J. Resilience and Risk Management

Quantum systems present novel operational concerns that require proactive management. Hardware fragility is a

significant issue because qubits are susceptible to noise, temperature fluctuations, and electromagnetic interference. Transition risks in cybersecurity emerge during the migration to post-quantum cryptography (PQC) and quantum key distribution (QKD), necessitating meticulous phasing to prevent these vulnerabilities. Moreover, quantum hardware frequently depends on specialized components and global suppliers, resulting in supply chain dependencies. Saudi Arabia must formulate contingency plans, establish redundancy mechanisms, and conduct risk audits to guarantee resilience in quantum-enabled infrastructure (QEI) systems.

VI. Conclusion and Future Research

As cities worldwide pursue unprecedented levels of efficiency, resilience, and sustainability, Saudi Arabia's Vision 2030 megaprojects, such as NEOM, The Line, and the Red Sea Project, are at the forefront of this transformation. These projects are large and ambitious, and they aim to develop cities from the ground up that are both smart and carbon-free. However, the computational demands of these environments, particularly when solving NP-hard issues related to energy management, traffic routing, and Urban Digital Twin (UDT) simulation, are rapidly outpacing the capabilities of classical systems. Heuristic approximations and traditional algorithms fall short of delivering real-time, scalable solutions, which could put advanced urban designs at risk in the long run.

This study establishes Quantum Computing (QC) as a fundamental technology for next-generation smart cities. QC is not just a future upgrade, but a strategic necessity that enables the development of hyper-efficient urban intelligence systems by overcoming classical bottlenecks. This study's core contribution is the establishment of the Hybrid Quantum-Classical Architecture (HQCA) and a methodologically grounded strategic roadmap, which together serve as the foundational blueprint for this transition. Two key contributions support this proposition: First, mapping core Smart City challenges to quantum algorithmic strengths: energy grid load balancing aligns with QAOA and VQE, dynamic traffic routing with quantum annealing, and UDT simulation with quantum machine learning. These mappings provide a clear technical rationale for the targeted deployment of quantum technologies. Second, this study proposes a phased adoption framework tailored to Saudi Arabia's strategic context. The framework is grounded in four pillars: talent development, infrastructure readiness, governance and ethics, and targeted pilots. The roadmap offers a structured pathway for embedding QC into the national innovation ecosystem in the next decade.

Several research directions are critical for realizing the full potential of quantum-accelerated smart cities (QASCs), building directly upon the strategic framework proposed here. Specifically addressing the need for evidence-based analysis, the immediate technical priorities are defined in two key areas. The first is formal problem formulation, which involves developing precise mathematical (e.g., QUBO or Hamiltonian) formulations for the key urban optimization problems identified (e.g., large-scale dynamic vehicle routing and real-time energy dispatch). This transition from problem class to formal quantum-compatible model is the essential next technical step. The second is Initial Benchmarking and Comparative Studies, where empirical benchmarking of hybrid quantum-classical algorithms must evaluate the performance of these models against state-of-the-art classical supercomputing solutions using realistic urban datasets, such as traffic networks with millions of nodes and energy grids with thousands of dynamic variables.

These benchmarks will endorse quantum advantage claims and guide the selection of algorithms for deployment in the future. Another area of focus is the mitigation of decoherence in quantum systems that operate in Internet of Things (IoT)-rich environments. Devices from the NISQ era are highly sensitive to noise, and urban sensor networks generate vast and volatile data streams. A robust middleware that can manage these interactions while preserving fidelity and minimizing latency is essential for the practical integration of these technologies.

Future research should investigate the socioeconomic aspects of quantum computing adoption. In addition to computational measures, it is essential to evaluate the comprehensive return on investment (ROI), which encompasses the effects on the quality of life, environmental sustainability, and long-term infrastructure expenses. Measuring these advantages will facilitate the justification of ongoing investments and connect quantum activities to national development objectives. Strategically addressing these difficulties will position Saudi Arabia to surpass traditional computational paradigms and establish itself as a global leader in quantum-enhanced urban innovation.

References

[1] S. E. Bibri and J. Krogstie, "The emerging data–driven Smart City and its innovative applied solutions for sustainability: the cases of London and Barcelona," 2020. doi: 10.1186/s42162-020-00108-6.

[2] M. Batty et al., "Smart cities of the future," 2012. doi: 10.1140/epjst/e2012-01703-3.

[3] V. Albino, U. Berardi, and R. M. Dangelico, "Smart cities: Definitions, dimensions, performance, and initiatives," Journal of Urban Technology, vol. 22, no. 1, pp. 3–21, 2015, doi: 10.1080/10630732.2014.942092.

[4] J. Preskill, "Quantum computing in the NISQ era and beyond," 2018. doi: 10.22331/q-2018-08-06-79.

[5] A. K. B. R. et al. Arute F., "Quantum supremacy using a programmable superconducting processor. Nature 574, 505–510 (2019)," Nature, vol. 574, no. August, pp. 505–510, 2019.

[6] E. Farhi, J. Goldstone, and S. Gutmann, "A Quantum Approximate Optimization Algorithm. arXiv e-prints, Article," arXiv preprint arXiv:1411.4028, 2014, [Online]. Available: http://arxiv.org/abs/1411.4028

[7] M. Schuld and F. Petruccione, "Supervised Learning with Quantum Computers," Quantum Sci Technol, vol. 17, p. 287, 2019, [Online]. Available: https://link.springer.com/10.1007/978-3-030-83098-4%0Ahttps://link.springer.com/content/pdf/10.1007/978-3-319-96424-9.pdf%0Ahttp://www.worldcat.org/oclc/1076208411

[8] A. Montanaro, "Quantum algorithms: an overview," npj Quantum Inf, vol. 2, no. 1, pp. 1–8, 2016.

[9] T. McCausland, "Digital Twins," 2021, Sage Publications Sage UK: London, England. doi: 10.1080/08956308.2022.1999637.

[10] A. Bashirpour Bonab, M. Fedele, V. Formisano, and I. Rudko, "Quantum Technologies for Smart Cities: A Comprehensive Review and Analysis," 2022. doi: 10.2139/ssrn.4231189.

[11] A. EL Azzaoui, T. Arif, H. Park, H. Chen, D. Camacho, and J. H. Park, "A Comprehensive Study on Quantum Computing Technologies in Smart City: Review and Future Directions," Human-centric Computing and Information Sciences, vol. 14, p. 65, 2024, doi: 10.22967/HCIS.2024.14.064.

[12] NEOM, "Reimagining Urban Living," NEOM. Accessed: Oct. 21, 2025. [Online]. Available: https://www.neom.com/en-us

[13] Conure, "Top 5 Quantum Computing Applications in Smart City Planning," Conure. Accessed: Oct. 21, 2025. [Online]. Available: https://www.conurets.com/top-5-quantum-computing-applications-in-smart-city-planning

[14] D. Venturelli, S. Mandrà, S. Knysh, B. O'Gorman, R. Biswas, and V. Smelyanskiy, "Quantum optimization of fully connected spin glasses," 2015. doi: 10.1103/PhysRevX.5.031040.

[15] J. Allcock and S. Zhang, "Quantum machine learning," Natl Sci Rev, vol. 6, no. 1, pp. 26–28, 2019, doi: 10.1093/nsr/nwy149.

[16] I. M. Georgescu, S. Ashhab, and F. Nori, "Quantum simulation," 2014. doi: 10.1103/RevModPhys.86.153.

[17] M. Mosca, "Cybersecurity in an era with quantum computers: Will we be ready?," IEEE Secur Priv, vol. 16, no. 5, pp. 38–41, 2018, doi: 10.1109/MSP.2018.3761723.

[18] V. S. Barletta, D. Caivano, A. Lako, and A. Pal, "Quantum as a Service Architecture for Security in a Smart City," 2023, Springer\. doi: 10.1007/978-3-031-43703-8_6.

[19] K. Bharti et al., "Noisy intermediate-scale quantum algorithms," Rev Mod Phys, vol. 94, no. 1, p. 15004, Feb. 2022, doi: 10.1103/RevModPhys.94.015004.

[20] A. A. Khan et al., "Software architecture for quantum computing systems — A systematic review," Journal of Systems and Software, vol. 201, p. 111682, 2023, doi: 10.1016/j.jss.2023.111682.

[21] C4IR, "Quantum Economy Landscape in Saudi Arabia. [pdf] Centre for the Fourth Industrial Revolution," C4IR Saudi Arabia. Accessed: Oct. 21, 2025. [Online]. Available: https://www.c4irsaudiarabia.org/docs/Quantum Economy Landscape in Saudi Arabia (23).pdf

[22] M. Swayne, "Saudi Arabia Lays Out Its Strategic Vision For The Quantum Era," The Quantum Insider. Accessed: Oct. 21, 2025. [Online]. Available: https://thequantuminsider.com/2025/01/06/saudi-arabia-lays-out-its-strategic-vision-for-the-quantum-era

[23] H. Hussain, M. Bin Javaid, F. S. Khan, A. Dalal, and A. Khalique, "Optimal control of traffic signals using quantum annealing," Quantum Inf Process, vol. 19, no. 9, 2020.

[24] R. Shikanai, M. Ohzeki, and K. Tanaka, "Quadratic Unconstrained Binary Formulation for Traffic Signal Optimization on Real-World Maps," J Physical Soc Japan, vol. 94, no. 2, p. 24001, Jan. 2025, doi: 10.7566/JPSJ.94.024001.

[25] F. Neukart, G. Compostella, C. Seidel, D. Von Dollen, S. Yarkoni, and B. Parney, "Traffic flow optimization using a quantum annealer," Frontiers in ICT, vol. 4, p. 29, 2017.

[26] H. Min, "Developing a smart port architecture and essential elements in the era of Industry 4.0," Maritime Economics & Logistics, vol. 24, no. 2, pp. 189–207, 2022, doi: 10.1057/s41278-022-00211-3.

[27] A. Ciacco, F. Guerriero, and G. Macrina, "Review of quantum algorithms for medicine, finance and logistics," Soft comput, vol. 29, no. 4, pp. 2129–2170, 2025, doi: 10.1007/s00500-025-10540-z.

[28] S. Vijayalakshmi, S. Dahiya, and S. P. Gayathri, "Smart Intelligence Aided Power and Energy Management BT - Smart Power Systems: Grid Modernization Using AI and IoT-Based Applications," S. Vijayalakshmi, L. J, L. Jacob, S. Dahiya, and R. Gunavathi, Eds., Cham: Springer Nature Switzerland, 2025, pp. 185–196. doi: 10.1007/978-3-031-89459-6_10.

[29] Y. Hirayama, "Diversity of Hybrid Quantum Systems," in Quantum Hybrid Electronics and Materials, Springer, 2022, pp. 1–14. doi: 10.1007/978-981-19-1201-6_1.

[30] J. Bandopadhyay and P. K. Roy, "Implementation of a novel enhanced hybrid multi-objective osprey optimization algorithm for off-grid hybrid system sizing," Evol Intell, vol. 18, no. 5, p. 103, 2025, doi: 10.1007/s12065-025-01083-1.

[31] Claudio. Conti, Quantum machine learning : thinking and exploration in neural network models for quantum science and quantum computing. Springer Nature, 2024.

[32] M. A. Rivera-Ruiz, A. Mendez-Vazquez, and J. M. López-Romero, "Time Series Forecasting with Quantum Machine Learning Architectures BT - Advances in Computational Intelligence," O. Pichardo Lagunas, J. Martínez-Miranda, and B. Martínez Seis, Eds., Cham: Springer Nature Switzerland, 2022, pp. 66–82.

[33] K. Kang, M. M. Y. Kuo, and W. Li, "STMMoE: A Spatio-Temporal Multimodal Mixture-of-Experts Model for Urban Traffic Prediction BT - Knowledge Management and Acquisition for Intelligent Systems," S. Wu, W. Li, X. Xu, and Y. Liu, Eds., Singapore: Springer Nature Singapore, 2025, pp. 49–64.

[34] J. Brence, D. Mihailović, V. V Kabanov, L. Todorovski, S. Džeroski, and J. Vodeb, "Boosting the performance of quantum annealers using machine learning," Quantum Mach Intell, vol. 5, no. 1, p. 4, 2023, doi: 10.1007/s42484-022-00092-y.

[35] B. Tasseff et al., "On the emerging potential of quantum annealing hardware for combinatorial optimization," Journal of Heuristics, vol. 30, no. 5, pp. 325–358, 2024, doi: 10.1007/s10732-024-09530-5.

[36] K. Sarker, "Harnessing Quantum Computing and AI for Enhanced Optimization in Renewable Energy-Driven Smart Grid Systems," Iranian Journal of Science and Technology, Transactions of Electrical Engineering, 2025, doi: 10.1007/s40998-025-00943-x.

[37] J. Blenninger et al., "Q-GRID: Quantum Optimization for the Future Energy Grid," KI - Künstliche Intelligenz, vol. 38, no. 4, pp. 339–349, 2024, doi: 10.1007/s13218-024-00866-5.

[38] I. Priyadarshini, "Swarm-intelligence-based quantum-inspired optimization techniques for enhancing algorithmic efficiency and empirical assessment," Quantum Mach Intell, vol. 6, no. 2, p. 69, 2024, doi: 10.1007/s42484-024-00201-z.

[39] E. Soleimanian, A. Afshar, A. Molajou, and M. Ghasemi, "Development of a Comprehensive Water Simulation Model for Water, Food, and Energy Nexus Analysis in Basin Scale," Water Resources Management, vol. 37, no. 12, pp. 4589–4621, 2023, doi: 10.1007/s11269-023-03558-1.

[40] A. Wicaksono, G. Jeong, and D. Kang, "WEFSiM: A Model for Water–Energy–Food Nexus Simulation and Optimization BT - Frontiers in Water-Energy-Nexus—Nature-Based Solutions, Advanced Technologies and Best Practices for Environmental Sustainability," V. Naddeo, M. Balakrishnan, and K.-H. Choo, Eds., Cham: Springer International Publishing, 2020, pp. 55–58.

[41] V. Naddeo, K.-H. Choo, and M. Ksibi, Water-Energy-Nexus in the Ecological Transition: Natural-Based Solutions, Advanced Technologies and Best Practices for Environmental Sustainability. Springer, 2022. [Online]. Available: https://doi.org/10.1007/978-3-031-00808-5

[42] F. Barrett-danes and F. Ahmad, "Quantum computing and cybersecurity: a rigorous systematic review of emerging threats, post-quantum solutions, and research directions (2019–2024)," Discover Applied Sciences, vol. 7, no. 10, p. 1083, 2025, doi: 10.1007/s42452-025-07322-5.

[43] M. Singh, S. K. Sood, and M. Bhatia, "Post-quantum Cryptography: A Review on Cryptographic Solutions for the Era of Quantum Computing," Archives of Computational Methods in Engineering, 2025, doi: 10.1007/s11831-025-10412-7.

[44] K. S. Rawat, P. Patel, and T. Sharma, "Heart diseases prediction system using quantum technology," Network Modeling Analysis in Health Informatics and Bioinformatics, vol. 14, no. 1, p. 123, 2025, doi: 10.1007/s13721-025-00623-0.

[45] V. K. Bukkarayasamudram et al., "Quantum computing revolution in healthcare: a systematic review of applications, issues and future directions," Artif Intell Rev, vol. 58, no. 12, p. 389, 2025, doi: 10.1007/s10462-025-11381-w.

[46] K. R. Bissett, J. Cadena, M. Khan, and C. J. Kuhlman, "Agent-Based Computational Epidemiological Modeling," J Indian Inst Sci, vol. 101, no. 3, pp. 303–327, 2021, doi: 10.1007/s41745-021-00260-2.

[47] P. B. Upama et al., "Quantum Machine Learning in Disease Detection and Prediction: a survey of applications and future possibilities," in 2023 IEEE 47th Annual Computers, Software, and Applications Conference (COMPSAC), 2023, pp. 1545–1551. doi: 10.1109/COMPSAC57700.2023.00238.

[48] S. S. Bhoi, A. Saini, A. Diro, S. Kaisar, and A. Rao, "Future Digital Identity Management with Quantum Secure Blockchain," IEEE Communications Surveys & Tutorials, p. 1, 2025, doi: 10.1109/COMST.2025.3608794.

[49] Z.-Z. Sun et al., "Quantum Blockchain Relying on Quantum Secure Direct Communication Network," IEEE Internet Things J, vol. 12, no. 10, pp. 14375–14385, 2025, doi: 10.1109/JIOT.2025.3526443.

[50] P. Chandre, H. Hingoliwala, A. Uttarkar, B. D. Shendkar, D. Lokare, and P. Sontakke, "Post-Quantum Cryptography: Securing Critical Infrastructure Against Emerging Quantum Threats," in 2024 IEEE 4th International Conference on ICT in Business Industry & Government (ICTBIG), 2024, pp. 1–7. doi: 10.1109/ICTBIG64922.2024.10911612.

[51] H. Zhang, K. Zhang, D. Rios Insua, and M. Gen, "Multi-objective capacitated location-routing problems with stochastic demands and time windows with applications to household solid waste management," Fuzzy Optimization and Decision Making, 2025, doi: 10.1007/s10700-025-09465-x.

[52] V. B. Pusuluri, M. J. Motam, P. V. R. Jitendara, P. Vetsa, and M. S. S. Vasana, "Shaping the Future of Logistics: Quantum-Inspired Optimization for Autonomous Deliveries," in 2025 6th International Conference on Control, Communication and Computing (ICCC), 2025, pp. 1–6. doi: 10.1109/ICCC64910.2025.11077310.

[53] Hariyanto, F. X. D. Kristianingsih, and R. Maharani, "Artificial intelligence in adaptive education: a systematic review of techniques for personalized learning," Discover Education, vol. 4, no. 1, p. 458, 2025, doi: 10.1007/s44217-025-00908-6.

[54] P. Lamichhane and D. B. Rawat, "Quantum Machine Learning: Recent Advances, Challenges, and Perspectives," IEEE Access, vol. 13, pp. 94057–94105, 2025, doi: 10.1109/ACCESS.2025.3573244.

[55] D. M. Braga and B. S. Rawal, "Quantum and AI-Enhanced Digital Twin Systems," in 2024 15th International Conference on Computing Communication and Networking Technologies, ICCCNT 2024, 2024, pp. 1–8. doi: 10.1109/ICCCNT61001.2024.10724642.

[56] A. Cheshmehzangi, "Living Models: Digital Twins for Climate-Responsive Urban Futures BT - AI Agency in Climate Emergency," A. Cheshmehzangi, Ed., Singapore: Springer Nature Singapore, 2025, pp. 83–92. doi: 10.1007/978-981-95-4192-8_8.

[57] M. Alhaddar and H. R. Kummitha, "Digitalization and sustainable branding in tourism destinations from a systematic review perspective," Discover Sustainability, vol. 6, no. 1, p. 1167, 2025, doi: 10.1007/s43621-025-01751-3.

[58] F. Dalipi, Z. Kastrati, and T. Öberg, "The Impact of Artificial Intelligence on Tourism Sustainability: A Systematic Mapping Review," in 2023 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE), 2023, pp. 119–125. doi: 10.1109/ICCIKE58312.2023.10131818.

[59] I. Bahreldin, H. Samir, R. Maddah, H. Hammad, and I. Hegazy, "Leveraging advanced digital technologies for smart city development in Saudi Arabia: Opportunities, challenges, and strategic pathways," 2025. doi: 10.1093/ijlct/ctaf044.

[60] A. Arruabarrena, "Quantum-enhanced battery placement for smart grids."

[61] M. Sakurai and J. Kokuryo, "Fujisawa sustainable smart town: Panasonic's challenge in building a sustainable society," Communications of the Association for Information Systems, vol. 42, no. 1, pp. 508–525, 2018, doi: 10.17705/1CAIS.04219.

[62] Fujitsu, "Fujitsu Quantum-Inspired Optimization Services Cut Traffic Jams and CO_2 Emissions at Hamburg Port," Fujitsu Global. Accessed: Oct. 21, 2025. [Online]. Available: https://www.fujitsu.com/emeia/about/resources/news/press-releases/2021/emeia-08122021-fujitsu-quantum-inspired-optimization-services-cut-traffic-jams-and-co2-emissions-at-hamburg-port.html

[63] W. Grice, M. Olama, A. Lee, and P. G. Evans, "Quantum Key Distribution Applicability to Smart Grid Cybersecurity Systems," IEEE Access, vol. 13, pp. 17398–17413, 2025, doi: 10.1109/ACCESS.2025.3533942.

[64] R. Coates, R. Dayal, T. Gagliardoni, E. Greplová, T. Humble, and R. Krauthamer, "World Economic Forum, 2022. Quantum Computing Governance Principles," 2022.

MetaEdge: A Meta-Learning-Based Auto-Selective Tool for Hardware-Aware Anomaly Detection on Edge Devices

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***Abstract*—The deployment of anomaly detection systems across heterogeneous edge computing environments faces significant challenges due to varying computational constraints and resource limitations. Existing approaches typically employ static model selection strategies that fail to adapt to diverse hardware capabilities, resulting in suboptimal detection performance and inefficient resource utilization. To address this, we propose MetaEdge, a novel hardware-aware framework that intelligently selects and deploys anomaly detection models based on specific device characteristics and hardware constraints. The MetaEdge framework introduces a systematic methodology that leverages meta-learning in the first stage to train a machine learning model to predict the top-k anomaly detectors by considering dataset characteristics. These candidates are then put through hardware-aware optimization that incorporates the hardware constraints of edge devices to ensure deployment feasibility. The framework evaluates 11 candidate anomaly detection algorithms spanning traditional machine learning and deep learning methods across four representative computing architectures ranging from ultra-constrained edge devices to GPU-accelerated cloud instances. Model conversion through ONNX standardization enables cross-platform deployment while maintaining detection capabilities. Experimental evaluation demonstrates the framework's effectiveness in achieving superior anomaly detection performance across diverse hardware configurations. The hardware-aware stage successfully identifies optimal model-hardware pairings, with the deployed models achieving up to 96.6% accuracy and 90.4% precision on edge devices. The framework demonstrates high accuracy in model selection decisions, with confidence scores providing meaningful hardware compatibility assessments that guide deployment. MetaEdge introduces a novel paradigm for hardware-aware anomaly detection in edge computing, demonstrating that meta-learning–driven model selection can deliver superior detection performance while adhering to stringent hardware constraints. By integrating automatic model selection with hardware-aware optimization, the proposed approach enables anomaly detection systems to intelligently adapt to diverse computing environments and maximize performance under resource constraints.**

***Keywords*—Anomaly detection; edge computing; hardware-aware optimization; machine learning; meta-learning; model selection; ONNX**

I. Introduction

The rapid expansion of the Internet of Things (IoT) has produced an extraordinary volume of data at the network edge. Billions of heterogeneous devices ranging from industrial sensors and autonomous vehicles to wearable health monitors generate continuous, high-velocity data streams. Real-time analysis of these data streams is crucial for extracting value and supporting intelligent applications. To meet this latency and bandwidth demands while strengthening data privacy, computation is increasingly migrating from centralized cloud infrastructures to distributed edge nodes. This architectural shift is necessary for applications that demand low latency, high bandwidth, and stronger data privacy; however, it also poses substantial challenges, especially for deploying advanced machine learning models on resource-constrained edge devices. Addressing this capability–constraint trade-off has become a central challenge for next-generation IoT systems [1], [2].

Anomaly detection, which involves identifying rare events or observations that deviate significantly from normal behavior, is one of the most critical tasks performed at the edge. Its importance spans domains: it supports predictive maintenance and fault avoidance in industrial systems, enables real-time patient monitoring and alerts in healthcare, and identifies intrusion and malware detection in cybersecurity [3]. However, deploying anomaly detection models on edge devices remains highly challenging. These devices operate under stringent constraints on computation, memory, and energy [4]. Offloading raw data to the cloud is often impractical given strict real-time requirements, privacy considerations, and communication costs [1]. Consequently, performing anomaly detection directly on the device, i.e., edge inference, has become increasingly necessary. Selecting an effective anomaly detection model further complicates edge deployment. Model performance depends strongly on data characteristics and anomaly types, and no single model is universally optimal [5]. Consequently, manual model selection becomes time-consuming and expertise-intensive, rendering it impractical for large-scale, heterogeneous edge environments. These limitations have motivated the development of automatic model selection tools that automate the end-to-end process from model choice to tuning. Within this paradigm, meta-learning approaches are particularly promising. Meta-learning leverages performance evidence from diverse prior tasks to recommend effective models for new, unseen tasks. It improves the performance on similar tasks and reduces costly, time-consuming retraining [6].

Even when a meta-learning system recommends an optimal model, it may still be infeasible if it exceeds the hardware

capabilities of the target edge device. A performance-optimized deep learning model, for instance, may demand more memory or computational resources than the device can supply [4]. This necessitates hardware-aware model selection in which device constraints are a primary consideration. The selected model must strike an appropriate balance between predictive performance and computational efficiency. This imperative has driven extensive work on model optimization techniques, such as quantization, pruning, and hardware-aware architecture design, as well as deployment-friendly runtimes such as TensorFlow Lite, to fit powerful models onto constrained platforms [7].

This study presents MetaEdge, a framework for automatic, hardware-aware selection of anomaly detection models for edge inference. This framework optimizes the trade-off between model accuracy and resource efficiency in a fully automated manner. First, a meta-learning-based model selection engine utilizes the meta-features of a given streaming dataset to generate a ranked list of promising anomaly detection models from a predefined candidate pool. Second, a hardware-aware selection module filters the ranked list using the specified hardware constraints of the target edge device, such as available memory, processor capabilities, and latency requirements, returning the best model that maximizes performance while remaining within those operational limits. Where applicable, the selected model is compiled into a lightweight deployment artifact (e.g., TFLite and ONNX) to ensure efficient on-device inference. Together, this end-to-end approach yields models that are not only accurate but also practical for real-world edge deployment.

The novelty of MetaEdge lies in three key aspects that distinguish it from prior work. First, while meta-learning approaches (e.g., AMLBID [6], MetaOOD [12]) have been applied to model selection and hardware-aware optimization techniques (e.g., LightESD [16], EdgeML [11]), they have been developed for edge deployment. MetaEdge is the first to systematically integrate both paradigms into a unified end-to-end framework specifically designed for anomaly detection on heterogeneous edge devices. Second, MetaEdge introduces a comprehensive synthetic hardware-learning dataset (254 configurations, 2,794 training samples) that explicitly captures the relationships between hardware constraints (memory, latency, energy) and model deployment characteristics. This dataset enables the hardware-aware module to learn realistic constraint-performance trade-offs, a capability absent in prior frameworks that rely on heuristic or rule-based hardware filtering. Third, MetaEdge provides empirical validation across real physical edge devices (Raspberry Pi 5, Orange Pi Zero 2W) combined with simulated cloud-edge profiles (AWS EC2 t2.micro, g4dn.xlarge), demonstrating practical deployment feasibility. This real-world validation, coupled with detailed per-device performance analysis, goes beyond the simulated or cloud-based evaluations common in prior work. Together, these contributions establish MetaEdge as a comprehensive, data-driven, and practically validated framework that advances the state-of-the-art in hardware-aware anomaly detection for edge computing.

The main contributions of this work are summarized as follows:

- Introduce MetaEdge, a framework that couples meta-learning-based model selection with hardware-aware selection for edge anomaly detection, narrowing the gap between theoretical performance and deployment on resource-constrained devices. The meta-learning module recommends the top-k models based on dataset characteristics, and the hardware-aware module evaluates these k candidates against target hardware specifications to select the model that best balances performance and deployment feasibility.
- Construct a hardware-learning dataset comprising 254 synthetic hardware configurations and comprehensive profiling of 11 candidate models, yielding 2,794 training samples. This dataset captures relationships between hardware constraints and model deployment characteristics across diverse scenarios.
- Design an efficient hardware-aware module that translates performance-based recommendations from the meta-learning module into deployment-ready selections under real-world hardware constraints. The module turns the hardware-learning dataset into a practical decision-making tool and outputs a probability distribution over all models (confidence scores), where each probability reflects the likelihood that a given model is the best choice for the specified hardware.
- Provide an empirical evaluation across a variety of practical edges, including two real devices (Raspberry Pi 5 and Orange Pi Zero 2W) using Amazon Web Services (AWS) Greengrass V2 and two simulated devices (g4dn.xlarge and a t2.micro) on AWS EC2. We also experiment with different streaming buffer sizes under various data-processing settings, giving us a well-rounded, deployment-ready assessment.

MetaEdge is evaluated along four dimensions: meta-learning-based model selection, hardware-aware model selection, model conversion effectiveness, and deployment feasibility. We first examined how available data volume affects model selection by varying the buffer size (500 vs. 1,000 samples). For each condition, the meta-learning module ranked candidate anomaly detectors and returned the top k models. Providing more buffered data makes the meta-learner both more confident and more accurate in its recommendations. Second, we tested the model conversion effectiveness by converting the models to lightweight deployment versions and comparing them with its original counterparts on two metrics: model file size and accuracy. The accuracy losses were minimal with only 0–3.8% degradation, and the size reductions were substantial of 55-70% across all models. Third, we validated the hardware-aware module by executing it in live deployments across four edge targets. Two were physical devices, a Raspberry Pi 5 (higher-end) and an Orange Pi Zero 2W (resource-constrained) and two were emulated edge profiles on AWS EC2: a t2.micro to represent a low-resource CPU environment and a g4dn.xlarge to represent a GPU-enabled, Jetson-like setting. For each device, we assess both the real-time feasibility and the anomaly detection performance of the selected model. This evaluation confirmed that MetaEdge consistently identified optimal

model–hardware pairings, with edge implementations achieving up to 96.6% accuracy and 90.4% precision.

The remainder of this study is organized as follows: Section II reviews related work and identifies the research gap. Section III details the architecture and methodology of our proposed MetaEdge framework. Section IV presents the experimental setup and a comprehensive evaluation. Finally, Section V concludes the study and discusses future research directions.

II. Related Work

This section provides a structured survey of the literature relevant to our automated, hardware-aware model selection framework for edge anomaly detection. We organize the discussion around three strands that collectively motivate our approach. First, we examine anomaly detection at the edge, with an emphasis on the distinctive constraints of resource-constrained devices and real-time processing, to establish the problem setting and the computational limits that necessitate intelligent model selection. Second, we review automated model selection and meta-learning approaches, evaluating how current frameworks leverage historical performance and meta-features to streamline decision-making while exposing gaps in device-level considerations. Third, we investigate hardware-aware optimization techniques for resource-constrained platforms, clarifying how current approaches address resource constraints and deployment challenges on edge devices. This analysis highlights the importance of incorporating device-level constraints directly into the model selection process. It also reveals critical gaps in existing work that fail to address the end-to-end path from model selection to hardware-constrained deployment, which motivates the comprehensive framework introduced in this study.

A. Lightweight Anomaly Detection for Edge Devices

Research on edge anomaly detection has gained significant attention with the proliferation of IoT devices and the attendant need for real-time decisions. Chatterjee and Ahmed [8] present an extensive survey of IoT anomaly detection methods, highlighting key challenges including limited computational resources, evolving normal behavior patterns, and the scarcity of labeled data. Their examination of 64 recent studies reveals a notable deficit of approaches for multi-sensor integration and concept drift management on constrained devices. Complementing this perspective, Jadhav and Kulkarni [4] examine anomaly detection within edge-computing networks, with particular attention to deep learning methods. Their survey underscores that anomalies at the edge pose substantial risks to enterprise networks and that monitoring and identifying abnormal behavior grow increasingly difficult as interconnections increase. While deep models appear promising, the authors underscore the difficulty of fitting such models within the memory and latency budgets of edge devices. Recent practical implementations have demonstrated both the strengths and the limitations of edge anomaly detection. Reis et al. [10] combine Isolation Forests with LSTM autoencoders within an edge AI framework for smart-home applications, achieving respectable accuracy but only with careful optimization for resource-constrained devices. Similarly, Patrikar and Parate [9] demonstrate video-surveillance anomaly detection at the edge, reporting substantial latency reductions while highlighting the inherent trade-off between model complexity and inference speed. Das et al. [12] propose LightESD, a fully automated, lightweight anomaly-detection method based on statistical learning. LightESD runs on-device without transferring data between the edge and the server and is designed for low latency, memory usage, and energy consumption, making it suitable for low-end edge hardware. The framework maintains competitive detection accuracy while consuming extremely low resources, enabling deployment on low-end edge devices. However, LightESD does not address hardware-aware model selection across heterogeneous devices and lacks explicit mechanisms for handling streaming concept drift in long-running deployments. It also focuses exclusively on statistical methods and does not incorporate meta-learning approaches for intelligent model selection, limiting its adaptability across diverse data characteristics. Collectively, these works frame the problem and underscore that effective solutions must balance detection quality with stringent resource constraints. The next subsection considers automated model selection and meta-learning as means to streamline selection.

B. Automated Model Selection for Edge Computing

The challenge of selecting appropriate machine learning models has motivated the development of automated model selection frameworks. Ying et al. [10] propose an automated model-selection framework for time-series anomaly detection that identifies suitable models and hyperparameters via an extensible selection layer and customized tuning. However, the design targets cloud-based deployments and leaves device constraints out of scope. In contrast, EdgeML [11] is an AutoML framework purpose-built for real-time deep-learning applications on edge devices. It addresses practical obstacles such as limited CPU resources and energy budgets and automates model selection and hyperparameter tuning to enable efficient on-device deployment and real-time inference without reliance on cloud resources. It additionally adapts to runtime conditions such as communication bandwidth fluctuations and varying computational loads. However, EdgeML focuses exclusively on deep neural network optimization and does not address the broader challenge of selecting appropriate anomaly detection algorithms based on data characteristics. Additionally, it lacks meta-learning capabilities for algorithm recommendation and is limited to neural network architectures rather than providing a comprehensive model selection framework. Meta-learning has emerged as an effective approach to automated model selection. Garouani et al. [6] introduce AMLBID, a meta-learning tool for industrial big data that achieves near O(1) complexity for model selection. The framework maintains a meta-knowledge base of algorithm performance across datasets and exploits meta-features to recommend optimal pipelines. Although effective in conventional computing settings, it does not address the distinctive constraints of edge deployments. Most recently, MetaOOD by Qin et al. [12] advances meta-learning for anomaly detection by introducing the first zero-shot, unsupervised framework for selecting out-of-distribution (OOD) detectors. Using language-model embeddings to represent datasets and models, it reports superior performance across 24 dataset pairs and 11 detectors. Nevertheless, the framework operates under effectively unconstrained compute

budgets and omits hardware-aware deployment considerations. These limitations motivate a shift toward hardware-aware machine learning, which explicitly incorporates device-level constraints into model design and deployment. The next subsection reviews this body of literature.

C. Hardware-Adaptive Model Optimization

The constraints of edge devices make hardware-aware optimization indispensable for the deployment of machine learning models. Shuvo et al. [2] present techniques for accelerating deep-learning inference on edge devices, outlining four major directions: novel architectures, optimization of existing methods, algorithm–hardware co-design, and efficient accelerator development. Their findings highlight the necessity of simultaneous hardware- and software-level optimization. Murshed et al. [1] review machine learning deployment at the network edge, outlining the core trade-offs between cloud processing and edge inference. Whereas the cloud offers vast compute capacity, edge deployment directly addresses latency, communication overhead, and privacy. The survey underscores the need for compression techniques, specialized tooling, and hardware-aware frameworks to make edge deployment practical. Researchers have explored multiple approaches to address the challenges of rapidly deploying machine-learning models on edge devices. One effective strategy is to design lightweight architectures specifically for edge deployment. Such architectures employ techniques such as depthwise-separable convolutions, low-rank factorization, and network pruning to improve efficiency without sacrificing accuracy [13]. In this context, MobileNet and ShuffleNet have emerged as popular choices for on-device image classification due to their compact designs and favorable accuracy–latency trade-offs on resource-limited hardware [14]. However, these architectures are mostly vision-centric and often must be retrained for each task and dataset; moreover, without optimized kernels, their speedups are hard to realize, especially for non-vision workloads or devices lacking appropriate operators. Another area of research is model compression for reducing the size and computation of neural networks. Techniques such as quantization and knowledge distillation have shown strong potential to shrink models while preserving accuracy. Pruning and structured sparsity further remove redundant parameters and, when supported by the runtime or hardware, can deliver real latency and energy savings, making them attractive for edge deployment [13]. However, compression can make models less robust when the data changes, hurt calibration, and miss rare events. The gains also depend on hardware/runtime support for low-precision or sparse operations (ops), and distillation needs a strong teacher, complicating use in streaming edge anomaly detection. Hardware-aware neural architecture search has become a promising strategy for tailoring models to specific deployment targets. Lee et al. [15] introduce HELP, a Hardware-adaptive Efficient Latency Predictor formulated via meta-learning to estimate device-specific performance. While compelling for neural architecture search, it addresses architecture design rather than model selection for anomaly detection and does not engage streaming constraints. Collectively, these studies underscore the necessity of embedding device constraints across the entire pipeline. The next subsection offers a research gap analysis that integrates these insights and motivates our proposed framework.

D. Research GAP

Table I presents a comparative analysis of existing approaches across deployment-relevant dimensions for edge-oriented anomaly detection model selection. The evaluation criteria include: Meta-Learning (whether the approach uses meta-learning techniques to automatically select models), Hardware-Aware (explicit consideration of computational and memory constraints during model selection), Edge-Specific (design tailored for edge computing environments with their unique limitations), Anomaly Detection (focus on anomaly detection tasks rather than general machine learning), Streaming Data (capability to handle real-time data streams), and Real Device Validation (empirical evaluation on real physical edge devices rather than simulations). As shown in Table I, existing work reveals several gaps for edge-based anomaly detection. Although automated model selection for anomaly detection exists [10] and meta-learning has been explored for general machine learning [6], [12], yet none of them combine meta-learning with hardware-aware selection tailored to edge-specific constraints.

Recent edge-specific frameworks such as LightESD [16] and EdgeML [11] demonstrate significant progress in addressing hardware constraints and edge deployment challenges, but both lack meta-learning capabilities for intelligent model selection. LightESD focuses exclusively on statistical methods without the ability to adapt to diverse data characteristics, while EdgeML is limited to deep neural network optimization and does not address the broader spectrum of anomaly detection algorithms. Hardware-aware approaches either concentrate on neural architecture search (e.g., HELP [15]) or offer ad hoc solutions for specific applications [9], [17], leaving the field without a rigorous, constraint-driven model selection strategy that explicitly optimizes under device-level constraints. Moreover, commonly used meta-learning paradigms implicitly assume ample computation and fail to address the real-time, streaming nature of edge workloads and their stringent resource budgets. Evaluation practices likewise rely on simulated environments or cloud-based deployments, with limited validation on real devices, despite the well-known divergence between reported metrics and performance on constrained hardware. These limitations motivate a unified framework that couples meta-learning-based recommendation with hardware-aware model selection for streaming anomaly detection at the edge. This study proposed the MetaEdge framework that spans the entire pipeline, from characterizing streaming data to selecting a deployment-ready model, while explicitly accounting for the practical constraints of real-world edge deployments.

TABLE I. COMPARATIVE SUMMARY OF RELATED APPROACHES ACROSS DEPLOYMENT-RELEVANT DIMENSIONS

Approach	Meta-Learning	Hardware-Aware	Edge-Specific	Anomaly Detection	Streaming Data	Real-Device Validation
Ying et al. [10]	✗	✗	✗	✓	✓	✗
AMLBID [6]	✓	✗	✗	✗	✗	✗
MetaOOD [12]	✓	✗	✗	✓	✗	✗
HELP [15]	✓	✓	✓	✗	✗	✗
Edge AI frameworks [9], [17]	✗	✓	✓	✓	✓	✓
LightESD [16]	✗	✗	✓	✓	✓	✓
EdgeML [11]	✗	✓	✓	✗	✓	✓
This work	✓	✓	✓	✓	✓	✓

The novelty of MetaEdge lies in how it bridges the gap between data-driven model recommendation and hardware-aware deployment. A pure meta-learning approach (e.g., AMLBID [6]) would recommend models based solely on data characteristics, ignoring hardware constraints and potentially selecting models that are not deployable on the target device. Conversely, a pure hardware-aware selection approach would select the most efficient model that fits within the hardware budget, but such a model may exhibit poor detection performance for the given data. Existing tools, such as EdgeML [11], focus on hardware-aware optimization for deep learning models yet lack a meta-learning component for recommending the most suitable model class based on data characteristics. LightESD [16] provides lightweight statistical methods but does not incorporate meta-learning or hardware-aware model selection across heterogeneous devices. MetaEdge, in contrast, integrates these two dimensions, using meta-learning to identify a shortlist of high-performing models for the data and then applying a hardware-aware module to select the model that best satisfies device constraints while maintaining strong detection performance. This two-stage approach provides a more holistic solution than existing methods by balancing data-driven accuracy and hardware-driven feasibility.

III. METHODOLOGY AND DESIGN

This section presents MetaEdge, an automated, hardware-aware model selection framework for anomaly detection at the edge. MetaEdge couples meta-learning–driven performance prediction with device-constrained selection to identify a single model that delivers high detection performance while meeting the computational, memory, and latency budgets of the target device. To maintain simplicity and reproducibility, the process is organized into a two-stage pipeline: meta-learning-based selection followed by hardware-aware selection. We first provide a comprehensive overview of the MetaEdge architecture, then present detailed descriptions of each component.

A. Framework Overview

Fig. 1 illustrates a two-stage pipeline for the MetaEdge framework. In the offline training (cloud) stage, training datasets and candidate ML/DL models are applied to meta-feature extraction and model evaluation to build a meta-knowledge dataset, which is transformed into a meta-learning dataset for training a meta-learning module (based on ASAD). In parallel, model profiling combined with hardware datasets produces a hardware-learning dataset, which is used to train a hardware-aware module. These two trained modules constitute the core of the MetaEdge engine. In the online selection (edge) stage, an edge device provides streaming data and hardware specifications; meta-features are extracted and fed into the MetaEdge, which selects and deploys the most suitable, hardware-optimized model for the device. Deployment outcomes and anomaly-detection signals form a feedback loop that enables the engine to adaptively select models on-device, guided by both data characteristics and hardware constraints.

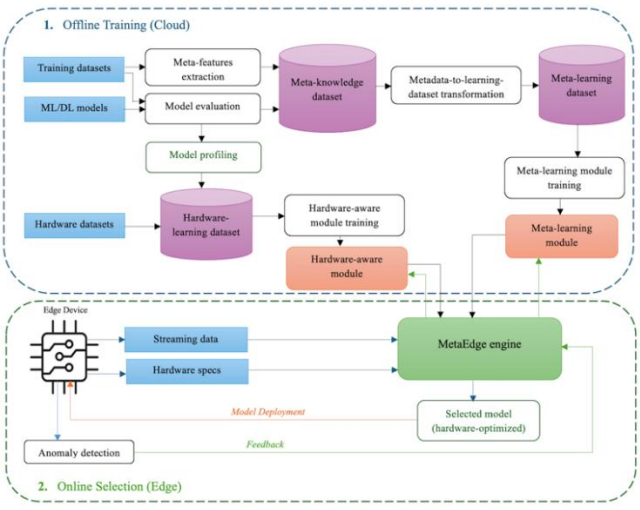


Fig. 1. The architecture of the MetaEdge framework.

MetaEdge integrates its meta-learning and hardware-aware components to select and deploy a hardware-optimized model on the device, demonstrating how historical performance data and hardware constraints can be systematically combined to deliver intelligent, deployment-ready model selection for edge environments, bridging the gap between theoretical model effectiveness and real-world applicability.

B. Meta-Learning Selection Module

The meta-learning engine forms the first stage of our framework, building upon our previous work, ASAD (Auto-Selective Anomaly Detection) [18]. We follow the same meta-learning logic and methodology established in ASAD, which leverages historical performance data across diverse datasets to recommend the most promising anomaly detection models for new, unseen data. The meta-learning stage operates offline to construct a large meta-knowledge dataset for model

recommendation. A diverse benchmark of labeled anomaly detection datasets (139 datasets derived from 60 bases across 11 domains) is assembled, and a broad set of candidate models is evaluated under a unified protocol and seven standard effectiveness metrics. In parallel, an extensive bank of 300 dataset-level meta-features is computed spanning six families: simple, statistical, information-theoretic, model-based, landmarking, and data-complexity to capture dataset size/shape, distributional behavior, and structural dependencies. These meta-features reliably characterize new datasets and guide accurate model selection. The result is a models-by-datasets performance matrix paired with per-dataset meta-feature vectors. This dataset is then transformed into a meta-learning dataset in which each instance contains dataset meta-features and a learning target that encodes the identity of the best-performing model. A supervised meta-learner is trained to map meta-features to predict performance using standard train-validation splits to avoid leakage across datasets. At inference time, the same meta-features are extracted from the incoming unseen dataset, and the meta-learner returns a ranked list of anomaly detectors, enabling fast, trial-free recommendation for new datasets.

In this edge-focused framework, we restrict the candidate model pool to eleven models (AE, MLP, GRU, LSTM, DeepSVDD, GAN, LOF, OCSVM, KMeans, GMM, and PCA) instead of the 80 ML/DL models used in the original ASAD approach. This restriction is specifically designed to prioritize models that are suitable for edge deployment while maintaining the proven effectiveness of the ASAD meta-learning methodology. To ensure deployability, each candidate must be convertible into a tiny, edge-ready artifact via TensorFlow Lite (TFLite) or Open Neural Network Exchange (ONNX) runtime, with support for quantization and lightweight inference. This toolchain requirement is precisely why we do not reuse the broader PyOD-based model list from ASAD: many of those implementations lack reliable TFLite/ONNX export paths and therefore do not meet strict latency/memory targets. Instead, we focus on a curated set that preserves coverage across reconstruction, sequence modeling, clustering, margin-based one-class classification, and local-density detection, chosen for their practical convertibility, stable runtime support, and compatibility with post-training optimizations, thereby preserving methodological rigor while guaranteeing real-world deployability. The current system is positioned as a proof-of-concept, demonstrating end-to-end feasibility under these toolchain constraints; the candidate pool can be expanded as TensorFlow Lite (TFLite) or ONNX support improves without altering the selection logic.

C. Hardware-Aware Selection Module

The hardware-aware selection module represents the second stage of our framework and constitutes our primary novel contribution. This module addresses the critical challenge of translating performance-based model recommendations from the meta-learning module into deployment-ready selections that satisfy real-world hardware constraints. The module operates through a systematic four-step process: synthetic dataset generation, model profiling, hardware learning dataset construction, and hardware-aware model training.

1) Hardware dataset generation: The foundation of hardware-aware model selection begins with the creation of a comprehensive synthetic dataset that represents the diversity of edge computing environments. This step is crucial because it establishes the training basis for learning hardware-performance relationships across different device configurations. We generated 254 synthetic samples, each representing a unique hardware configuration encountered in edge scenarios. The sample size was chosen to provide sufficient coverage of the space of deployment scenarios while maintaining computational tractability for training. Each scenario represents a unique combination of hardware constraints and deployment requirements and is characterized by seven critical features that directly impact model deployment feasibility. The seven features used in the hardware dataset are presented in Table II.

TABLE II. THE SEVEN FEATURES USED IN THE HARDWARE DATASET

Hardware Constraint Features		
Feature	**Definition**	**Importance**
Max_Ram	Maximum available RAM in megabytes	Represent device memory capacity limits
Max_Inference	Maximum acceptable inference latency in milliseconds	Capture real-time performance requirements
Max_Size	Maximum allowable model size in megabytes	Reflect storage and bandwidth constraints
Max_Energy	Maximum energy consumption per inference in millijoules	Address battery-powered device limitations
Deployment Requirement Features		
Feature	**Definition**	**Importance**
Requires_Tflite	A binary indicator (1/0) for TensorFlow Lite format	Essential for mobile deployment optimization
Requires_Onnx	A binary indicator (1/0) for ONNX format	Support cross-platform compatibility
GPU_Available	A binary indicator (1/0) for GPU availability	Enabling hardware-specific optimization

The deployment scenarios were generated using an equal distribution approach with balanced representation across distinct deployment contexts. The process reflects realistic combinations observed in commercial edge devices, ensuring comprehensive coverage of the deployment space. These synthetic hardware configurations serve as the foundation for constructing diverse deployment scenarios. Each configuration represents a distinct set of device capabilities and constraints that will later be used to determine optimal model selection based on constraint satisfaction and deployment requirements.

2) Comprehensive model profiling: Model profiling is the bridge between algorithmic performance and deployment reality. It extracts deployment-specific characteristics that are

essential for hardware-aware decision making but are often overlooked by traditional model selection. During training, all 11 candidate models are comprehensively profiled so that the hardware-aware selector learns a complete mapping from hardware constraints to deployment feasibility across the entire model space. This comprehensive approach is essential because the selector must understand the deployment characteristics of every possible model choice to make informed, hardware-aware decisions.

Profiling spans the memory and storage footprint, runtime efficiency, and format compatibility. On the memory side, runtime RAM during inference ranges from 0.02 MB for PCA to 0.98 MB for LSTM, while on-disk model size ranges from 0.001 MB for KMeans and PCA to 0.113 MB for LSTM. For hardware-accelerated inference, GPU memory requirements vary from 0 MB for traditional ML models to 90 MB for GANs. Efficiency metrics include single-inference latency from 0.68 ms (PCA) to 527.63 ms (LSTM) and energy on MCUs, from 0.04 mJ (PCA) to 29.02 mJ (LSTM). Format compatibility is captured through TFLite and ONNX: deep learning models support TFLite conversion, typically yielding a 10–15% size reduction relative to the original model, whereas traditional ML models are exported to ONNX for cross-platform deployment; corresponding TFLite and ONNX sizes are logged for each model.

The profiling reveals distinct deployment characteristics across model categories. Deep learning models, AutoEncoder, MLP, GRU, LSTM, DeepSVDD, and GAN, support TFLite optimization for mobile targets, benefit from GPU acceleration (30–90 MB GPU RAM), and generally require higher resource usage (0.77–0.98 MB RAM, 11.54–29.02 mJ per inference) with moderate-to-high latency (209.79–527.63 ms). Traditional machine-learning models, LOF, OCSVM, KMeans, GMM, and PCA, export cleanly to ONNX, require minimal resources (0.02–0.07 MB RAM, 0.04–0.17 mJ per inference), deliver ultra-low latency (≈0.68–3.11 ms), and do not require GPU acceleration. For computational efficiency, the strategy differs between training and inference. Training profiles all 11 models to cover the full deployment characteristic space. At inference time, only the top K recommended models from the meta-learning stage are profiled, which reduces profiling overhead by around 64% on average when k=4 (from 11 to 4 models) while preserving selection quality within the constrained candidate set.

3) Hardware-learning dataset construction: The hardware-learning dataset construction represents the critical integration phase that combines the synthetic hardware configurations from Step 1 (Hardware Dataset Generation) with the comprehensive model profiling results from Step 2 (Comprehensive Model Profiling). This step produces the final training dataset with ground truth labels that are determined through a hardware-focused scoring algorithm. It captures the complex relationships between hardware constraints and model deployment characteristics across diverse deployment scenarios.

The hardware-learning dataset construction process expands the 254 synthetic hardware configurations from Step 1 into a comprehensive training dataset. Using an equal distribution approach, each of the 254 hardware configurations is combined with all 11 candidate models, resulting in 2,794 total training samples (254 configurations × 11 models). This balanced distribution ensures that the meta-selector receives equal learning exposure to each model's deployment characteristics, preventing bias toward any algorithm. The integration with model profiling data enables the selection of the optimal model for each scenario through systematic constraint evaluation.

$$FinalScore = Eff_{Score} + Format_{Bonus} + Device_{Bonus} \quad (1)$$

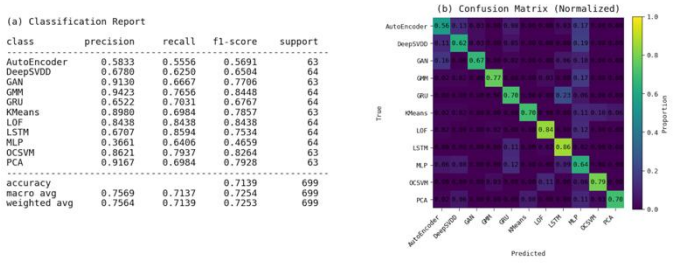
The ground truth label assignment employs a hardware-aware scoring algorithm that determines the best-fitting model for each deployment scenario. Each candidate model is assigned a composite suitability score computed as the sum of an efficiency-based score (Eff_{Score}) and deployment-specific bonuses ($ormat_{Bonus}$ and $Devic\,e_{Bonus}$). The final score is defined as in Eq. (1). The efficiency score is calculated as a weighted linear combination of normalized resource metrics, given by Eq. (2):

$$Eff_{Score} = 0.3 \cdot RAM_{eff} + 0.3 \cdot Speed_{eff} + 0.2 \cdot Size_{eff} + 0.2 \cdot Energy_{eff} \quad (2)$$

The hardware-aware scoring algorithm prioritizes multiple factors, including memory efficiency, speed, format compatibility, and device-specific constraints, in a weighted evaluation. It first applies hard constraints to filter candidates: any model that violates critical limits on Max_Ram, Max_Inference, Max_Size, or Max_Energy is eliminated; models incompatible with required formats (Requires_Tflite, Requires_Onnx) are filtered out; and GPU needs must match device capabilities (Gpu_Available). Among the remaining models, those with lower RAM requirements receive higher scores in memory-constrained scenarios, while faster inference is favored for latency-sensitive deployments. Support for the required format (TFLite or ONNX) earns a compatibility bonus, and GPU availability together with energy limits further adjust each model's overall suitability score. For each of the 2,794 scenarios, the algorithm evaluates all 11 candidate models against the scenario's specific constraints. After constraint filtering and priority-weighted scoring, the model with the highest composite score becomes the ground truth label (BestModel) for that scenario. This approach ensures that the hardware-aware selector learns realistic deployment decisions that reflect both technical constraints and deployment priorities.

4) Hardware-aware model training and optimization: The final step involves training a classifier to predict the optimal model given the integrated hardware and deployment features. This step transforms the comprehensive dataset into a practical decision-making tool for hardware-aware model selection. A Random Forest was selected as the hardware-aware selection algorithm due to its ability to handle mixed feature types, robustness to feature scaling differences, and interpretability through feature importance analysis [19]. The training process starts with data preprocessing, including standardization and label encoding to ensure consistent feature scaling and proper

handling of categorical variables. An 80/20 stratified train-test split maintains balanced class representation across all 11 anomaly detection models. The training step produces a classifier that predicts the optimal model selection among all 11 candidate anomaly detection algorithms based on hardware constraint features. It also outputs a probability distribution (confidence scores) over all models, where each probability indicates the likelihood that a particular model is the best choice for the specified hardware.



(a) Classification Report

class	precision	recall	f1-score	support
AutoEncoder	0.5833	0.5556	0.5691	63
DeepSVDD	0.6780	0.6250	0.6504	64
GAN	0.9130	0.6667	0.7706	63
GMM	0.9423	0.7656	0.8448	64
GRU	0.6522	0.7031	0.6767	64
KMeans	0.8980	0.6984	0.7857	63
LOF	0.8438	0.8438	0.8438	64
LSTM	0.6707	0.8594	0.7534	64
MLP	0.3661	0.6406	0.4659	64
OCSVM	0.8621	0.7937	0.8264	63
PCA	0.9167	0.6984	0.7928	63
accuracy			0.7139	699
macro avg	0.7569	0.7137	0.7254	699
weighted avg	0.7564	0.7139	0.7253	699

(b) Confusion Matrix (Normalized)

Fig. 2. Performance of the hardware-aware classifier: (a) Classification report; (b) Normalized confusion matrix.

Fig. 2 shows strong, class-consistent performance across 11 categories. The multi-class model achieved 71.4% overall accuracy (699 samples), with macro-averaged precision 0.7569, recall 0.7137, and F1-score 0.7254, indicating balanced performance across classes. The row-normalized confusion matrix shows a clear, dominant diagonal where most classes (7 out of 11) achieve ≥ 0.70 recall, with particularly strong performance for LSTM (0.86), LOF (0.84), OCSVM (0.79), and GMM (0.77). Off-diagonal entries are low and diffuse, indicating minimal systematic confusion and confirming the model's ability to reliably discriminate among the competing approaches. These results represent a significant improvement over random selection and validate the effectiveness of constraint-driven feature-engineering and hardware-focused scoring.

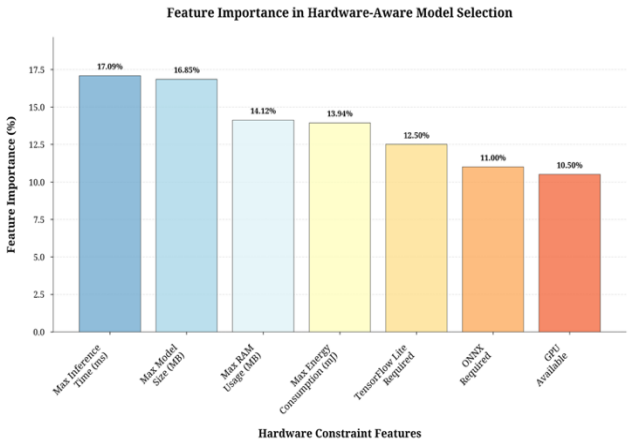


Fig. 3. Feature importance analysis of the hardware-aware model selection.

The Random Forest feature importance analysis reveals the relative contribution of each input feature to the selection decision, as illustrated in Fig. 3. The feature-importance analysis indicates that deployment constraints tied to latency and footprint dominate model selection: Max_Inference contributes the most at 17.09%, followed by Max_Size at 16.85%. Resource limits are next with Max_RAM (14.12%) and Max_Energy (13.94%), highlighting the importance of running efficiently on devices with limited memory and power. Platform compatibility matters but is secondary, with Requires_Tflite (12.50%) and Requires_Onnx (11.00%). GPU Availability has the lowest but still meaningful impact (10.50%), suggesting decisions are driven more by edge-device constraints than by access to accelerators.

D. MetaEdge Engine Construction

The MetaEdge engine is constructed by seamless integration of the hardware-aware selection module and the meta-learning module through a two-stage decision process. During inference, the meta-learning module first generates top-k model recommendations based on dataset characteristics. The hardware-aware module then evaluates these k candidates against the target hardware specifications to select the best candidate model that balances performance potential with deployment feasibility. A key design decision in MetaEdge is this two-stage architecture: by first filtering with meta-learning and then applying hardware-aware optimization, the system constrains the hardware-aware module to the top-K models while gaining important practical advantages, including computational efficiency by reducing the candidate pool, interpretability through a clear separation of data-driven and hardware-driven decisions, and proven effectiveness across diverse deployment scenarios. This design prioritizes data-driven model selection as the primary driver, using hardware constraints as a secondary refinement filter, reflecting a deliberate trade-off between optimality and deployment efficiency.

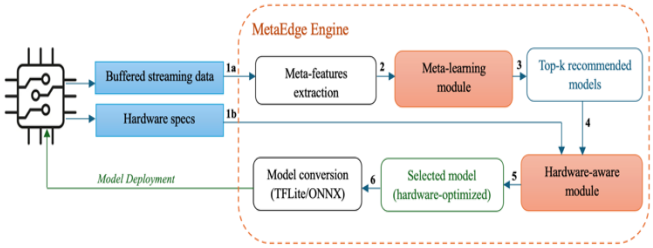


Fig. 4. Workflow of the MetaEdge engine.

Fig. 4 illustrates the detailed workflow of MetaEdge. First, the incoming streaming data is buffered, and the buffered data is sent along with the target hardware specifications to the MetaEdge engine. Then, at the MetaEdge, a two-stage decision process is performed to select the best deployable anomaly-detection model. In the first stage, the meta-learning module extracts the meta-features of the buffered streaming data and recommends the top-k anomaly detectors based only on the data characteristics. In the second stage, the hardware-aware module uses the hardware specifications and converts them into a standardized feature vector to generate probability predictions (confidence scores) for every model in the candidate pool, not just the top-k from the meta-learning module. The confidence score represents the hardware-aware estimate of the probability that a given model is the most suitable option for a

given hardware specification. Despite having complete probability information for all 11 models, the system restricts the selection to only the top-k models identified by the meta-learning selection module. Therefore, the hardware-aware selection module selects the model with the highest probability among the filtered top-k. The selected model is then trained on the buffered data and converted to compact models using the required format (TFLite or ONNX). Algorithm 1 presents the integrated two-stage selection process of MetaEdge.

Algorithm 1 Two-Stage Model Selection of MetaEdge.

Input: Dataset meta-features M; device specifications D; meta-learner module ML; hardware-aware module HM; K (default K=3)
Output: Selected model $M_{optimal}$, confidence score conf

// **Stage 1:** Meta-learning recommendation

Top_K_models ← *ML.recommend (M,K=3)*

// **Stage 2:** Hardware-aware selection

Device_features ← $[D.max_{ram_{mb}}, D.max_{inference_{ms}}, D.max_{size_{mb}}, D.max_{energy_{mJ}}, D.requires_{tflite}, D.requires_{onnx}, D.gpu_{available}]$

Device_features_scaled ← $Scaler.transform(Device_features)$

Prob_all ← $HM.predict_proba(Device_features_scaled)$

All_predictions ← $Map\ (All_candidate_models,\ Prob_all)$

Filtered_predictions ← $Filter\ (All_predictions, Top_K_models)$

$(M_{optimal}, conf) \leftarrow arg\ max\ (filtered_predictions)$

Return $M_{optimal}$, conf

IV. Experimental Results

This section reports a comprehensive evaluation of the MetaEdge framework along four dimensions: meta-learning-based model selection, hardware-aware model selection, model conversion effectiveness, and deployment feasibility. All experiments were executed on AWS. We used Amazon SageMaker notebook instances to provide a scalable, reproducible setup, and stored models, training data, and results in Amazon S3 for reliable persistence and access. The stream-processing pipeline consumed the skin dataset and implemented a buffer abstraction to emulate cold-start and warm-buffer conditions, enabling a realistic assessment under varied operating scenarios. We tested MetaEdge on four representative edge platforms spanning a wide compute range from a constrained Orange Pi Zero to a high-performance EC2 g4dn.xlarge with a GPU. The two higher-end platforms were instantiated as AWS EC2 instances to reflect practical cloud–edge deployments. The overarching goal is to show that MetaEdge can adapt model selection to device constraints while maintaining acceptable anomaly-detection performance, and to quantify the benefits of its two-stage selection strategy in real-world edge settings.

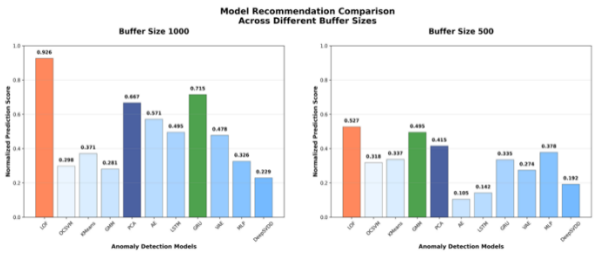


Fig. 5. Model recommendation comparison across different buffer sizes.

We examined how available data volume affects model selection by varying the buffer size (500 vs. 1,000 samples). For each condition, the meta-learning module ranked candidate anomaly detectors and returned the top three. With a 500-sample buffer, it favored LOF, GMM, and PCA; with a 1,000-sample buffer, it favored LOF, GRU, and PCA. As illustrated in Fig. 5, increasing the buffer from 500 to 1,000 samples yielded a 76% average gain in the meta-learner's prediction score. Confidence in LOF rose from 0.527 to 0.926, with corresponding improvements for GRU and PCA. Overall, providing more buffered data makes the meta-learner both more confident and more accurate in its recommendations.

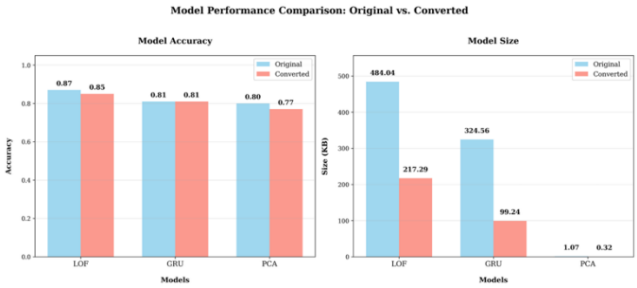


Fig. 6. Model performance comparison (Original vs. Converted).

To evaluate anomaly detection capability, we trained the top three models recommended by the meta-learner: LOF, GRU, and PCA on a 1,000-sample buffer from the skin dataset. We then produced lightweight deployment versions. Where supported, TensorFlow models were exported to .tflite using the official TensorFlow Lite converter; scikit-learn models were converted to ONNX with skl2onnx. In our case, LOF and PCA (scikit-learn) were converted to ONNX, and the GRU model was exported to ONNX via tf2onnx as a fallback mechanism. To validate the effectiveness of these conversions, we compared each converted model with its original counterpart on two metrics: model file size and accuracy (see Fig. 6). Accuracy losses were minimal: LOF decreased from 0.87 to 0.85 (−2.3%), GRU was unchanged at 0.81, and PCA declined from 0.80 to 0.77 (−3.8%). All converted models remained above 75% accuracy. Size compression was substantial: LOF shrank from 484.04 KB to 217.29 KB (−55%), GRU from 324.56 KB to 99.24 KB (−69%), and PCA from 1.07 KB to 0.32 KB (−70%). These reductions, ranging from 55% to 70% make the models well-suited for resource-constrained edge deployments.

TABLE III. THE SPECIFICATIONS OF EDGE DEVICES

Edge Device	Real/ Simulated	Device Specifications
T2.Micro 	Simulated	1 vCPU, 1 GB RAM, no GPU; Low-to-moderate network performance [20].
G4dn.Xlarge 	Simulated	4 vCPUs, 16 GB RAM, 1× NVIDIA T4 (16 GB VRAM), 125 GB NVMe local storage, up to 25 Gbps networking [21].
Raspberry Pi 5 	Real	Quad-core Arm Cortex-A76, 2.4 GHz, VideoCore VII GPU; LPDDR4X-4267 RAM 8 GB; dual 4Kp60 micro-HDMI; Wi-Fi 5 and Bluetooth 5.0 [22].
Orange Pi Zero 2W 	Real	quad-core Cortex-A53 (up to 1.5 GHz), Mali-G31 MP2 GPU; 1 GB LPDDR4 ; Wi-Fi 5 and Bluetooth 5.0 [23].

We validated the hardware-aware module by executing it in live deployments across four edge targets. Two were physical devices, a Raspberry Pi 5 (higher-end) and an Orange Pi Zero 2W (resource-constrained), provisioned with AWS IoT Greengrass v2 and packaged via Amazon SageMaker Edge Manager. To widen the hardware spectrum, we also emulated edge profiles on AWS EC2: a t2.micro to represent a low-resource CPU environment and a g4dn.xlarge to represent a GPU-enabled, Jetson-like setting. Device specifications are summarized in Table III. The hardware-aware module leverages each device's specifications to choose the best model from the meta-learner's candidates (LOF, GRU, and PCA), assigning a confidence score to each. Detailed per-device confidence scores for all models are presented in the following subsections.

A. Edge Device 1: Orange Pi Zero

The Orange Pi Zero is one of the resource-constrained platforms, and its confidence scores reflect the framework's ability to adapt to severe hardware limits. LOF is the preferred option at 45% confidence (see Fig. 7), indicating that classical algorithms are best suited to resource-limited devices. PCA is a strong alternative at 25%, underscoring the preference for lightweight, classical approaches. By contrast, the GRU receives 0% confidence, consistent with the view that neural networks are impractical on this class of hardware. Overall, the distribution shows hardware-aware reasoning: traditional ML models dominate the shortlist (LOF 45%, PCA 25%, KMeans 15%), appropriately prioritizing resource-efficient choices for reliable deployment under tight constraints.

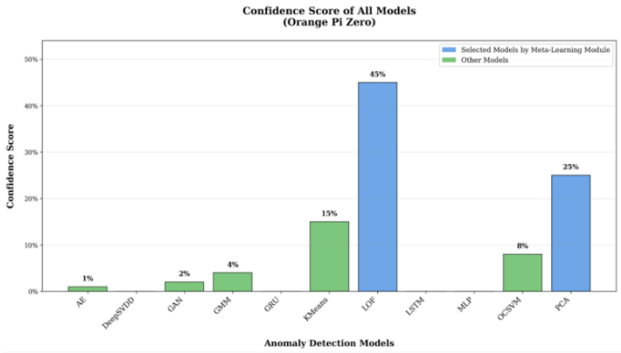


Fig. 7. Confidence scores of the Orange Pi Zero device.

To assess real-time feasibility, we deployed the selected LOF model on the Orange Pi Zero. The inference traces (see Fig. 8) remained stable across 6,000 samples with no anomalous spikes. Latency was tightly centered at 17.36 ms and consistently under 20 ms per sample, meeting real-time requirements for lightweight devices. Chunk-level analysis over 120 windows showed steady performance with only minor fluctuations. While not the fastest platform, the Orange Pi Zero ran LOF inference reliably, confirming that on-device anomaly detection is feasible even on microcontroller-class hardware.

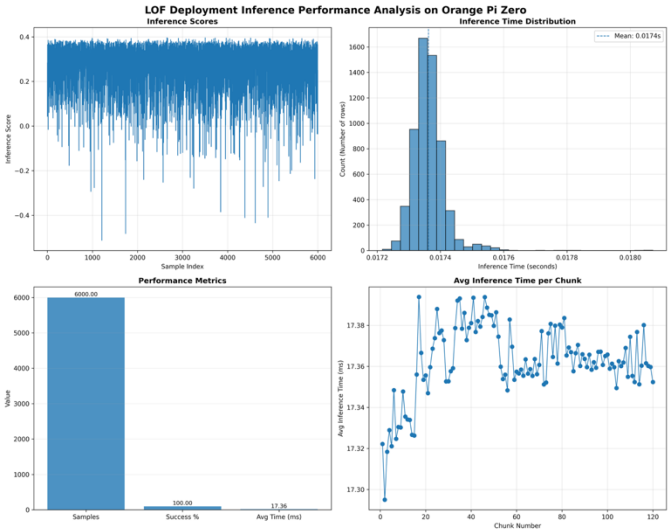


Fig. 8. Inference performance of the Orange Pi Zero device.

Running LOF on the Orange Pi Zero shows that simple, lightweight methods can work well on limited hardware, with 81.0% accuracy, as shown in Fig. 9. Precision is 29.4%, meaning one in three alerts corresponds to a true anomaly, a trade-off that favors responsiveness over selectivity on low-power devices. Recall is 79.1%, so the system catches most of the anomalies useful in settings where missing an event such as equipment faults and security issues is worse than raising extra alerts. Specificity is 81.2%, indicating reasonable discrimination of normal behavior given the algorithm's simplicity and small computational footprint. Overall, the F1 score is 42.8%, and the average precision (AP) is 0.456, reflecting moderate separation between classes under tight resource limits. The confusion matrix (TN = 4,434; FP = 1,026; FN = 113; TP = 427) confirms this profile: more false alarms than some higher-powered

platforms, but strong sensitivity that is well suited to applications where missing an anomaly is costlier than investigating extra alerts. Taken together, these results make the Orange Pi Zero and LOF combination a practical fit for distributed sensor networks, remote monitoring, and other IoT deployments where power, cost, and connectivity limitations demand efficient local processing.

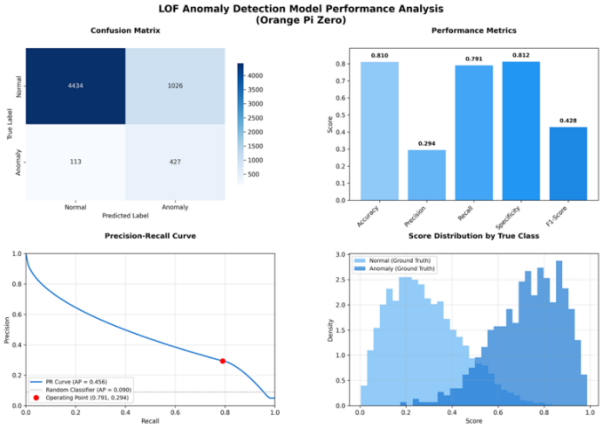


Fig. 9. Performance of a LOF model on Orange Pi Zero: (a) Confusion matrix; (b) Metrics summary; (c) Precision–recall curve; (d) Score distributions by class.

B. Edge Device 2: EC2 T2.Micro

The EC2 t2.micro serves as another resource-constrained target, with limited RAM and tight latency budgets. LOF remains the leading choice at 35% confidence, down from 45% on the Orange Pi Zero, suggesting that the different resources on t2.micro allow closer competition (as shown in Fig. 10). GAN reaches 20% confidence but is excluded because it was not selected by the meta-learning module. Overall, classical options still dominate the viable set PCA at 15% while non-selected candidates such as KMeans (12%) and AutoEncoder (8%) register only moderate confidence.

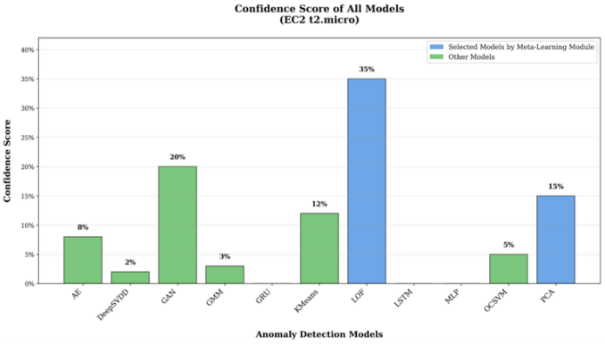


Fig. 10. Confidence scores of T2.micro.

To assess the real-time viability of the chosen LOF model, we deployed it on AWS EC2 t2.micro instances using AWS IoT Greengrass v2. Fig. 11 summarizes the edge-side inference results. The line plot tracks raw anomaly scores across 6,000 streaming samples; scores are normalized to the [0, 1] range and exhibit steady behavior without abrupt spikes. The accompanying histogram reports per-sample latency: the mean inference time was 2.58 ms, with most samples completing under 3 ms. Latencies ranged from 2.34 ms to 12.68 ms indicating efficient and comparatively stable performance on constrained hardware. A chunk-level view (CHUNK_SIZE = 50) further showed uniform throughput across 120 chunks, with no evident degradation or drift. Despite limited CPU and memory, the LOF model sustained stable throughput and accuracy, supporting its suitability for lightweight deployment on t2.micro edge device.

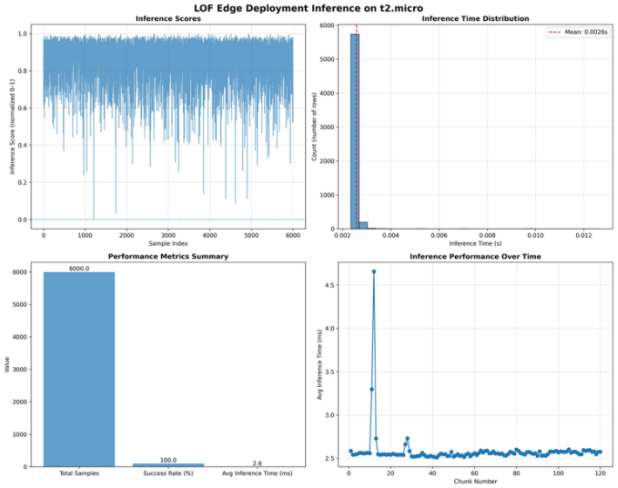


Fig. 11. Inference performance of the T2.micro device.

On an AWS T2.micro instance, the LOF model achieves 76.5% accuracy (see Fig. 12), demonstrating that useful anomaly detection can be achieved on a very low-cost instance. Precision is 23.9%, so about one in four alerts is a real issue, a reflection of the limited CPU and memory on this class of VM, which caps model complexity. Recall comes in at 73.9%, meaning the system catches the most important anomalies, which is valuable when the cost of missing an event could outweigh savings on infrastructure. Specificity is 76.8%, a reasonable level of "normal vs. abnormal" separation for such a constrained setup. Overall, the F1 score is 36.1% and the AP is 0.403, consistent with moderate discriminative power for cost-sensitive use cases. The confusion matrix (TN=4,191; FP=1,269; FN=141; TP=399) shows a higher false-alarm rate, but acceptable recall, which is ideal for cost-sensitive environments that use alerts to prompt lightweight verification.

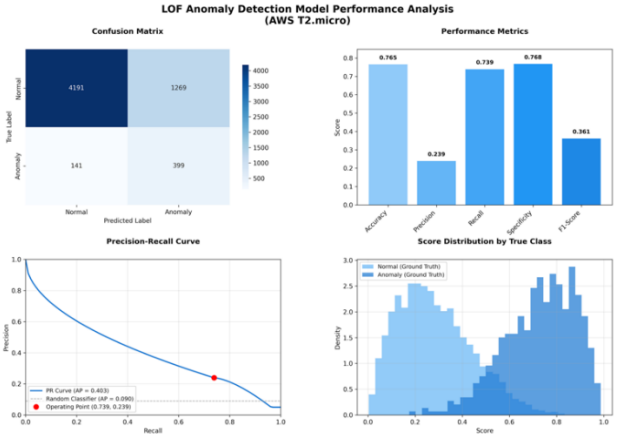


Fig. 12. Performance of a LOF model on T2.micro: (a) Confusion matrix; (b) Metrics summary; (c) Precision–recall curve; (d) Score distributions by class.

C. Edge Device 3: Raspberry Pi 5

The Raspberry Pi 5 marks a clear inflection point where the framework begins to favor deep learning and adapts to support neural models. On this device, a GRU is selected with 28% confidence (see Fig. 13), indicating the system's capacity to accommodate more advanced algorithms as resources increase. This choice supports the framework's principle of scaling model complexity with available compute, enabling neural network–based methods when they become practical and advantageous for anomaly detection. Notably, an LSTM registers 42% confidence among the models that were filtered out. This suggests the hardware-aware selector would have preferred LSTM over GRU for this configuration, but the upstream meta-learning stage, driven by data characteristics, did not choose it. This rigid two-stage pipeline can therefore constrain optimal hardware-aware decisions when the meta-learning and hardware signals diverge.

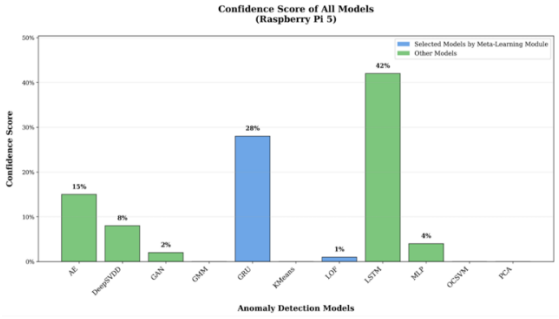


Fig. 13. Confidence scores of the Raspberry Pi 5.

To verify the GRU model's real-time viability, we deployed it on a Raspberry Pi 5. Fig. 14 summarizes the edge-side inference results. Outputs remain stable across all 6,000 samples, with scores confined to the [0, 1] range. Latency is extremely low, an average of 0.076 ms, with the vast majority of inferences finishing under 0.1 ms. A chunk-level analysis over 120 chunks shows flat, highly consistent throughput with no signs of drift or degradation. Overall, the Raspberry Pi 5 executes the GRU model with ultra-low latency and negligible variance, confirming its suitability for real-time anomaly detection at the edge.

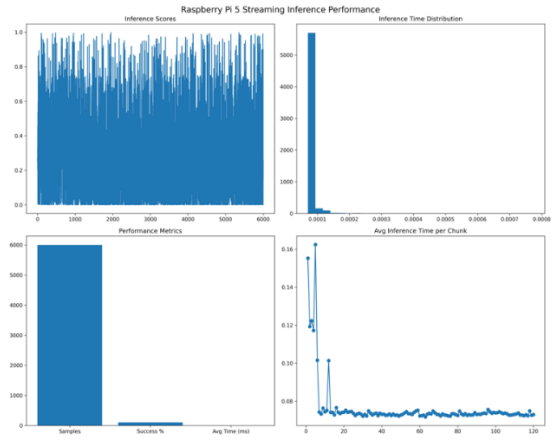


Fig. 14. Inference performance of the Raspberry Pi 5 device.

As shown in Fig. 15, running a GRU model on the Raspberry Pi 5 delivers standout anomaly detection, topping all platforms in our test with 96.6% accuracy. Precision reaches 90.4%, meaning 9 out of 10 alerts are real, which significantly reduces the cost of chasing false alarms. The model's 69.7% recall reflects a deliberate tilt toward accuracy over sensitivity, which is useful in settings where false positives are more costly than the occasional miss. Specificity is an exceptional 99.3%, indicating the system almost never flags normal behavior. Overall performance is strong, with an F1 score of 78.7% and an AP of 0.818. The confusion matrix shows 5,420 correctly identified normal events and 376 correctly identified anomalies, with only 40 false alarms and 164 missed anomalies, evidence of tight control over false positives while capturing a substantial share of true anomalies. These results demonstrate the model's ability to achieve high-performance anomaly detection on edge computing hardware with minimal computational overhead.

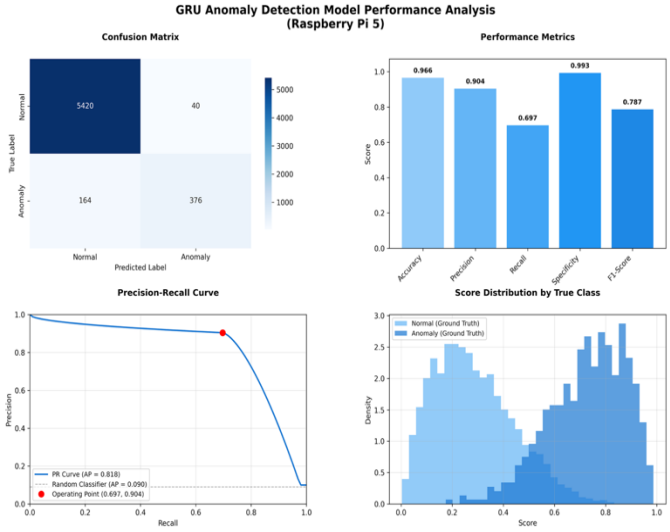


Fig. 15. Performance of a GRU model on Raspberry Pi 5: (a) Confusion matrix; (b) Metrics summary; (c) Precision–recall curve; (d) Score distributions by class.

D. Edge Device 4: EC2 G4dn.Xlarge

The EC2 g4dn.xlarge evaluation shows how the framework performs in a resource-rich, GPU-accelerated setting. As shown in Fig. 16, with ample compute, the system elevates deep learning and selects a GRU with 18% confidence, illustrating its ability to take advantage of advanced hardware. This aligns with the framework's scaling strategy: as constraints ease, more sophisticated neural architectures become preferable. While GRU was prioritized as a top 3 meta-learning choice, LSTM attained 55% confidence, exceeding the GRU by more than threefold, suggesting substantial promise under different dataset conditions. As expected on this class of hardware, traditional ML methods receive negligible confidence (mostly under 5%), avoiding underutilization of the platform. Overall, the high-performance scenario confirms that the framework adjusts model complexity to match available resources, enabling efficient use of advanced edge infrastructure.

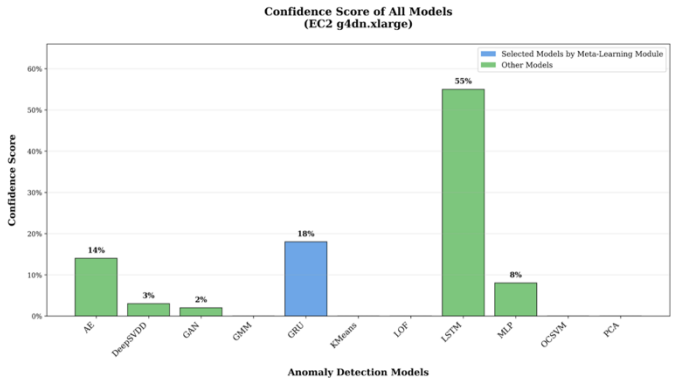


Fig. 16. Confidence scores of G4dn.Xlarge.

To validate the real-time operational feasibility of the selected LOF model, deployments were executed on AWS EC2 instances G4dn.Xlarge using AWS IoT Greengrass V2. The GRU edge deployment inference results for EC2 instance G4dn.Xlarge are shown in Fig. 17. The line chart shows GRU's raw sequence modeling outputs across 6,000 streaming samples, bounded between 0 and 1. The scores remained stable without spikes, reflecting consistent prediction quality. The histogram confirms ultra-stable latency, with most samples completing near 0.07 ms. The narrow range (0.066–0.298 ms) and extremely low variance (std: 0.0053 ms) validate the predictability of GPU execution. Chunk-level latency (120 chunks, 50 samples each) was nearly flat, with no systematic drift, confirming sustained throughput. The GRU model leveraged G4dn.Xlarge's GPU capabilities to deliver extremely consistent, ultra-low-variance inference performance, ideal for precision-critical deployments.

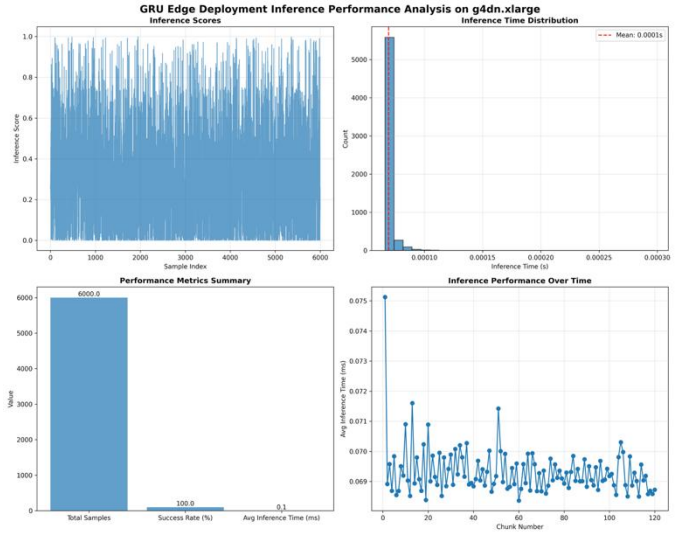


Fig. 17. Inference performance of G4dn.xlarge device.

Running a GRU model on an AWS G4dn.xlarge delivers solid anomaly detection with 89.0% accuracy, highlighting how high-performance hardware helps with complex pattern recognition. Precision is 43.2%, about two of every five alerts are true, a clear step up from our statistical baselines, while keeping throughput high thanks to GPU acceleration. Recall is 69.6%, so the system catches nearly 70% of real anomalies, and specificity is 90.9%, showing it is strong at recognizing normal behavior. Overall, the model posts an F1 of 53.3% and an AP of 0.512, indicating good discrimination across thresholds, as shown in Fig. 18. The confusion matrix shows TN=4,965, FP=495, FN=164, and TP=376, reflecting a balanced trade-off between detection and false alarms. In practice, this GPU-accelerated setup is well-suited to production workloads that need both high performance and straightforward scalability.

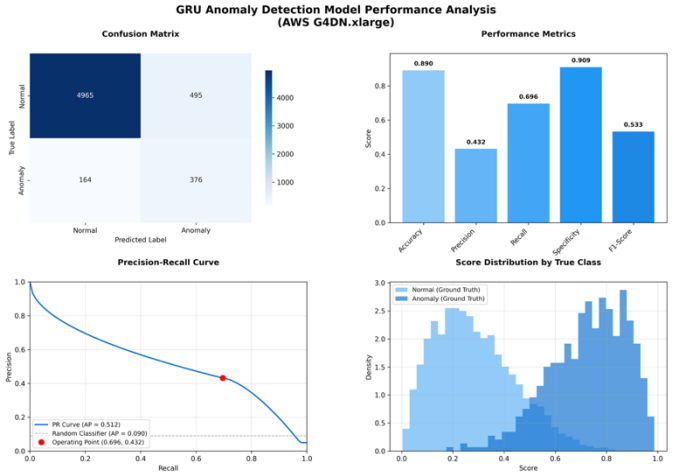


Fig. 18. Performance of a GRU model on G4dn.Xlarge: (a) Confusion matrix; (b) Metrics summary; (c) Precision–recall curve; (d) Score distributions by class.

E. Results Summary

MetaEdge shows strong hardware-aware model selection: its confidence score distributions adapt to the computational limits of the four evaluated devices. The Random Forest meta-selector produces probabilities ranging from 0% for clearly incompatible choices to 55% for the best hardware–model pairs. Concretely, LOF scores 45% confidence on the Orange Pi Zero and 35% on EC2 t2.micro, while GRU reaches 28% on the Raspberry Pi 5 and becomes viable on EC2 g4dn.xlarge, evidence that the framework scales model complexity progressively with available resources. The model conversion process through ONNX standardization achieves remarkable success with only 0–3.8% degradation, while delivering substantial size reductions of 55-70% across all models. These reductions enable practical edge deployment without sacrificing detection capability, effectively bridging the gap between theoretical performance and real-world deployment constraints.

Across deployments, the models deliver strong anomaly detection and validate MetaEdge's two-stage selection strategy. The Raspberry Pi 5 leads all platforms with 96.6% accuracy and 90.4% precision, surpassing all other configurations in this study. The AWS G4dn.xlarge follows with 89.0% accuracy using GPU acceleration, while the LOF model maintains consistent recall on constrained devices (79.1% and 73.9% on the Orange Pi Zero and EC2 t2.micro, respectively). MetaEdge balances performance and deploy ability by first using meta-learning to shortlist high-performing candidates, then applying hardware-aware constraints to ensure each model fits device resources. This produces sensible adaptations: traditional ML is selected for tight edge environments, and deep learning is enabled where hardware permits. The result is superior anomaly

detection across diverse edge settings without sacrificing computational efficiency or deployment reliability.

V. Conclusion

This study presents MetaEdge, a hardware-aware framework for model selection that tackles the challenge of deploying effective anomaly detection across heterogeneous edge devices. It combines meta-learning with hardware-aware optimization to enable practical deployment without compromising detection quality. The framework makes high-accuracy model-selection decisions, with confidence scores that provide meaningful assessments of hardware compatibility to guide deployment strategies. MetaEdge uses ONNX standardization for model conversion to enable cross-platform deployment while minimizing accuracy loss, yielding 0–3.8% degradation and a 55–70% reduction in model size.

Experimental results demonstrate superior anomaly-detection performance across diverse hardware configurations. The hardware-aware stage consistently identifies optimal model–hardware pairings, and the deployed models exhibit strong detection performance. On a Raspberry Pi 5, MetaEdge achieves 96.6% accuracy and 90.4% precision under strict computational constraints, outperforming the other tested implementations. On an AWS g4dn.xlarge instance, GPU acceleration yields 89.0% accuracy. The LOF model maintains stable recall on resource-constrained devices (79.1% and 73.9%), providing a reliable baseline for such deployments.

MetaEdge demonstrates that automated, hardware-aware model selection can jointly identify models from data meta-features and align them with device constraints. The framework operates across heterogeneous platforms from ultra-constrained edge nodes to GPU-accelerated systems, enhancing on-device anomaly detection while adhering to strict resource budgets. Beyond empirical gains, MetaEdge offers methodological guidance for distributed anomaly detection and clarifies the trade-offs inherent in hardware-aware optimization. It establishes a robust foundation for future adaptive edge computing systems, capable of intelligently adjusting their performance based on available computational resources and deployment constraints.

In practice, MetaEdge supports real-world deployment by providing a systematic workflow for selecting accurate models that satisfy explicit resource budgets across diverse devices, reducing trial-and-error when transitioning from experimental evaluation to on-device operation. As with any deployment-oriented framework, MetaEdge operates within the assumptions of the profiled model space and observed device conditions; however, its modular design allows these profiles to be incrementally expanded and updated as deployment scale, anomaly characteristics, and hardware diversity evolve. To further strengthen applicability at scale, future work will extend the profiling process and model registry to broader model families and a wider range of devices, support lightweight online learning to maintain performance under concept drift and changing anomaly patterns, enable model personalization to device- and context-specific conditions, and explore cross-device collaborative learning to improve robustness across heterogeneous edge deployments, while reducing runtime overhead through offline profiling and caching.

Acknowledgment

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References

[1] M. G. Sarwar Murshed, C. Murphy, D. Hou, N. Khan, G. Ananthanarayanan, and F. Hussain, "Machine Learning at the Network Edge: A Survey," ACM Computing Surveys (CSUR), vol. 54, no. 8, Oct. 2021, doi: 10.1145/3469029.

[2] M. M. H. Shuvo, S. K. Islam, J. Cheng, and B. I. Morshed, "Efficient Acceleration of Deep Learning Inference on Resource-Constrained Edge Devices: A Review," Proceedings of the IEEE, vol. 111, no. 1, pp. 42–91, Jan. 2023, doi: 10.1109/JPROC.2022.3226481.

[3] P. Schneider and F. Xhafa, "Anomaly detection: Concepts and methods," Anomaly Detection and Complex Event Processing over IoT Data Streams, pp. 49–66, Jan. 2022, doi: 10.1016/B978-0-12-823818-9.00013-4.

[4] S. Jadhav and A. Kulkarni, "Comprehensive Survey on Detection of Anomalies in Edge Computing Network and Deep Learning Solutions," 2025, doi: 10.5220/0013344100004646.

[5] D. H. Wolpert and W. G. Macready, "No free lunch theorems for optimization," IEEE Transactions on Evolutionary Computation, vol. 1, no. 1, pp. 67–82, 1997, doi: 10.1109/4235.585893.

[6] M. Garouani, A. Ahmad, M. Bouneffa, M. Hamlich, G. Bourguin, and A. Lewandowski, "Using meta-learning for automated algorithms selection and configuration: an experimental framework for industrial big data," J Big Data, vol. 9, no. 1, pp. 1–20, Dec. 2022, doi: 10.1186/S40537-022-00612-4/TABLES/8.

[7] S. M. Raza, S. M. H. Abidi, M. Masuduzzaman, and S. Y. Shin, "Lightweight deep learning for visual perception: A survey of models, compression strategies, and edge deployment challenges," Neurocomputing, vol. 656, p. 131357, Dec. 2025, doi: 10.1016/J.NEUCOM.2025.131357.

[8] A. Chatterjee and B. S. Ahmed, "IoT anomaly detection methods and applications: A survey," Internet of Things, vol. 19, p. 100568, Aug. 2022, doi: 10.1016/J.IOT.2022.100568.

[9] D. R. Patrikar and M. R. Parate, "Anomaly detection using edge computing in video surveillance system: review," Int J Multimed Inf Retr, vol. 11, no. 2, pp. 85–110, Jun. 2022, doi: 10.1007/S13735-022-00227-8.

[10] Y. Ying, J. Duan, C. Wang, Y. Wang, C. Huang, and B. Xu, "Automated Model Selection for Time-Series Anomaly Detection," Aug. 2020, doi: 10.1145/nnnnnnn.nnnnnnn.

[11] Z. Zhao, K. Wang, N. Ling, and G. Xing, "EdgeML: An AutoML Framework for Real-Time Deep Learning on the Edge," IoTDI 2021 - Proceedings of the 2021 International Conference on Internet-of-Things Design and Implementation, pp. 133–144, May 2021, doi: 10.1145/3450268.3453520.

[12] E. Tang, B. Yang, and X. Song, "MetaOOD: Automatic Selection of OOD Detection Models," Transactions on Machine Learning Research, vol. 2025, 2025, Accessed: Sep. 28, 2025. [Online]. Available: https://github.com/yqin43/metaood.

[13] Z. Li, H. Li, and L. Meng, "Model Compression for Deep Neural Networks: A Survey," Computers 2023, Vol. 12, Page 60, vol. 12, no. 3, p. 60, Mar. 2023, doi: 10.3390/COMPUTERS12030060.

[14] Y. Xue, "Comparison Of Conventional and Lightweight Convolutional Neural Networks for Image Classification," Highlights in Science, Engineering and Technology, vol. 38, pp. 988–993, Mar. 2023, doi: 10.54097/HSET.V38I.5986.

[15] H. Lee, S. Lee, S. Chong, and S. J. Hwang, "HELP: Hardware-Adaptive Efficient Latency Prediction for NAS via Meta-Learning," 2021, Neural information processing systems foundation. Accessed: Sep. 28, 2025. [Online]. Available: https://pure.kaist.ac.kr/en/publications/help-hardware-adaptive-efficient-latency-prediction-for-nas-via-m.

[16] R. Das and T. Luo, "LightESD: Fully-Automated and Lightweight Anomaly Detection Framework for Edge Computing," 2023 IEEE International Conference on Edge Computing and Communications (EDGE), pp. 150–158, Jul. 2023, doi: 10.1109/EDGE60047.2023.00032.

[17] M. J. C. S. Reis and C. Serôdio, "Edge AI for Real-Time Anomaly Detection in Smart Homes," Future Internet 2025, Vol. 17, Page 179, vol. 17, no. 4, p. 179, Apr. 2025, doi: 10.3390/FI17040179.

[18] N. Rashid, R. Mehmood, F. Alqurashi, S. Alqahtany, and J. M. Corchado, "ASAD: A Meta Learning-Based Auto-Selective Approach and Tool for Anomaly Detection," IEEE Access, 2024, doi: 10.1109/ACCESS.2024.3524908.

[19] A. Liaw and M. Wiener, "Classification and Regression by randomForest," vol. 2, no. 3, 2002, Accessed: Oct. 04, 2025. [Online]. Available: http://www.stat.berkeley.edu/.

[20] "Amazon EC2 T2 Instances – Amazon Web Services (AWS)." Accessed: Oct. 06, 2025. [Online]. Available: https://aws.amazon.com/ec2/instance-types/t2/.

[21] "Now Available – EC2 Instances (G4) with NVIDIA T4 Tensor Core GPUs | AWS News Blog." Accessed: Oct. 06, 2025. [Online]. Available: https://aws.amazon.com/blogs/aws/now-available-ec2-instances-g4-with-nvidia-t4-tensor-core-gpus/?utm_source=chatgpt.com.

[22] "Computers - Product Information Portal - Raspberry Pi." Accessed: Oct. 06, 2025. [Online]. Available: https://pip.raspberrypi.com/categories/505-computers.

[23] "Orange Pi - Orangepi." Accessed: Oct. 06, 2025. [Online]. Available: http://www.orangepi.org/html/hardWare/computerAndMicrocontrollers/details/Orange-Pi-Zero-2W.html.

A Bio-Inspired Behavior-Based Hybrid Framework for Ransomware Detection

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***Abstract*—Ransomware remains a critical and evolving cybersecurity threat, increasingly rendering traditional signature-based detection techniques ineffective. While modern machine learning models achieve high detection accuracy, they often operate as opaque "black boxes", introducing a significant explainability gap that undermines analyst trust. In addition, behavior-based anomaly detection systems frequently suffer from high false-positive rates, limiting their operational viability. To address these challenges, this study adopts a Design Science Research Methodology to develop a novel, interpretable, multi-stage ransomware detection framework. The proposed architecture integrates three complementary components: a bio-inspired Negative Selection Algorithm from Artificial Immune Systems to filter benign behavioral patterns, a first-order Markov chain model to capture probabilistic deviations in execution sequences, and a Random Forest ensemble classifier to synthesize these signals for final decision-making. The framework is evaluated using a dual-pipeline experimental design on real-world ransomware and benign software samples, enabling controlled comparison between probabilistic and pattern-based behavioral modeling. Experimental results demonstrate that the proposed approach achieves high detection performance while maintaining a low false-positive rate and providing interpretable behavioral evidence. Overall, the framework offers a principled balance between detection effectiveness and interpretability, addressing key limitations of existing ransomware detection systems.**

Keywords*—Ransomware; Artificial Immune Systems (AIS); anomaly detection; Negative Selection Algorithm; Markov chain; Random Forest; hybrid framework

I. Introduction

Computers and the Internet have revolutionized many aspects of daily life, offering unprecedented opportunities for communication, information exchange, and economic growth [1]. This digital transformation, accelerated by rapid advancements in information technology, has significantly improved global living standards [2]. However, the rise of the digital age has also presented new challenges in the form of cyber threats [3], [4].

Ransomware has rapidly transformed into a significant global cybersecurity challenge by employing advanced cryptographic techniques, polymorphic code mutations, and anti-analysis mechanisms to avoid detection [5], [6], [7]. The increasing sophistication of these attacks renders the traditional signature-based detection systems ineffective. These static pattern-matching approaches are fundamentally unable to combat the dynamic and evasive nature of 0-day and polymorphic ransomware variants [8], [9], [10].

High-profile incidents, such as the 2021 Colonial Pipeline attack, demonstrate the devastating impact of ransomware on critical infrastructures. This incident highlighted severe vulnerabilities and led to a notable fuel shortage along the US East Coast [11]. This threat is further exacerbated by the "Ransomware-as-a-Service" (RaaS) model, which enables cybercriminals with minimal technical expertise to launch large-scale, sophisticated attacks [12].

In response to the failure of static methods, the research community has increasingly focused on dynamic and behavior-based malware detection using machine learning (ML). behavior-based approaches inspired by biological systems, particularly the Human Immune System, have demonstrated promise in detecting previously unseen malware variants through adaptive and anomaly-driven mechanisms [13]. However, despite their effectiveness, existing immune-inspired and hybrid detection architectures often remain limited in their ability to robustly model complex runtime behavior and to adapt to the evolving tactics of modern ransomware [14]. This motivates the need for a more formalized and empirically validated behavior-centric detection framework.

Our systematic review of the domain from 2015 to 2025 reveals three critical gaps that impede the deployment of robust real-world defenses:

- The Explainability Gap (G1): Many high- performing models, particularly deep learning architectures, operate as "black boxes" [15]. Security analysts cannot trust or act on alerts that they do not understand, making interpretability a critical, unsolved requirement [16].
- The False Positive Gap (G2): Behavior-based anomaly detection is notoriously "noisy". Legitimate software, such as file compressors and backup tools, often performs intensive I/O operations that mimic ransomware [17]. This leads to a high false positive rate (FPR), and the resulting alert fatigue renders many systems unusable in operational contexts [18].
- The AIS-ML Gap (G3): While Artificial Immune Systems (AIS), particularly the Negative Selection Algorithm (NSA), are theoretically ideal for the "self" vs. "non-self" discrimination problem, their application in ransomware detection remains limited and non-

standardized [19]. The value of AIS-ML hybrids is a significant and under-explored research area.

To address these three gaps, this study proposes a novel, interpretable, AIS-hybrid framework for ransomware detection. Following a rigorous Design Science Research Methodology (DSRM) [20], we present the complete design artefact of a system specifically engineered to solve these problems.

Our contributions are:

- Novel Hybrid Detection Architecture: We propose a bio-inspired, behavior-based ransomware detection framework that integrates an Artificial Immune System (Negative Selection Algorithm), probabilistic Markov chain behavioral profiling, and Random Forest classification in a unified, multi-stage architecture. Unlike prior studies that employ these techniques in isolation or simple pairwise combinations, this work formalizes their complementary integration into a single explainable detection pipeline.
- AIS-Based Behavioral Noise Reduction: We introduce an NSA-driven behavioral filtering mechanism that removes benign "self" API-call patterns prior to classification, substantially reducing behavioral noise and mitigating false positives commonly observed in anomaly-based ransomware detectors.
- Probabilistic Behavioral Explainability: We incorporate a first-order Markov chain model trained on benign execution traces to quantify the likelihood of observed API-call transitions. This probabilistic profiling enables interpretable detection decisions by highlighting statistically rare behavioral sequences rather than opaque feature activations.
- Controlled Dual-Pipeline Evaluation: We design and evaluate two detection pipelines under identical experimental conditions, NSA–Markov–RF and NSA–n-gram–RF, allowing a controlled assessment of the contribution of probabilistic behavioral modeling to detection performance and interpretability.

The remainder of this study is organized as follows: Section II reviews related work and identifies key research gaps. Section III presents the theoretical framework underlying the proposed hybrid detection architecture. Section IV describes the proposed methodology, including evaluation metrics and comparative pipeline design. Section V reports the experimental evaluation, covering dataset construction, experimental setup, detection results, and analysis of the Markov behavioral modeling contribution. Section VI discusses the theoretical and practical implications of the findings, including threat modeling, computational feasibility, and future research directions. Finally, Section VII concludes the study.

II. Literature Review

A. Ransomware Detection Techniques

Ransomware detection methods rely heavily on signature-based and heuristic techniques [21], [22]. Signature matching fails against obfuscated or polymorphic variants [23], [24]. Heuristic approaches improve this by looking for suspect behaviors, such as mass file encryption [25], but they suffer from high false positive rates (FPR), as benign software, that is, backup tools that can exhibit similar behaviors [26], [27].

To combat these novel threats, researchers have turned to machine learning for behavioral data [5]. Dynamic analysis frameworks such as Cuckoo/CAPE sandboxes were used to extract runtime API call sequences as features for ML models [28], [29]. However, these ML-driven methods introduce their own critical challenges, namely: 1) Limited Explainability (G1), as many models are "black boxes", and 2) Persistent False Positives (G2), as benign apps still mimic ransomware behavior.

B. Machine Learning and Ensembles

A range of ML algorithms has been successfully applied to ransomware detection. Tree-based Decision methods (J48, C5.0) and ensemble methods (Random Forest, gradient boosting) have shown high accuracy in classifying ransomware vs. good-ware binaries [30], [31]. Moreover, [32] used a Random Forest classifier on extracted file features and achieved ~97.7% accuracy in distinguishing ransomware, although with a somewhat elevated false-positive rate in practical scenarioslink.springer.com. Random Forest (RF), in particular, has become popular owing to its strong performance and resistance to overfitting. It combines multiple decision trees to vote on the class, which tends to smooth out noise and outlier effects.

Khammas's results illustrate both the promise and pitfall of pure ML: high accuracy is attainable, but the cost of false alarms can be significant if the model latches onto features that overlap with legitimate softwarelink.springer.com. Recent studies have emphasized explainable machine learning. For instance, techniques like SHAP (Shapley Additive Explanations (SHAPs) have been employed to interpret feature importance in ransomware classifiersarxiv.orgarxiv.org, and uncertainty estimation has been added to random forests to identify low confidence. These trends highlight the growing recognition that detection models must be not only accurate but also transparent and reliable for analysts. This limitation of pure ML-only models was exemplified in the work of [21]. In their initial research, they proposed a lightweight 10-feature Random Forest model. However, to improve the performance in their follow-up work, they were forced to hybridize this model with a static, signature-based hash filter [33]. This progression demonstrates the practical limitations of the pure ML approach (G2) and highlights the need for a more dynamic, adaptive hybrid. While [33] resorted to a static filter, our framework proposes a novel hybrid with a true adaptive technique (AIS) to solve this exact problem, directly addressing the G3 gap.

C. Markov Chain Models in Malware Behavior

Markov models provide a stochastic way to model sequences of events, which is highly relevant for ransomware behavior (often characterized by sequences of file accesses or API calls). Researchers have applied both Markov chains [34] and Hidden Markov Models (HMMs) [35] for malware and ransomware analyses. An early example was the use of Markov chains to model system call sequences for anomaly detection in host intrusion detection systems. In ransomware-specific research, [36] proposed a two-stage detection approach, first modelling API call sequences with Markov chains, and then applying a

Random Forest (RF) classifier. Their system trained separate models for benign and ransomware behaviors to capture the malicious transition probabilities. Despite achieving 97.3% accuracy, their hybrid model still suffered from a non-negligible 4.8% false-positive rate (FPR). This result confirms that while Markov models can encapsulate sequential behavior, a high FPR remains a key drawback. Crucially, the authors suggested that "additional anomaly detection" could reduce these false alarms [37].

This insight provides a direct motivation for our framework, which integrates an AIS-based anomaly detector, the NSA, as the precise component required to filter out benign patterns and solve this identified gap. Although HMM-based approaches can classify ransomware families, they often require substantial training data and are computationally heavy. This is precisely why our framework leverages a first-order Markov Chain, which provides the significant advantage of being lightweight and interpretable. A simple transition probability matrix allows a security analyst to examine which specific API call transitions are deemed 'rare' or suspicious, directly addressing the G1 (Explainability) gap.

D. Artificial Immune Systems (AIS) and Negative Selection

Artificial Immune System (AIS) algorithms are inspired by the human immune system's ability to distinguish "self" (normal body cells) from "non-self" (foreign pathogens). In AIS, the negative-selection algorithm (NSA) is one of the most prominent techniques for anomaly detection. Originally introduced by [38], [39], the NSA generates a set of detectors that do not match any known "self" patterns. During detection, any pattern that failed to match the self-set was flagged as an anomaly. NSA has been applied to cybersecurity to detect novel threats, with some work combining it with positive selection to improve the detection of unknown malware [40].

In the context of ransomware, AIS has been shown to be effective. For example, [41] developed a V-detector AIS model for ransomware that learns to divide sequence space. Moreover, [42] proposed an improved double-layer NSA that achieved a higher coverage of non-self-space and improved detection rates. The success of these studies demonstrated that bio-inspired methods can enhance ransomware anomaly detection. However, AIS methods alone typically provide only binary anomaly judgments. For example, the NSA can identify a pattern as "suspicious" but cannot classify why or if it is specifically ransomware. This limitation is precisely why the hybrid approach is very powerful. By combining AIS with machine learning, AIS can act as an upstream filter or feature generator for a more robust ML classifier.

To explicitly position the proposed framework with respect to existing ransomware detection approaches, Table I presents a conceptual comparison highlighting key architectural and design differences.

TABLE I. CONCEPTUAL COMPARISON OF THE PROPOSED FRAMEWORK WITH REPRESENTATIVE RANSOMWARE DETECTION APPROACHES

Study	Behavior	AIS/ NSA	Markov	ML	Explainable	FB
[29]	Partial	✗	✗	RF	✗	Static hash filtering
[32]	✓	✗	✓	RF	Limited	✗
[37]	✓	✓	✗	✗	Limited	Partial
[38]	✓	✓	✗	✗	✗	Partial
This work	✓	✓	✓	✓	✓	✓

III. THEORETICAL FRAMEWORK

A. Overview

The proposed framework builds upon earlier immune-inspired malware detection architectures that employed a multi-stage design and Negative Selection–based anomaly filtering [13]. While prior work established the feasibility of immune-system-inspired detection, it did not explicitly investigate fine-grained sequential behavioural modelling or adaptive feature representations for ransomware detection. This study extends those ideas by introducing a hybrid framework that integrates NSA filtering, sequential modelling, and machine-learning-based classification, supported by rigorous experimental evaluation.

The proposed ransomware detection framework follows a multilayered architecture inspired by immune system principles and probabilistic modelling.

At a high level, it can be conceptualized as a dual-stage pipeline: an anomaly detection stage that flags potentially malicious behavior and a classification stage that confirms and labels the ransomware. These stages correspond to the Negative Selection Algorithm and the Random Forest classifier, respectively, with a Markov Chain model bridging them by providing probabilistic features of the behavior. Fig. 1 (conceptual diagram) illustrates how raw execution traces flow through the layers of the system from data acquisition to the final decision. The architecture is modular, meaning that each component has a distinct role and a well-defined input-output interface, which aids both in conceptual clarity and in actual implementation.

B. Data and Feature Representation

We assume as input the dynamic behavior traces of programs, specifically focusing on the API call sequences observed during program execution. This choice is guided by extensive evidence that API call patterns are highly indicative of ransomware behavior. Ransomware typically invokes cryptographic APIs, file system calls, etc. [43], [44]. Let an execution trace be represented as a sequence of API call events: $S = [s_1, s_1, \ldots, s_n]$, s_i is an API function name or a token representing a specific action. In our framework, we derive two parallel representations from this sequence: 1) a set of binary features or anomaly markers from the NSA indicating whether certain anomalous patterns were detected and 2) a set of

probabilistic features from the Markov chain model quantifying how likely each observed transition is under a normal profile. These features were then concatenated to form a composite feature vector for classification.

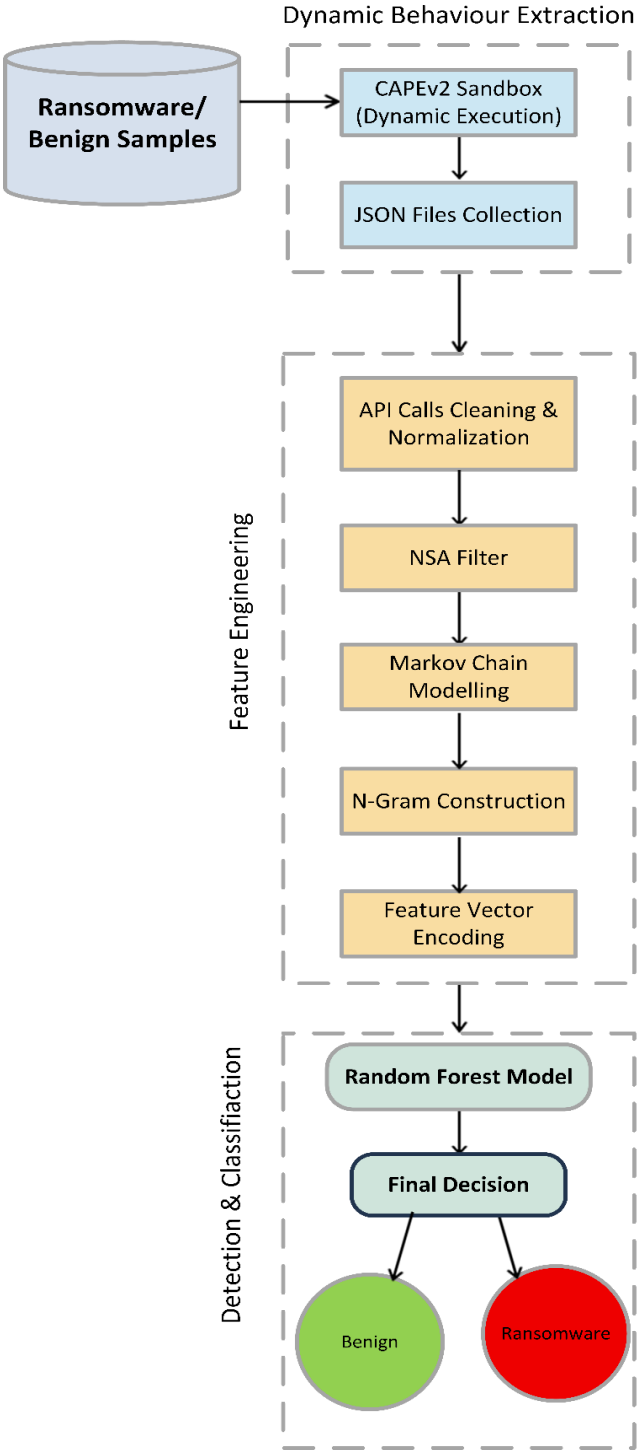


Fig. 1. The proposed NSA-Markov-RF theoretical framework (Pipeline 1).

C. Negative Selection Algorithm (NSA) Component

The NSA is responsible for learning the profile of normal (benign) API call sequences and generating detectors for any sequence patterns that deviate from this norm. Formally, we define a self-set $\mathcal{S}$ consisting of abstractions of benign API sequences. Each element of $\mathcal{S}$ could be, for example, an n-gram of API calls or some fixed-length substring of normal sequences, encoded as a string or binary vector. The NSA then creates a collection of detectors $\mathcal{D} = \{d_1, d_2, \ldots, d_m\}$ such that none of the detectors matches any element of $\mathcal{S}$ within a certain matching rule or threshold. A common approach is to use r-contiguous bit matching for the binary-encoded strings [42]. In our context, we might encode API calls or their hashed values in binary format and generate detectors that do not occur in any benign trace up to a certain Hamming distance. During detection, for a given sequence S, the NSA scans for any detector $d \in \mathcal{D}$ that is a substring of S or matches some features of S. If any such detector is found, it signals the presence of a non-self-pattern, that is, a potential anomaly.

Mathematically, let $f: \text{Sequence} \rightarrow \{0,1\}^m$ be a function that maps an input sequence to a binary vector of detector activations, where the k-th component $f_k(S) = 1$ if and only if detector d_k matches the sequence S. The output of the NSA stage can then be considered an anomaly feature vector $A = f(S)$. If all components of A are 0, the sequence was entirely self-like (no anomalies detected); if one or more components are 1, those indicate specific detectors (specific patterns) that were triggered. We emphasize that NSA in our framework serves as a feature generator and filter, rather than a final decision maker: the presence of an anomaly pattern raises suspicion but does not by itself convict the program as ransomware. This helps reduce false positives, as benign outliers might occasionally trigger detectors but will be further scrutinized in later stages.

D. Markov Chain Model

In parallel with the NSA analysis, the framework uses a First-Order Markov Chain to model the likelihood of the observed sequence of API calls. A first-order Markov chain assumes that the probability of each API call depends only on the immediately preceding call. We derive a Transition Probability Matrix (TPM) P of size $N \times N$, where N is the number of unique API calls (states). Each entry $P_{ij} = \Pr(s_{t+1} = j \mid s_t = i)$ represents the probability of transitioning from API call i to API call j in a benign execution trace. We estimate these probabilities from a training set of benign sequences by frequency counting (i.e., maximum likelihood estimation for the Markov chain). Let $C(i,j)$ denote the count of transitions from state i to j in all benign traces. Then the estimated transition probability is:

$$P_{ij} = \frac{C(i,j)}{\sum_k C(i,k)} \quad (1)$$

for each state i that appears in the training data (the denominator is the total count of all transitions out of state i). By construction, for each state i, the probabilities sum to 1 ($\sum_j P_{ij} = 1$), making each row of P a distribution over next state. Given the matrix P, the sequence $S = [s_1, \ldots, s_n]$ from a program run can be assigned a likelihood score under the benign-behavior model:

$$\Pr(S \mid \text{benign-model}) = \prod_{t=1}^{n-1} P_{s_t s_{t+1}}, \quad (2)$$

i.e., the product of probabilities for each consecutive transition in the sequence. If this probability is very low or equivalently the log-likelihood sum is very low, it indicates that the sequence contains transitions that were rarely or never observed in benign runs – a strong sign of anomalous (possibly malicious behavior. In practice, rather than using a single product of probabilities, which can underflow and also over-emphasize long sequences, we extract features from the Markov model, such as minimum transition probability observed in the sequence, average transition probability, and number of transitions below a certain low-probability threshold. Each of these features helps quantify how "normal" or "abnormal" the control flow of the program is, according to the benign profile. For example, a ransomware might introduce an API call sequence that jumps between unrelated system functions in a way a normal program never would, yielding a very low P_{ij} for those transitions. By including such metrics, we capture sequential anomalies different from those the NSA detectors find, where NSA might catch specific known-bad patterns, whereas Markov probabilities catch statistically rare patterns.

It is worth noting that one could also build a Markov chain for ransomware behavior, specifically as [36] did, training separate models for ransomware and benign. In our theoretical design, we focus on modeling benign behavior (self) through the Markov chain, analogous to how NSA models self; this keeps the approach biased towards anomaly detection. However, extending the framework to include a second Markov model for ransomware is feasible if sufficient ransomware data is available; it would essentially provide additional features or a parallel likelihood ratio between "malicious" and "benign" models.

E. Random Forest Classification

Random Forest Classification: The final stage of the pipeline is a Random Forest classifier that ingests the combined feature vector and outputs a classification: ransomware or benign. The feature vector X for a given program execution includes features from both NSA and the Markov model and potentially other metadata or features derived from dynamic analysis. For example, X might include: the count of NSA detectors triggered and which specific ones, though high-dimensional, could be represented via one-hot encoding or a count of anomalies, the minimum/average transition probability from the Markov analysis, the length of the sequence, etc. Because NSA and Markov modeling are the core novel features, the dimensionality of this feature space is relatively moderate and interpretable: NSA contributes m binary features, if we have m detectors, and Markov contributes a fixed number of statistical features. This structured feature space is well-suited to a Random Forest classifier, which can handle mixed binary/continuous inputs and is robust to irrelevant features.

Random Forest (RF) is an ensemble of decision trees where each tree is trained on a bootstrapped sample of the data and typically uses a random subset of features at each split. The ensemble's prediction is the majority vote of the trees for classification or the average probability. We denote the RF classifier as $h(X)$, which outputs a probability score $p = h(X)$ representing the confidence that the sample is ransomware (malicious). The RF essentially learns decision rules that combine the presence/absence of certain anomaly patterns and the values of Markov anomaly scores to distinguish ransomware from legitimate software. An example rule a tree might learn: "IF detector_5 is triggered (an anomaly in file encryption API usage) AND the minimum API transition probability < 0.001 (very novel sequence) THEN classify as ransomware." In training, the RF will naturally give more weight to features that yield better splits between ransomware and benign, which provides a form of built-in feature selection. Empirically, Random Forest has been shown to perform well on malware classification tasks, sometimes outperforming deep learning on structured behavioral features, and offers faster training.

To make a binary decision from the RF's output probability, we define a decision threshold τ. The classifier assigns the label "Ransomware" if $p \geq \tau$, and "Benign" otherwise. A common default is $\tau = 0.5$ for balanced errors, but in security, we might choose a lower threshold to favor catching malware (at the expense of some false positives). In a theoretical analysis, one can discuss optimizing τ based on metrics like the F-score. For instance, one could select τ that maximizes the F_2-score (which weights recall higher) to ensure ransomware is caught early. The threshold optimization is part of the Decision Evaluation Layer of the framework.

F. Integration of Components

The theoretical robustness of this framework is rooted in the synergistic integration of its three components. This design creates a multi-dimensional feature space where each component addresses a distinct aspect of anomaly detection, a strategy that aligns with modern calls for layered, hybrid detection frameworks [45], [46]. The Negative Selection Algorithm (NSA) functions as an "immune filter," identifying qualitative anomalies by matching patterns that are definitionally "non-self" and should not exist in benign operation. In parallel, the Markov model acts as a statistical profiler, identifying quantitative anomalies by flagging behavioral sequences that, while not strictly impossible, are highly improbable under the learned model of benign behavior [47]. For instance, the RF can learn to disregard a minor qualitative anomaly flagged by the NSA as a potential false positive if the Markov model assigns a high probability to the sequence, indicating an overall normal behavioral flow. Conversely, a sample that triggers multiple NSA detectors and exhibits a cascade of low-probability transitions presents a feature vector that the RF can decisively classify as malicious.

This integration yields a significant benefit: a high degree of explainability, which is a critical requirement for building trust in automated detection systems [48]. Unlike monolithic "black box" models, which are a noted challenge in security-critical environments [49], a classification event can be deconstructed into its constituent, human-readable parts. The system can provide evidence for why a sample was flagged, detailing both the qualitative detectors triggered by anomalous patterns and the quantitative unlikelihood of its behavioral flow.

This evidence renders the model's internal logic transparent and its outputs auditable [50]. Conceptually, this hybrid model fuses biological anomaly detection with probabilistic behavioral profiling to produce a classification that is both resilient and interpretable. Its resilience stems from this multi-modal design;

the framework does not rely on a single indicator of maliciousness. An adversary must therefore simultaneously evade discrete, pattern-based NSA detectors and mimic the statistical profile of benign behavior, presenting a significantly more complex evasion challenge [34].

Finally, the framework is both modular and extensible. One could incorporate additional features, such as the frequency of file modifications or network connections opened, alongside the API sequence features. While our design uses Random Forest for its proven balance of performance and interpretability, other classifiers like SVM or XGBoost could also be employed.

The core contribution of this study, however, is the integrated NSA-Markov-RF architecture (termed Pipeline 1). To rigorously validate the novel contributions of this specific hybrid design, our proposed methodology (detailed in Section 5) is based on a dual-pipeline comparison. This test will benchmark our probabilistic framework (Pipeline 1) against an alternative hybrid, NSA-N-gram-RF (termed Pipeline 2), to empirically quantify the specific improvements of using a Markov model.

In summary, the proposed theoretical framework is a synergistic integration of three well-established algorithmic pillars: the Negative Selection Algorithm from AIS theory, first-order Markov chains from probability theory, and the Random Forest from ensemble learning. While prior work has validated each component individually for security applications, our primary contribution is the formal design of this cohesive, multi-modal system. This study has articulated this design, demonstrating how the unique, emergent benefits of resilience and interpretability arise from this specific combination.

IV. Proposed Methodology

This study adopts the Design Science Research Methodology (DSRM) framework [20], which is especially well-suited for developing and evaluating novel cybersecurity artefacts. DSRM ensures that artefact creation is grounded in both practical relevance and theoretical rigor. Our ransomware detection framework is constructed and validated in accordance with the following DSRM stages:

- Problem Identification and Motivation: We identified key limitations in current detection approaches, namely, a lack of interpretability (G1) and high false positives (G2) and justified the need for a hybrid, behaviorally aware system (G3).
- Design and Development: We designed a multilayered detection artefact combining a Negative Selection Algorithm (NSA), a probabilistic Markov model, and a Random Forest classifier (Section IV). This artefact is instantiated in two comparative pipelines for controlled evaluation.
- Demonstration: The detection system is implemented and executed on dynamic API trace data collected from both benign applications and ransomware samples.
- Evaluation: We empirically evaluate system performance using standard classification metrics, emphasizing Recall and False Positive Rate (FPR), and using F2-score optimization to reflect real-world detection priorities.
- Communication: This study serves as the primary vehicle for communicating the artefact design, theoretical justification, and validation methodology to the research community.

A. Evaluation Metrics

Model performance will be assessed using a comprehensive suite of standard evaluation metrics: Accuracy, Precision, Recall (Detection Rate), F2-Score, and False Positive Rate (FPR). Emphasis is placed on minimizing FPR. Furthermore, due to the asymmetric cost of errors in ransomware detection were failing to detect an active infection (False Negative) is more damaging than triggering a benign false alarm. This study prioritizes Recall and adopts the F2-Score as the principal optimization target. The F2-Score weights Recall twice as heavily as Precision, thereby aligning metric selection with the risk model inherent to the domain.

To determine the optimal operating point of the classifier, the decision threshold τ will be tuned using a grid search across the interval $[0.1, 0.9]$, with the optimal τ^* defined as the threshold maximizing the F2-Score on a validation subset.

B. Baseline Models and Comparative Hypothesis

To assess the efficacy of the proposed framework, we define a structured comparative evaluation across two distinct pipeline configurations. Both configurations share a common NSA pre-filtering stage and a Random Forest classifier. This strategy isolates the effect of the Markov chain behavioral profiler by comparing it directly with a static, pattern-based encoding scheme (adaptive n-gram).

1) Pipeline 1: NSA - Markov - Random Forest (Full Hybrid Architecture)

This is the proposed end-to-end detection framework, comprising:

- Negative Selection Algorithm (NSA): Eliminates benign "self" behavior patterns from the dynamic trace to generate an anomaly-prone residual signal.
- First-Order Markov Chain Profiler: Models the transition probabilities of the remaining "non-self" API call sequences to quantify behavioral abnormality.
- Random Forest Classifier (RF): Predicts the likelihood of ransomware execution using a feature set that includes Markov likelihood scores and statistical API call metrics.

2) Pipeline 2: NSA-N-gram-Random Forest (Baseline Hybrid)

This configuration retains the NSA filtering stage but replaces the probabilistic Markov model with a flexible n-gram feature extractor:

- Negative Selection Algorithm (NSA): Performs initial filtering to exclude benign behaviors.

- Adaptive N-gram Encoding: Extracts variable-length API call n-gram patterns from the NSA-filtered trace to capture structural nuances in the remaining signal.
- Random Forest Classifier (RF): Classifies the resulting feature vector to predict ransomware presence.

V. Experimental Evaluation

A. Dataset and Sample Collection

To evaluate the proposed ransomware detection framework, a balanced dataset consisting of ransomware and benign software samples was constructed and analyzed in a controlled sandbox environment. The dataset was designed to capture a diverse range of ransomware behaviors while reflecting realistic benign application activity. Ransomware samples were collected from a public malware repository [51]a well-established and actively maintained malware repository widely used in academic research and threat intelligence. Samples span the period from 2015 to June 2023, capturing nearly a decade of ransomware evolution. A structured keyword-based query using the *tag:ransom* was employed to identify binaries explicitly labeled as ransomware. Metadata such as SHA-256 hash, file type, family signature, and classification tags were used for verification and filtering.

To focus specifically on Windows crypto-ransomware, the following selection criteria were applied:

- Only PE32 (exe) Windows executables were retained.
- Locker-type ransomware variants that primarily restrict access through screen locking without performing file encryption were excluded.
- Samples were required to contain the "ransom" or "ransomware" classification tags.

Using this process, 1,200 ransomware samples were initially shortlisted. From this pool, 100 representative samples were selected based on family diversity, file quality, and temporal distribution. These samples span 40 distinct ransomware families, including LockBit, STOP, GandCrab, Dharma, REvil, Chaos, and Babuk, ensuring broad behavioral coverage across both early-generation and modern ransomware variants. Moreover, benign samples consisted of 100 legitimate Windows applications drawn from diverse software categories, including productivity tools, security software, media players, development tools, compression utilities, browsers, and document management software. Examples include VLC, WinRAR, Docker Desktop, Bitdefender, Firefox, and Blender. These applications were selected to represent realistic user activity and to expose the detection system to benign behaviors that may superficially resemble ransomware operations, thereby reducing false positives.

All samples, both malicious and benign, were executed in the same sandbox environment using CAPEv2 (Config And Payload Extraction, version 2) to ensure consistency in behavioral logging. During execution, API call sequences and runtime behaviors were captured and used as input for feature extraction and classification.

B. Dataset Curation and Labelling Considerations

Ransomware family labelling presents inherent challenges due to inconsistent naming conventions across antivirus (AV) vendors. To ensure reliability during sample selection, only binaries classified as ransomware by at least ten distinct AV engines were initially retained. However, because family-level labels often vary across vendors, family attribution was refined using post-execution analysis from the CAPEv2 sandbox, which integrates heuristic detection, YARA-based signatures, and static indicators. These labels were manually cross-validated against outputs from high-confidence AV engines, including Kaspersky, Bitdefender, and ESET. In cases of disagreement, a consistency-based majority approach was used to finalize family assignments.

A further challenge involved distinguishing active ransomware samples from dead or partially executing binaries. Some samples failed to execute payloads or produced empty behavioral reports due to packing, sandbox incompatibilities, or execution failures. To mitigate this, samples were screened for successful execution using multiple indicators, including execution duration, API call density, presence of cryptographic API usage, ransom-note artifacts, and CAPEv2 heuristic scores. Additionally, to address execution failures caused by packing or wrapper layers, samples were subjected to a pre-analysis inspection phase. Binaries identified as packed through heuristic analysis were manually or automatically unpacked prior to sandbox execution, ensuring that the core ransomware payload was behaviorally observable during dynamic analysis. Samples exhibiting no meaningful behavioral activity were excluded.

Although an initial pool of approximately 1,200 ransomware samples was identified, only 100 behaviorally expressive samples were retained for analysis. This curation process ensured that the final dataset prioritized behavioral validity, family diversity, and execution reliability, which is essential for behavior-based ransomware detection models.

C. Experimental Setup and Pipeline Configuration

Based on the evaluation design defined in Section IV, two pipeline configurations were implemented and evaluated under identical experimental conditions. Both pipelines share the same dataset, sandbox execution environment, feature extraction process, and Random Forest classifier configuration. The only difference lies in the behavioral modeling stage, allowing a controlled assessment of the impact of probabilistic Markov modeling.

D. Detection Performance Results

Table II summarizes the detection performance of the two proposed pipelines.

The results demonstrate that both pipelines achieve strong detection performance. Pipeline 2 attains perfect classification accuracy for higher-order n-gram configurations under the evaluated dataset, confirming the effectiveness of NSA-based filtering combined with supervised learning. Pipeline 1 achieves comparably high accuracy and recall while maintaining a consistently low false-positive rate across evaluation folds.

TABLE II. PERFORMANCE COMPARISON OF PROPOSED DETECTION PIPELINES

Pipeline	Accuracy	Recall (TPR)	False Positive Rate (FPR)	Explainability
NSA–Markov–RF (Pipeline 1)	98.5%	≈99.3%	< 1%	High (NSA detectors + probabilistic transitions)
NSA–N-gram–RF (Pipeline 2)	100%	100%	0%	Moderate (feature importance via RF)

E. Contribution of Markov Behavioral Modeling

While both pipelines demonstrate high classification accuracy, Pipeline 1 incorporates a probabilistic behavioral modeling layer that captures sequential API-call likelihoods rather than relying solely on structural pattern frequency. Markov-derived features quantify how likely observed API-call transitions are under a benign behavioral model, enabling the detection system to distinguish between rare but legitimate activity and behavior that is statistically inconsistent with normal execution.

This probabilistic profiling contributes to stable detection performance across diverse behavioral patterns and provides interpretable evidence in the form of low-probability transition sequences. As a result, Pipeline 1 offers enhanced behavioral transparency without sacrificing detection effectiveness.

VI. CONTRIBUTIONS AND DISCUSSION

The proposed NSA–Markov–RF ransomware detection framework makes several important contributions to the field of cybersecurity and malware detection, particularly in the context of behavior-based defenses.

- Novel Hybrid Architecture (Solves G3): We introduce a novel hybrid detection architecture that integrates an Artificial Immune System (AIS) anomaly filter, a probabilistic Markov chain model, and an ensemble machine learning classifier (Random Forest) in one unified framework. This addresses the G3 (AIS-ML) gap by proposing a formal, synergistic integration of these components, which prior works have typically been used only in isolation or in simpler pairwise combinations. Moreover, each component is grounded in a well-established theory. By formally describing the framework and providing equations for key processes such as detector generation and transition probability computation, we ensure the design is transparent and reproducible.
- Improved Explainability (Solves G1): A key contribution is improved explainability, directly addressing the G1 (Explainability) gap. Because the model's decision is based on human-comprehensible components such as "detector X matched" or "transition Y→Z had a low probability", analysts can interpret why an alert was raised, building trust in the system [52].
- Robust and Adaptive Classification: The use of an ensemble classifier (RF) confers robustness through bagging and vote aggregation [32]. Furthermore, the framework is modular and adaptive.
- Addressing False Positives (Solves G2): Our framework explicitly tackles the G2 (False Positive) gap. By using the NSA to proactively filter "self" behavior, the classifier is provided with a cleaner, anomaly-focused feature space. This provides a direct answer to the high FPR noted in prior work, such as the 4.8% FPR in the Markov-RF model by [36].

In sum, our theoretical framework not only proposes a specific solution but also advances discourse on how to design ransomware detection systems that are comprehensive, transparent, and resilient.

A. Discussion of the Theoretical Implications

The framework offers several theoretical advantages and implications that contextualize its value.

- Comparative Analysis: The proposed hybrid model provides a layered, defense-in-depth. More specifically, our validation methodology (Section V) is designed to compare Pipeline 1 (NSA-Markov-RF) against Pipeline 2 (NSA-Adaptive N-gram-RF). While both pipelines benefit from the NSA's 'non-self' filtering, the Markov component (P1) provides a probabilistic, behavioral model, whereas the n-gram component (P2) provides a static, pattern-matching one. This is a crucial distinction: an n-gram model (P2) can be evaded if an adversary uses known malicious patterns in a new or rare order. The Markov model (P1), however, is designed to detect precisely this type of anomaly: a sequence of individually plausible API calls combined in a probabilistically rare way. This multi-faceted approach, blending different AI techniques, is in line with what recent surveys suggest for improving novel threat detection [53].
- Explainability and Analyst Trust: The interpretability of our framework means that in a real-world setting, it could generate not just an alert but also a diagnosis. For instance: "Alert: Suspected Ransomware. Reasoning: Detectors D5 and D7 triggered (unseen file encryption sequence), and sequence transition probability average = 0.002 (below normal threshold)." Such feedback is invaluable to an analyst triaging the alert and directly addresses a major criticism of AI in security, the lack of trust in opaque, "black box" models [54].
- Performance Considerations: A potential concern is computational overhead, especially at runtime. NSA detector generation was performed offline during training. During operation, although checking many detectors can be computationally demanding, the use of short, fixed-length behavioral patterns allows for efficient pattern matching. In practice, this ensures that the system is lightweight and suitable for real-time detection. Markov chain calculations are computationally trivial, and Random Forest classification is fast and parallelizable [55].

B. Limitations and Future Work

While promising, the theoretical framework has limitations that must be acknowledged:

- Dependency on Quality of Training Data: The NSA's effectiveness hinges on a comprehensive representation of "self." If benign training data are not comprehensive, the NSA may generate flawed detectors. This limitation is common to all behavior-based models that must learn a "normal" baseline [56].
- Evasion Tactics: Attackers can try to evade each component by mimicking normal API call transitions to fool the Markov model. However, our framework raises a bar for evasion: an adversary must evade both pattern-based detectors and the probabilistic sequence model simultaneously, which is a significantly more complex challenge [46].
- False Positive Handling: A persistent challenge for anomaly-based detection is the handling of false positives. By design, such systems will inevitably flag benign but unusual activities such as those performed by legitimate compression utilities that deviate from the established "self" profile. While the Random Forest classifier is trained to learn and distinguish these benign anomalies, a practical, operational deployment would almost certainly benefit from a supplemental whitelist of known-safe, signed applications. This measure would further reduce false positive noise and substantially improve security analyst trust in the system.

C. Threat Model and Evasion Considerations

The threat model assumes ransomware adversaries capable of employing code obfuscation, packing, and behavioral variation to evade signature-based and static detection mechanisms. Attackers may attempt to mimic benign API-call sequences or reorder known malicious operations to bypass pattern-based classifiers.

The proposed framework raises the bar for evasion by combining complementary detection mechanisms. NSA-based filtering targets previously unseen behavioral patterns, while the Markov chain profiler detects statistically improbable API-call transitions even when individual calls appear benign. To evade detection, an adversary must simultaneously suppress NSA detector activation and maintain transition probabilities consistent with benign execution profiles, which significantly constrains evasion strategies.

While advanced attackers may attempt to gradually adapt behavior to resemble benign profiles, such mimicry reduces operational efficiency and increases attack complexity. The framework, therefore, provides resilience against common behavioral evasion techniques without relying on static signatures.

D. Computational Feasibility and Runtime Considerations

The proposed framework is designed to be computationally feasible for practical deployment. NSA detector generation is performed offline during the training phase, eliminating runtime overhead associated with detector creation. During detection, NSA-based matching operates on short, fixed-length behavioral patterns, enabling efficient pattern comparison.

The Markov chain component incurs minimal computational cost, as transition probability lookup and aggregation are linear in the length of the observed API-call sequence. Random Forest classification is well-suited to real-time analysis due to its parallelizable structure and fast inference time.

Overall, the framework introduces limited runtime overhead beyond standard dynamic behavior analysis and is suitable for near real-time ransomware detection in sandboxed or endpoint monitoring environments.

E. Future Improvements

This theoretical work can be extended in several ways. One potential improvement is employing a higher-order Markov chain or a Hidden Markov Model (HMM) to capture long-term dependencies. The other is to incorporate Positive Selection (another AIS algorithm) in tandem with NSA to detect both known-malicious "antigen signatures" and unknown "non-self" anomalies, as proposed in other AIS-hybrid research [57]. Additionally, exploring Explainable AI (XAI) tools such as SHAP [58] on the Random Forest could precisely quantify the contribution of each feature to a decision, essentially auditing the model's knowledge.

F. Scientific and Practical Impact

Scientifically, our work bridges multiple research areas: bio-inspired security, probabilistic modelling, and machine learning. Practically, the enormous and growing financial and operational costs of ransomware incidents, which cost organizations an average of $4.75 million per breach (excluding the ransom), create a clear need for such tools[59]. Our framework's emphasis on adaptability and its focus on fundamental behaviors (which persist even as tactics evolve) make it a forward-looking approach. It provides a balanced trade-off between detection power and interpretability, building upon validated components from the literature to create a multilayered detection system.

VII. Conclusion

This study presented a bio-inspired, behavior-based hybrid framework for ransomware detection that integrates a Negative Selection Algorithm, probabilistic Markov chain behavioral modeling, and Random Forest classification. The framework addresses key limitations of existing ransomware detection approaches by combining anomaly filtering, probabilistic sequence analysis, and supervised learning within a transparent and modular architecture.

Experimental evaluation using real-world ransomware and benign software samples demonstrated that both evaluated pipelines achieve strong detection performance. While the NSA–N-gram–RF pipeline attained perfect classification accuracy under selected configurations, the NSA–Markov–RF pipeline provided enhanced behavioral interpretability through probabilistic transition modeling while maintaining a consistently low false-positive rate.

By enabling detection decisions to be explained in terms of anomalous behavioral patterns and statistically rare execution sequences, the proposed framework directly addresses the

explainability and false-positive challenges that limit the operational adoption of machine-learning-based ransomware detection systems. Future work will explore early-stage detection, adaptive learning under concept drift, and extension of the framework to additional malware categories.

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REFERENCES

[1] Y. O. Okoro, M. Oladeinde, O. J. Akindote, A. O. Adegbite, and T. O. Abrahams, "Digital communication and U.S. economic growth: A comprehensive exploration of technology's impact on economic advancement,"Computer Science and IT Research Journal, vol. 4, no. 3, pp. 351–367, Jan. 2024, doi: 10.51594/csitrj.v4i3.687.

[2] S. Kaggwa, D. I. Akinwolemiwa, S. O. Dawodu, P. U. Uwaoma, O. J. Akindote, and S. O. Eloghosa,, "Digital transformation and economic development: A review of emerging technologies' impact on national economies," World Journal of Advanced Research and Reviews, vol. 20, no. 3, pp. 888–905, Dec. 2023, doi: 10.30574/wjarr.2023.20.3.2541.

[3] B. T. Familoni,, "Cybersecurity challenges in the age of AI: Theoretical approaches and practical solutions," Computer Science & IT Research Journal, vol. 5, no. 3, pp. 703–724, Mar. 2024, doi: 10.51594/csitrj.v5i3.930.

[4] T. Sendjaja, E. Prastiawan, Y. Suryani, and E. Fatmawati, "Cybersecurity In The Digital Age: Developing Robust Strategies To Protect Against Evolving Global Digital Threats And Cyber Attacks," International Journal of Science and Society, vol. 6, no. 1, pp. 1008–1019, 2024, doi: 10.54783/ijsoc.v6i1.1098.

[5] M. Masum, M. Jobair Hossain Faruk, H. Shahriar, K. Qian, D. Lo, and M. Islam Adnan, "Ransomware Classification and Detection With Machine Learning Algorithms," in Proc. 2022 IEEE 12th Annual Computing and Communication Workshop and Conference (CCWC), pp. 316–322, 2022, doi: 10.1109/CCWC54503.2022.9720869.

[6] G. Nagar, "The Evolution of Ransomware: Tactics, Techniques, and Mitigation Strategies," International Journal of Scientific Research and Management (IJSRM), vol. 12, no. 06, pp. 1282–1298, Jun. 2024, doi: 10.18535/ijsrm/v12i06.ec09.

[7] S. , Kamil, H. S. A. S. , Norul, A. , Firdaus, and O. L. Usman, "The Rise of Ransomware: A Review of Attacks, Detection Techniques, and Future Challenges," in 2022 International Conference on Business Analytics for Technology and Security, ICBATS 2022, Institute of Electrical and Electronics Engineers Inc., 2022. doi: 10.1109/ICBATS54253.2022.9759000.

[8] R. Agrawal, J. W. Stokes, K. Selvaraj, and M. Marinescu, "Attention in recurrent neural networks for ransomware detection," in Proc. 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 3222–3226, May 2019, doi: 10.1109/ICASSP.2019.8682899.

[9] S. Poudyal and D. Dasgupta, "AI-Powered Ransomware Detection Framework," in 2020 IEEE Symposium Series on Computational Intelligence, SSCI 2020, Institute of Electrical and Electronics Engineers Inc., Dec. 2020, pp. 1154–1161. doi: 10.1109/SSCI47803.2020.9308387.

[10] E. S. Alomari, R. R. Nuiaa, Z. A. A. Alyasseri, H. J. Mohammed, N. S. Sani, M. I. Esa, and B. A. Musawi, "Malware Detection Using Deep Learning and Correlation-Based Feature Selection," Symmetry (Basel), vol. 15, no. 1, Jan. 2023, doi: 10.3390/sym15010123.

[11] J. Beerman, D. Berent, Z. Falter, and S. Bhunia, "A Review of Colonial Pipeline Ransomware Attack," in Proceedings - 23rd IEEE/ACM International Symposium on Cluster, Cloud and Internet Computing Workshops, CCGridW 2023, Institute of Electrical and Electronics Engineers Inc., 2023, pp. 8–15. doi: 10.1109/CCGridW59191.2023.00017.

[12] A. A. M. Ali Alwashali, N. A. A. Rahman, and N. Ismail, "A Survey of Ransomware as a Service (RaaS) and Methods to Mitigate the Attack," in Proceedings - International Conference on Developments in eSystems Engineering, DeSE, Institute of Electrical and Electronics Engineers Inc., 2021, pp. 92–96. doi: 10.1109/DESE54285.2021.9719456.

[13] M. A. , Salah, M. F. , Marhusin, and R. Sulaiman, "A Two-stage Malware Detection Architecture Inspired by Human Immune System," in Cyber Resilience Conference (CRC), IEEE, 2018. doi: 10.1109/CR.2018.8626867.

[14] M. A. , Salah, M. F. , Marhusin, and R. Sulaiman, "Malware Research Directions: A Look into Ransomware," Asian Journal of Information Technology, vol. 16, no. 6, 2017.

[15] S. Gulmez, A. G. Kakisim, and I. Sogukpinar, "XRan: Explainable deep learning-based ransomware detection using dynamic analysis," Computers & Security, vol. 139, Art. no. 103703, Apr. 2024, doi: 10.1016/j.cose.2024.103703.

[16] L. Albshaier, S. Almarri, and M. M. H. Rahman, "Earlier Decision on Detection of Ransomware Identification: A Comprehensive Systematic Literature Review," Aug. 01, 2024, Information, , vol. 15, no. 8, Aug. 2024, doi: 10.3390/info15080484.

[17] A. Alraizza and A. Algarni, "Ransomware Detection Using Machine Learning: A Survey," Sep. 01, 2023, Big Data and Cognitive Computing, vol. 7, no. 3, Sep. 2023, doi: 10.3390/bdcc7030143.

[18] H. J. Chittooparambil, B. Shanmugam, S. Azam, K. Kannoorpatti, M. Jonkman, and G. N. Samy, "A review of ransomware families and detection methods," in Advances in Intelligent Systems and Computing, Springer Verlag, 2019, pp. 588–597, June. 2019. doi: 10.1007/978-3-319-99007-1_55.

[19] P. Sharma and K. Chaudhary, "Bio-Inspired Negative Selection Tested for Ransomware Anomaly Detection," in Computing and Machine Learning, CML 2024, Lecture Notes in Networks and Systems, vol. 856, pp. 237–250, Dec. 2024. doi: https://doi.org/10.1007/978-981-97-7571-2_19.

[20] K. Peffers, T. Tuunanen, M. A. Rothenberger, and S. Chatterjee, "A design science research methodology for information systems research," Journal of Management Information Systems, vol. 24, no. 3, pp. 45–77, Dec. 2007, doi: 10.2753/MIS0742-1222240302.

[21] S. H. Kok, A. Abdullah, N. Z. Jhanjhi, and M. Supramaniam, "Ransomware, Threat and Detection Techniques: A Review," IJCSNS International Journal of Computer Science and Network Security, vol. 19, no. 2, Feb. 2019.

[22] A. Lumazine, G. Drakos, M. Salvatore, et al., "Ransomware Detection in Network Traffic Using a Hybrid CNN and Isolation Forest Approach." Authorea, Oct. 2024, doi: 10.22541/au.172901014.44599790/v1.

[23] S. Satpathy and P. K. Swain, "Graph-contrast ransomware detection (GCRD) with advanced feature selection and deep learning," Discover Computing, vol. 28, no. 1, Dec. 2025, doi: 10.1007/s10791-025-09651-w.

[24] E. Landril, S. Valente, G. Andersen, and C. Schneider, "Ransomware Detection through Dynamic Behavior-Based Profiling Using Real-Time Crypto-Anomaly Filtering," Control System Engineering, Oct. 2024.

[25] B. Barchuk and K. Volkov, "Antivirus evasion techniques in modern malware," World Journal of Advanced Research and Reviews, vol. 26, no. 2, pp. 3154–3166, May 2025, doi: 10.30574/wjarr.2025.26.2.1966.

[26] F. A. Aboaoja, A. Zainal, F. A. Ghaleb, B. A. S. Al-rimy, T. A. E. Eisa, and A. A. H. Elnour, "Malware Detection Issues, Challenges, and Future Directions: A Survey," Applied Sciences, vol. 12, no. 17, Sep. 2022, doi: 10.3390/app12178482.

[27] K. Goeschel, "Reducing false positives in intrusion detection systems using data-mining techniques utilizing support vector machines, decision trees, and naive Bayes for off-line analysis," in SoutheastCon, IEEE, pp. 1–6, March. 2016 doi: 10.1109/SECON.2016.7506774.

[28] D. Sgandurra, L. Muñoz-González, R. Mohsen, and E. C. Lupu, "Automated Dynamic Analysis of Ransomware: Benefits, Limitations and use for Detection," arXiv preprint arXiv:1609.03020, Sep. 2016, doi: 10.48550/arXiv.1609.03020.

[29] N. Scaife, H. Carter, P. Traynor, and K. Butler, "CryptoLock (and Drop It): Stopping Ransomware Attacks on User Data," Proceedings of the IEEE International Conference on Distributed Computing Systems (ICDCS), pp. 303-312, June. 2016, doi: 10.1109/ICDCS.2016.46.

[30] J. A. Herrera-Silva and M. Hernández-Álvarez, "Dynamic Feature Dataset for Ransomware Detection Using Machine Learning Algorithms," Sensors, vol. 23, no. 3, Feb. 2023, doi: 10.3390/s23031053.

[31] Y.-C. Wu and Y.-L. Chang, "Ransomware Detection on Linux Using Machine Learning with Random Forest Algorithm," TechRxiv, June. 2024, doi: 10.36227/techrxiv.171778770.06550236/v1.

[32] B. M. Khammas, "Ransomware Detection using Random Forest Technique," ICT Express, vol. 6, no. 4, pp. 325–331, Dec. 2020, doi: 10.1016/j.icte.2020.11.001.

[33] S. H. Kok, A. Abdullah, and N. Z. Jhanjhi, "Early detection of crypto-ransomware using pre-encryption detection algorithm," Journal of King Saud University - Computer and Information Sciences, vol. 34, no. 5, pp. 1984–1999, May. 2022, doi: 10.1016/j.jksuci.2020.06.012.

[34] S. Li, Q. Zhou, R. Zhou, and Q. Lv, "Intelligent malware detection based on graph convolutional network," Journal of Supercomputing, vol. 78, no. 3, pp. 4182–4198, Feb. 2022, doi: 10.1007/s11227-021-04020-y.

[35] M. A. Saleh, "A Proactive Approach for Detecting Ransomware based on Hidden Markov Model (HMM)," International Journal of Intelligent Computing Research, vol. 10, no. 3, Sep. 2019.

[36] J. Hwang, J. Kim, S. Lee, and K. Kim, "Two-Stage Ransomware Detection Using Dynamic Analysis and Machine Learning Techniques," Wireless Personal Communications, vol. 112, no. 4, pp. 2597–2609, Jun. 2020, doi: 10.1007/s11277-020-07166-9.

[37] R. A. Mowri, M. Siddula, and K. Roy, "Application of Explainable Machine Learning in Detecting and Classifying Ransomware Families Based on API Call Analysis," arXiv preprint arXiv:2210.11235, Nov. 2022, doi: 10.48550/arXiv.2210.11235.

[38] S. Forrest; A.S. Perelson; L. Allen; R. Cherukuri, "Self-nonself discrimination in a computer," in Proceedings of 1994 IEEE Computer Society Symposium on Research in Security and Privacy, , pp. 202-212, May, doi: 10.1109/RISP.1994.296580.

[39] S. A. Hofmeyr, "An Immunological Model of Distributed Detection and Its Application to Computer Security," Ph.D. dissertation, Univ. of New Mexico, Albuquerque, NM, USA, 1999.

[40] H. Alrubayyi, G. Goteng, and M. Jaber, "AIS for Malware Detection in a Realistic IoT System: Challenges and Opportunities," Network, vol. 3, no. 4, pp. 522–537, Dec. 2023, doi: 10.3390/network3040023.

[41] T. Lu, Z. Lu, W. Shunye, and G. Qi, "Ransomware detection based on V-detector negative selection algorithm," in 2017 International conference on security, pattern analysis, and cybernetics (SPAC), IEEE, pp. 531–536, Dec. 2017, doi: 10.1109/SPAC.2017.8304335.

[42] T. Lu, Y. Du, J. Wu, and Y. Bao, "Ransomware detection based on an improved double-layer negative selection algorithm," in Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering, LNICST, Springer, pp. 46–61, March. 2020, doi: 10.1007/978-3-030-43215-7_4.

[43] Y. Feng, C. Liu, and B. Liu, "Poster : A New Approach to Detecting Ransomware with Deception," In 38th IEEE symposium on security and privacy, May. 2017.

[44] A. Gazet, "Comparative analysis of various ransomware virii," Journal in Computer Virology, vol. 6, no. 1, pp. 77–90, Feb. 2010, doi: 10.1007/s11416-008-0092-2.

[45] N. , Maheswaran, S. Bose, G. Logeswari, and T . Anitha., "Hybrid Intrusion Detection System Using Machine Learning Algorithm," in Proceedings of Data Analytics and Management, Springer, pp. 333–346, March. 2023, doi: 10.1007/978-981-19-7615-5_30.

[46] G. Li, S. Wang, Y. Chen, J. Zhou, and Q. Zhao, "A Hybrid Framework for Ransomware Detection Using Deep Learning and Monte Carlo Tree Search," OSFPREPRINTS, 2024.

[47] Q. Al-Na'amneh, A. N. Nasayreh, R. Al Mamlook, H. Gharaibeh, A. M. Alsheyab, and M. Almaiah, "Improving memory malware detection in machine learning with random forest-based feature selection," in Risk Assessment and Countermeasures for Cybersecurity, IGI Global, pp. 96–114, 2024 doi: 10.4018/979-8-3693-2691-6.ch006.

[48] H. Manthena, J. C. Kimmel, M. Abdelsalam, and M. Gupta, "Analyzing and Explaining Black-Box Models for Online Malware Detection," IEEE Access, vol. 11, pp. 25237–25252, March. 2023, doi: 10.1109/ACCESS.2023.3255176.

[49] H. Manthena, S. Shajarian, J. C. Kimmell, M. Abdelsalam, S. Khorsandroo, and M. Gupta, "Explainable Artificial Intelligence (XAI) for Malware Analysis: A Survey of Techniques, Applications, and Open Challenges," IEEE Access, vol. 13, pp. 61611–61640, March. 2025, doi: 10.1109/ACCESS.2025.3555926.

[50] A. I. Udofot, O. M. Oluseyi, and E. B. Edim, "Explainable AI for cyber security. Improving transparency and trust in intrusion detection systems," International Journal of Advances in Engineering and Management, vol. 06, no. 12, pp. 229–240, Dec. 2024, doi: 10.35629/5252-0612229240.

[51] abuse.ch, "MalwareBazaar: A repository of malware samples." Accessed: Dec. 15, 2025. [Online]. Available: https://bazaar.abuse.ch/

[52] U. Ahmed, Z. Jiangbin, A. Almogren, S. Khan, M. T. Sadiq, A. Altameem, and A. U. Rehman, "Explainable AI-based innovative hybrid ensemble model for intrusion detection," Journal of Cloud Computing, vol. 13, no. 150, Oct. 2024, doi: 10.1186/s13677-024-00712-x.

[53] Y. Guo, "A Review of Machine Learning-Based Zero-Day Attack Detection: Challenges and Future Directions," Computer Communications, Vol. 198, pp. 175–185, Jan. 2023, doi: 10.1016/j.comcom.2022.11.001.

[54] N. Capuano, G. Fenza, V. Loia, and C. Stanzione, "Explainable Artificial Intelligence in CyberSecurity: A Survey," IEEE Access, vol. 10, pp. 93575–93600, Sep. 2022, doi: 10.1109/ACCESS.2022.3204171.

[55] M. Al-Omari and Q. A. Al-Haija, "Performance Analysis of Machine Learning-Based Intrusion Detection with Hybrid Feature Selection," Computer Systems Science and Engineering, vol. 48, no. 6, pp. 1537–1555, Sep. 2024, doi: 10.32604/csse.2024.056257.

[56] U. Urooj, B. A. S. Al-Rimy, A. Zainal, F. A. Ghaleb, and M. A. Rassam, "Ransomware Detection Using the Dynamic Analysis and Machine Learning: A Survey and Research Directions," Applied Sciences (Switzerland), vol. 12, no. 1, Jan. 2022, doi: 10.3390/app12010172.

[57] P. Hońko, "Adaptive Positive-Negative Selection Approach," in Journal of Physics: Conference Series, Institute of Physics Publishing, vol. 1061, no. 1, p. 012020 April. 2018. doi: 10.1088/1742-6596/1061/1/012020.

[58] S. Lundberg and S.-I. Lee, "A Unified Approach to Interpreting Model Predictions," in Proc. 31st International Conference on Neural Information Processing Systems (NIPS), pp. 4768–4777, 2017.

[59] IBM, "Cost of a Data Breach Report 2025 The AI Oversight Gap think report," 2025. Accessed: Nov. 16, 2025. [Online]. Available: https://www.ibm.com/reports/data-breach.

A Resilient Framework for Industry 5.0 WSNs: Enhancing Network Lifetime via a Lightweight Reputation Ledger and Hybrid AI

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***Abstract*—Wireless Sensor Networks (WSNs) play an increasingly important role in Industry 5.0 cyber–physical systems, where resilience, trust, and energy efficiency are essential under dynamic operating conditions. However, their limited resources, scattered deployment, and continuous operation make these networks highly susceptible to unusual behavior and cyberattacks. Such issues can compromise data quality, disrupt network reliability, and shorten the overall lifespan of the system. To address these challenges, this study examines WSN resilience as a combined problem of anomaly detection accuracy, fault isolation latency, and network lifetime under realistic fault and energy constraints. At the core of the framework is a Model Context Protocol (MCP), which combines a supervised LightGBM classifier with an unsupervised LSTM autoencoder to capture both event-driven and temporal anomalies in sensor data. Complementing this is a compact "Micro-Ledger" system that updates trust values for each node by monitoring behavior and using streamlined consensus rules. Together, they create a continuous feedback mechanism that isolates suspicious nodes while keeping energy consumption in check. The framework is evaluated using a set of resilience-oriented metrics, including fault detection latency, Mean Time To Failure (MTTF), reputation convergence behavior, and overall network lifetime. Experiments conducted in a Digital Twin simulation environment report an F1-score of 0.997, an 18.7% improvement in network lifetime, and a Micro-Ledger storage overhead of approximately 98 KB. While the current validation is simulation-based, the proposed design can be extended to physical deployments through adaptive trust weighting, cluster-head redundancy, and probation-based node reintegration.**

Keywords*—Wireless Sensor Networks (WSNs); Industry 5.0; anomaly detection; lightweight blockchain; trust management; network lifetime; Digital Twin

I. Introduction

Industry 5.0, or the fifth industrial revolution, ushers in an altogether new paradigm that seeks to make production systems more human-centered and focus on sustainability and resilience [1]. At the heart of Industry 5.0 will be IoE, encompassing the interlinking of cyber-physical spaces through Wireless Sensor Networks or WSNs, which will be able to connect the two environments of physical and digital. A typical WSN contains thousands of spatially distributed sensor nodes that capture data and transport information continuously. This decentralized approach has its own merits—the intelligent automation, the adaptive control—but at the same time, it gives rise to important vulnerabilities because of the energy-constrained and distributed nodes [2].

Outliers or anomalous data points caused by malicious intrusions, hardware failures, or environmental interference degrade network performance, data integrity, and energy efficiency [3]. These anomalies increase communication overhead and maintenance costs and, hence, reduce network lifetime. In such environments, resilience is no longer limited to fault tolerance alone but also includes timely anomaly recognition, trust-aware decision-making, and sustained operation under resource constraints.

While anomaly detection, trust management, and blockchain-based integrity have each been studied in isolation, their joint role in sustaining long-term resilience and network lifetime in Industry 5.0 WSNs remains underexplored. In particular, existing approaches often lack adaptive trust evolution driven by real-time anomaly evidence. Industry 5.0 extends earlier industrial paradigms by emphasizing resilience, sustainability, and human-centric cyber–physical systems [23]. ML approaches to anomaly detection show promise; however, applications in dynamic IoT and WSN often struggle to generalize across heterogeneous anomaly types and dynamically changing operating conditions. [4]. Similarly, single-model classifiers, such as Support Vector Machines and Decision Trees, have lower performance while dealing with heterogeneous sensor data [5]. Beyond detection accuracy, system-level resilience metrics such as fault detection latency, recovery behavior, and network lifetime are equally critical in practical WSN deployments.

Recent research in deep learning has enhanced detection accuracy through the temporal dependencies modeled on sequential data. For example, LSTM-based networks have achieved high performance in detecting time-series anomalies in WSNs [6]. However, these networks still suffer from some limitations when used in isolation, as they cannot detect event-based and time-series anomalies in dynamic environmental conditions [7].

While blockchain mechanisms have been extensively explored to ensure data integrity and auditability in WSNs, the consensus protocols commonly adopted are computationally expensive, such as PoW, thus being infeasible for energy-constrained sensor nodes. Lightweight blockchain designs have recently been proposed, although they are often passive data storage rather than active adaptive trust systems. Besides, most of the earlier studies fail to address changing behavior of

network nodes, an essential factor in accurate and dynamic trust levels. However, when used purely as a passive data store, blockchain mechanisms offer limited support for adapting to evolving node behavior or mitigating energy drain caused by unreliable sensors.

Addressing these challenges calls for an integrated multilayer resilience framework, coherent with the principles of Industry 5.0. The key contributions of this work can be summarized as follows:

- Hybrid Anomaly Detection (Model Context Protocol - MCP): A hybrid architecture combining LightGBM and LSTM Autoencoder models aims to improve detection accuracy across multiple anomaly types [12].
- Lightweight "Micro-Ledger" for Dynamic Trust Management: A blockchain-based reputation system for resource-constrained WSNs, which improves node trust evaluation and energy efficiency [13].
- Closed-loop feedback mechanism: Integration of anomaly detection results with the Micro-Ledger to support automated isolation of persistently unreliable nodes [14].
- Digital Twin Validation: Simulation and testing on a Digital Twin environment to assess resilience under induced network noise and channel interference conditions [15].

The present study focuses on simulation-based validation within a Digital Twin environment to analyze resilience behavior under controlled fault conditions. Extensions to physical deployments, more complex attack models, and adaptive trust policies are discussed as part of future research directions.

II. Related Work

The security, reliability, and longevity of WSNs have been recognized as key challenges in the evolution of both Industry 5.0 and the IoT [16]. Accordingly, resultant topics related to these areas have been actively reviewed across a wide variety of domains, with particular attention given to anomaly detection, blockchain-enabled trust management, and energy-efficient network design. Despite these active developments, there is still a dire need for integrated frameworks that bring these components together into a cohesive, resilient architecture.

A. Anomaly Detection in WSNs and IoT Systems

ML and DL have emerged as the key technologies for anomaly detection in WSNs/IoT systems in recent times [17]. For instance, Al-Qatf et al. showed that ML classifiers such as Support Vector Machines and Decision Trees could efficiently detect intrusions in sensor networks [18]. Further research by Otoum et al. applied Random Forests, presenting enhancements in the detection performance of IoT-based intrusion detection systems.

Deep Learning improved the detection capabilities by learning complex temporal and nonlinear patterns present in time series data. Malhotra et al. introduced the concept of LSTM Autoencoders, which perform anomaly detection by learning normal system behavior and subsequently finding deviations from it [20].

Similarly, Lee et al. have also demonstrated effectiveness in fault detection in vibration-based cyber-physical systems using LSTM Autoencoders [21]. Despite these advances, single-model approaches remain limited in detecting multiple types of anomalies in heterogeneous WSN environments [22]. Hybrid or ensemble architectures combining different models have also been proposed to overcome this limitation and offer increased robustness. For example, Khairullah and Alsenani showed that hybrid frameworks that integrate both gradient boosting and deep learning improved the consistency of anomaly detection. This idea directly inspired the Model Context Protocol (MCP) proposed in this research, which integrated both LightGBM and LSTM Autoencoder to perform high-precision, multi-type anomaly detection.

B. Blockchain-Based Trust Management for WSNs

Immutability, decentralization, and tamper resistance properties of blockchain technology have made it attractive for securing IoT and WSN data [25]. The early frameworks rely on blockchain primarily for data integrity, where sensor readings are stored in an immutable ledger to avoid unauthorized changes [26]. Later, other works extended the blockchain use to authentication and access control for IoT networks, improving data confidentiality and accountability [24].

However, most of such systems relied on the resource-intensive consensus algorithms like Proof-of-Work (PoW), which is impractical for energy-limited sensor nodes [22]. To alleviate this, Deng et al. presented a lightweight Proof-of-Authority–based trust mechanism that has been proposed to reduce consensus overhead in resource-constrained Wireless Sensor Networks [8]. This Scheme with the help of Proof-of-Authority consensus, reduced the computational overhead significantly without compromising the integrity of trust [25].

Stefanescu et al. have also highlighted the importance of lightweight blockchain architectures for IoT, showing how customized consensus models can increase scalability [26]. In addition, Sahraoui and Bachir proposed adaptive “Blockchained Things,” presenting blockchain models which dynamically adapt node trust over time [19]. Several studies have shown that blockchain architectures can be adapted for IoT environments, although scalability and storage overhead remain open challenges [9]. However, few of them really integrate behavioral trust evaluation with blockchain mechanisms, which is the gap that this study tries to address through its Micro-Ledger. The latter continuously updates node reputation based on behavioral evidence.

Despite these advances, many blockchain-based solutions remain largely passive, focusing on secure storage or authentication rather than actively adapting trust in response to node behavior. Moreover, assumptions of static trust or reliance on a single validating authority may limit resilience in long-running, large-scale WSN deployments. Blockchain-enabled trust frameworks for heterogeneous IoT devices have been explored to provide decentralized accountability without

centralized authorities [10]. Trust-based mechanisms have also been applied to mitigate malicious or unreliable node behavior in distributed sensor networks [11].

C. Resilience and Network Lifetime in Industry 5.0 WSNs

The operational lifetime of WSNs has long been a focal point of optimization efforts. Classic approaches, including energy-aware routing, node clustering, and sleep scheduling, which reduce communication overhead, generally do not take long-term effects caused by security and trust into consideration [21].

Untrusted or malfunctioning nodes may continuously transmit incorrect data that would cause redundant communication and energy wastage [21].

To counter this, the contributions of Han et al. have stressed the importance of combining trust management with energy optimization and have proposed frameworks capable of isolating or quarantining unreliable nodes [21]. Recent works extend this concept by integrating security, trust, and energy efficiency for better robustness of the network [14]. The framework now extends this fundamental idea by integrating AI-based anomaly detection with blockchain-based trust management to realize a self-regulating, energy-aware, and adaptive WSN suitable for Industry 5.0 ecosystems [20]. In the context of Industry 5.0, resilience is increasingly viewed as a system-level property that encompasses fault tolerance, trust evolution, and sustained energy efficiency, rather than isolated security or routing optimizations.

In summary, existing research provides valuable insights into anomaly detection, blockchain-enabled trust, and energy-aware WSN design. However, an integrated framework that tightly couples hybrid AI-based anomaly detection with adaptive, lightweight trust management—while explicitly targeting network lifetime and resilience in Industry 5.0 settings—remains limited. This gap motivates the framework proposed in this study.

III. The Proposed Framework

This section presents the proposed resilience framework designed to enhance security, trust, and network lifetime in Wireless Sensor Networks operating under Industry 5.0 conditions. The framework is conceived as a modular, multi-layer system in which anomaly detection, trust evaluation, and energy-aware decision-making are tightly coupled through a closed feedback loop. Rather than treating these components independently, the design emphasizes their interaction over time as sensor behavior and network conditions evolve. Each component of the framework is formally defined in terms of its role, inputs, and outputs, and is later supported by mathematical modeling and algorithmic descriptions to ensure reproducibility. The framework is evaluated within a Digital Twin simulation environment, which enables controlled fault injection and repeatable analysis of resilience behavior prior to physical deployment. While the framework leverages edge-based coordination at the cluster level, its design allows for extensions such as role rotation and redundancy to mitigate centralized failure risks. The remainder of this section details the high-level architecture, operational methodology, edge intelligence module, and lightweight reputation ledger that together realize the proposed framework.

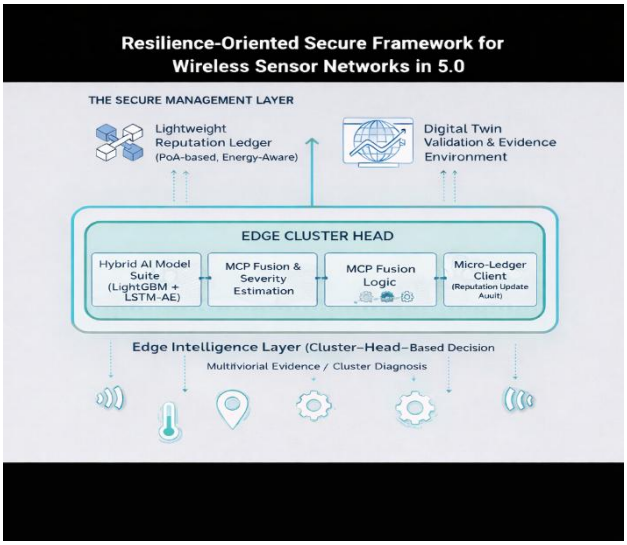


Fig. 1. High-level architecture of the proposed WSN resilience framework.

A. System Architecture

The proposed architecture consists of three interdependent layers, conceptually illustrated in Fig. 1. The architecture is designed to support decentralized sensing, edge-level intelligence, and trust-aware coordination while maintaining low computational and communication overhead.

Formally, the wireless sensor network is modeled as a graph $G = (V, E)$, where $V = \{v_1, v_2, \ldots, v_N\}$represents the set of sensor nodes and Edenotes wireless communication links. Nodes are organized into clusters, each coordinated by a cluster head responsible for local inference and trust management.

- IoE Layer (Perception Layer): This layer represents distributed sensor nodes deployed in physical environments. Each of these nodes collects multivariate data on phenomena such as temperature, motion, and GPS coordinates, which are transmitted to cluster heads for aggregation and analysis. To reduce redundant communication, raw sensor readings are locally aggregated before transmission to the cluster head.
- Edge Intelligence Layer: At the cluster head level, local inference is performed using a hybrid AI detection mechanism that balances detection accuracy with edge-level resource constraints, called the Model Context Protocol (MCP). MCP fuses a LightGBM Classifier and an LSTM Autoencoder to identify both event-based and temporal anomalies efficiently. This keeps bandwidth utilization low and also enhances security by processing data at the network edge.
- Secure Management Layer: This layer introduces a Lightweight Reputation Ledger—the "Micro-Ledger"—that keeps track of the reputation status of each node based on blockchain principles. The ledger records node behavior in a verifiable and tamper-resistant format to enable dynamic trust adjustments and isolate unreliable nodes. Reputation updates are

triggered by observed node behavior rather than static assumptions, allowing trust to evolve over time.

Although the cluster head coordinates local inference and ledger updates, the architecture does not assume permanent leadership. Backup cluster heads may be selected based on residual energy and reputation, enabling role rotation in the event of failure or compromise.

B. Framework Methodology

The proposed framework operates as an event-driven process executed at the cluster-head level. Incoming sensor data are processed sequentially, enabling timely anomaly detection, trust updates, and adaptive responses to evolving network conditions. The layered architecture of the proposed resilience framework, including the IoE layer, edge intelligence layer, and secure management layer, is illustrated in Fig. 2.

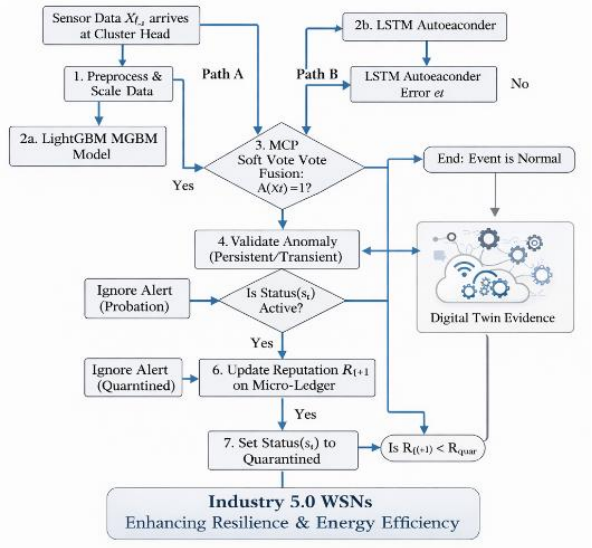


Fig. 2. Methodology flowchart of the anomaly detection and reputation management process.

- Data Preprocessing: At each time step t, the cluster head receives a multivariate sensor vector $\mathbf{x}_t = [x_t^{(1)}, x_t^{(2)}, \ldots, x_t^{(d)}]$, where d denotes the number of monitored features. Normalization of raw sensor inputs is done in order to maintain consistency across heterogeneous devices and ensure fair weighting in anomaly detection.
- Packet Loss and Fault Modeling: To reflect realistic operating conditions, the framework accounts for communication impairments and sensor faults. Packet loss is modeled as a Bernoulli process with loss probability p_l, while sensor faults are introduced probabilistically to simulate intermittent and persistent deviations in sensor behavior.
- Parallel Anomaly Detection: The LightGBM classifier and LSTM Autoencoder process input data in parallel. Their outputs are fused by a soft-voting fusion rule, such that an anomaly is declared when either model detects an anomalous pattern. This design maximizes recall while maintaining high precision.

Detected anomalies are not treated uniformly. Each anomaly is associated with a severity score derived from model confidence and temporal persistence, allowing the framework to distinguish transient sensor noise from sustained or potentially malicious behavior.

- Reputation Update Procedure: In case of anomaly detection, the framework evaluates whether the detected anomaly reflects persistent abnormal behavior or a benign, transient deviation based on validation within the Digital Twin environment. Reputation adjustments are based on behavioral assessment rather than model error attribution, ensuring that nodes are not penalized solely due to transient detection uncertainty.
- Blockchain Transaction Logging: Every reputation adjustment generates an entry in the Micro-Ledger, including node ID, event type, timestamp, and reputation change. This immutable record provides a transparent audit trail and supports future accountability.

The time elapsed between the onset of abnormal behavior and its identification is recorded as fault detection latency, serving as a key indicator of the framework's responsiveness. Validation within the Digital Twin enables controlled injection of noise, packet loss, and faulty node behavior, providing repeatable conditions for evaluating detection accuracy and trust adaptation.

C. The Edge Intelligence Module (MCP)

The Edge Intelligence Module, referred to as the Model Context Protocol (MCP), serves as the decision-making core of the proposed framework. It is designed to identify heterogeneous anomalies at the network edge while balancing detection accuracy with computational and energy constraints.

Relying on a single detection model often limits robustness in dynamic WSN environments, where anomalies may appear as isolated events or evolve gradually over time. To address this, MCP combines complementary learning paradigms that capture both instantaneous deviations and longer-term temporal patterns.

1) LightGBM for event-based anomaly detection: LightGBM is an efficient gradient-boosted decision tree framework that is well-suited for structured telemetry data commonly produced by sensor nodes. It does an excellent job of catching discrete or event-based anomalies without much computational overhead at the edge. Within MCP, LightGBM primarily contributes to detecting event-driven anomalies, such as sudden threshold violations or abnormal feature combinations.

2) LSTM autoencoder for sequential anomaly detection: The LSTM Autoencoder proposed by Malhotra et al. models sequential dependencies in the time series, thereby detecting anomalies based on temporal reconstruction errors. Several improved variants, including that, have demonstrated that the LSTM Autoencoder maintains good resistance to noise in dynamic environments. While effective in modeling normal temporal behavior, the autoencoder alone may overlook

abrupt, non-sequential anomalies, motivating its integration with a complementary model.

3) MCP fusion logic: The outputs of the LightGBM classifier and the LSTM autoencoder are combined using a soft-voting strategy. An observation is flagged as anomalous when either model reports abnormal behavior, prioritizing anomaly recall while maintaining high precision. In which the final decision denotes computationally as:

$$A(Xt) = \max(yLGBM, yLSTM)$$

In addition to the binary anomaly decision, MCP retains model confidence and reconstruction error information. These signals are later used to estimate anomaly severity and temporal persistence, enabling differentiated trust responses rather than uniform penalization. By performing inference at the cluster head, MCP reduces unnecessary data transmission and supports timely detection without imposing continuous computational load on individual sensor nodes.

D. The Lightweight Reputation Ledger

The Lightweight Reputation Ledger, referred to as the Micro-Ledger, provides a decentralized yet energy-aware mechanism for tracking node behavior over time. Its primary objective is to translate anomaly evidence into adaptive trust decisions without imposing the computational overhead of conventional blockchain systems.

The Micro-Ledger acts as the trust management backbone of the framework. Unlike other traditional blockchains, which implement consensus based on mining, such as Proof-of-Work, the underlying model followed by the Micro-Ledger is a form of Proof-of-Authority. This minimizes computational overhead and energy consumption in resource-constrained WSNs. Although Proof-of-Authority is employed to minimize energy consumption, the framework does not assume unconditional trust in a single validator. Reputation consistency checks and periodic leadership rotation can be incorporated to mitigate validator compromise.

1) Energy-efficient consensus: Proof-of-Authority (PoA): This is because the PoA model minimizes most overhead by eliminating energy-intensive computational puzzles while guaranteeing the immutability and verifiability of blocks. Such architectures result in high trust assurance with minimal energy use in IoT networks.

The proposed framework integrates hybrid AI detection with adaptive blockchain trust management, enabling a resilient, self-healing WSN architecture that can operate for an extended period under the extreme constraints of Industry 5.0 ecosystems.

2) The reputation management algorithm: Reputation updates are driven by observed behavioral patterns rather than model errors. When sustained or high-severity anomalous behavior is identified, the corresponding node's reputation is reduced proportionally, whereas stable and reliable behavior results in gradual reputation reinforcement.

Let $s_t \in [0,1]$ denote the anomaly severity score at time t, derived from detection confidence and temporal persistence. The reputation score R_i of node i is updated incrementally as a function of s_t, allowing minor transient deviations to have limited impact while penalizing persistent abnormal behavior more strongly.

- Automatic Quarantine: If any node's reputation degrades below the threshold Rth = 50, it is automatically quarantined, and any related data will not be included in any future analysis to conserve energy.
- Nodes whose reputation falls below the quarantine threshold are temporarily isolated from active participation. A probation mechanism allows quarantined nodes to be re-evaluated after a cooling-off period, during which limited observation data may be collected to assess behavioral recovery before potential reintegration.

To bound storage overhead over extended operation, the Micro-Ledger can employ sliding-window retention or periodic summarization of historical entries, ensuring scalability on resource-constrained cluster heads.

IV. Experimental Setup and Evaluation

This section describes the experimental design used to evaluate the proposed framework in terms of detection performance, resilience, and energy efficiency. The evaluation is conducted within a controlled Digital Twin simulation environment, enabling repeatable analysis under varying fault, noise, and communication impairment conditions. Both component-level metrics and system-level resilience indicators are considered to provide a comprehensive assessment.

A. Dataset

The experiments made use of the ToN-IoT dataset. The dataset contains labeled telemetry and network traffic traces collected from heterogeneous IoT devices under both normal and attack conditions, making it suitable for anomaly detection and resilience evaluation. It was one of the most adopted benchmarks related to the evaluation of intrusion and anomaly detection models within the IoT and WSN context.

Extensive preprocessing was done before training and evaluation on the raw data. Telemetry streams were combined into one multivariate time series, indexed by timestamps. Based on the correlation and leakage analysis, missing values, duplicates, and non-informative features were removed. The selected features included temperature, motion, GPS latitude, pressure, and humidity; Feature selection was guided by correlation analysis and information leakage checks to remove redundant and non-informative attributes. Normalization ensures that features with different physical units contribute proportionally to the learning process.

This final dataset was then divided into 70% training and 30% testing subsets, as done in standard best practices for anomaly detection studies. The split was performed chronologically to preserve temporal dependencies in the sensor streams and to avoid information leakage between training and testing phases. This approach guarantees sufficient diversity for both the supervised and unsupervised model components within the MCP.

While the ToN-IoT dataset provides a diverse and widely used benchmark, it is employed here to support controlled evaluation rather than to claim exhaustive coverage of all real-world failure scenarios.

B. The Digital Twin Simulation Environment

The framework was implemented on a custom-made Digital Twin built in Streamlit that mirrored a virtual replica of the WSN to analyze system behavior in real-time. The Digital Twin serves as a pre-deployment validation tool, allowing controlled experimentation and systematic observation of system behavior under reproducible conditions.

The simulated network consists of multiple sensor nodes organized into clusters, with configurable parameters such as node count, communication reliability, and fault injection intensity. Simulation runs are executed over extended event sequences to capture long-term trust evolution and energy trends.

Notable interactive features of the environment included composable features to facilitate investigatory inquiry, including, but not limited to, the following:

- Live Simulation Dashboard: An environment that monitors exhibited model performance metrics and current metrics for model accuracy, precision, and recall, as well as the most recent state of the Reputation Ledger.
- Noise Injection Control: The capability to introduce Gaussian noise to sensor readings in order to represent environmental interference and evaluate the overall robustness of the detection models. Noise intensity is varied across simulation runs to evaluate detection robustness under increasing environmental interference.
- Packet Loss Simulator: A proportion of sensor packets was randomly omitted as a representation of channel impairments and connectivity loss. Packet loss is modeled probabilistically to reflect unstable wireless links commonly observed in real-world WSN deployments.
- Faulty Sensor Selector: Faulty nodes are configured to exhibit persistent or intermittent abnormal behavior, enabling evaluation of the framework's ability to distinguish transient deviations from sustained faults.
- Manual Data Interface: Novel sliders for each sensor with user-defined sender values, which served as an opportunity for near real-time anomaly assessment.

The simulated nature of this assessment allows for a repeatable experimental scenario while enabling a fine-grained observation regarding detection efficacy and trust management operations within dynamic environments. This simulation-based setup enables detailed resilience analysis while avoiding hardware-dependent variability, thereby supporting fair and repeatable evaluation.

C. Evaluation Metrics

In order to thoroughly evaluate the performance of the framework, the selected metrics are grouped into model-level performance indicators and system-level resilience indicators to reflect both detection accuracy and long-term network behavior.

1) Model performance metrics: The AI model performance was evaluated using four standard classification measures: Accuracy, Precision, Recall, and F1-Score:

- Accuracy: The proportion of instances that were correctly classified.
- Precision: The fraction of instances classified as anomalies that were, in fact, true anomalies, which reveals the effectiveness of the model in terms of false alarms.
- Recall: The fraction of true anomalies that were classified as anomalies by the model.
- F1-Score: The harmonic mean of precision and recall, which indicates the overall detection ability of the detection model.

These metrics together reflect the model's ability to identify anomalies reliably while minimizing benign or non-malicious anomalies essential for energy-efficient operation in WSNs [6].

2) Framework evaluation metrics: To quantify system-level resilience, the following metrics are defined:

- Fault Detection Latency (FDL): The time difference between the onset of abnormal node behavior and its detection by the framework.
- Mean Time To Failure (MTTF): The expected operational time before a node or cluster enters a failure state due to sustained faults.
- Mean Time To Recovery (MTTR): The average duration required for the system to isolate or mitigate a faulty node after detection.
- Reliability Index: A measure of the probability that the network remains operational over time under fault conditions.

Formally, fault detection latency is computed as:

$$FDL = tdetect - tfault$$

where, t_{fault}denotes the time of fault onset and t_{detect}denotes the detection time.

In order to assess system-level resilience and efficiency, three metrics were developed:

- Time to Quarantine (TTQ): The count of events taken for the system to recognize and quarantine a reliably faulty sensor node. TTQ serves as a discrete approximation of recovery responsiveness and complements MTTR in event-driven simulations. Low TTQ is indicative of a faster adaptive response and stronger resilience of the network.
- Network Lifetime Improvement: The percentage improvement in total energy consumption compared to

what would have happened without the proposed trust mechanism. Network lifetime is inferred from cumulative energy consumption across nodes over the simulation horizon. This metric is easily interpretable, as it represents energy savings directly due to the quarantine of unreliable nodes.

- Blockchain Storage Overhead: The final size (in kilobytes) of the Micro-Ledger object at the end of a complete simulation, indicating the success of the lightweight blockchain design given the resource constraints of the underlying architecture. This metric reflects the scalability of the trust mechanism under prolonged operation.

When taken together, these evaluation metrics provide a comprehensive assessment of AI accuracy, adaptive trust performance, and computational efficiency.

D. Mathematical Formulation of the Framework

The wireless sensor network is modeled as a set of N sensor nodes represented by a graph $G = (V, E)$, where $V = \{v_1, v_2, \dots, v_N\}$ denotes the nodes and E represents wireless communication links between them.

At the discrete time step t, the cluster head receives an aggregated feature vector:

$$xt = [xt(1), xt(2), \dots, xt(d)]$$

where, d is the number of monitored features.

1) AI-based anomaly detection: The Model Context Protocol (MCP) combines a supervised classifier and an unsupervised reconstruction-based model.

- LightGBM produces binary predictions: $y_{LGBM} \in \{0,1\}$
- while the LSTM autoencoder computes a reconstruction error: $e_t = \| X_t - \hat{X}_t \|$.

An anomaly is detected by the autoencoder when e_t > θ, where θ is a predefined threshold learned from normal behavior.

The final anomaly decision A_t is obtained using a soft-voting fusion rule:

$$A_t = y_t\text{^}GB \vee \mathbb{1}(e_t > \theta),$$

where, ∨ denotes the logical OR operation and 𝟙(·) is the indicator function.

To differentiate transient deviations from persistent abnormal behavior, an anomaly severity score s_t ∈ [0,1] is defined as a function of detection confidence and temporal persistence. Higher values of s_t indicate sustained or high-confidence anomalies, while lower values correspond to minor or short-lived deviations.

2) Reputation update rule: Each node v_i maintains a dynamic reputation score R_i(t). When an anomaly is detected at time t, the reputation score is updated as:

$$R_i(t+1) = R_i(t) - \alpha \cdot s_t,$$

where, α > 0 is a scaling factor controlling penalty strength. In the absence of anomalies, reputation is gradually reinforced:

$$R_i(t+1) = R_i(t) + \beta,$$

where, β > 0 is a small reinforcement constant.

If R_i(t) falls below a predefined threshold R_th, the node is placed into a quarantine state, and its data are excluded from further analysis until re-evaluation conditions are satisfied.

This mathematical formulation links anomaly detection outcomes with trust evolution, providing a formal basis for analyzing resilience and network lifetime within the proposed framework.

Through the integration of a robust data-driven modeling approach, a mathematical trust formulation, and simulation-based validation of both modeling and trust framework results, this study establishes a reproducible basis for authoring a trustworthy WSN integrated with AI–blockchain technology. The study and replicable data considered Industry 5.0 conditions to assess the AI–blockchain-integrated WSN's resilience.

V. Results and Discussion

This section discusses the experimental results obtained from the Digital Twin simulations, focusing on anomaly detection performance, resilience under adverse conditions, and the impact of trust-aware mechanisms on network lifetime. The results are interpreted in relation to baseline approaches commonly used in WSN and IoT security literature.

The proposed resilient framework of WSNs is assessed using the Digital Twin environment in respect of:

1) the accuracy of anomaly detection,
2) the system's resilience under adverse network conditions, and
3) its impact on the network lifetime and energy efficiency.

A. Experiment 1: AI Model Performance Evaluation

The first experiment was to check the base performance of LightGBM and LSTM Autoencoder along with their hybrid fusion, which is called the Model Context Protocol (MCP), using the ToN-IoT dataset. As represented in Table I, the hybrid MCP architecture was able to outperform both its model components in anomaly detection.

Compared to traditional single-model approaches such as standalone tree-based classifiers or reconstruction-based detectors, the hybrid MCP demonstrates a clear advantage in balancing precision and recall. Similar trends have been reported in recent hybrid intrusion detection studies, where combining complementary models improves robustness under heterogeneous data distributions.

TABLE I. PERFORMANCE COMPARISON OF DETECTION MODELS ON THE CLEAN TEST SET

Model	Accuracy	Precision	Recall	F1-Score
LightGBM	0.985	0.992	0.991	0.991
LSTM Autoencoder	0.913	0.985	0.914	0.948
MCP (Soft Vote)	0.996	0.995	0.999	0.997

Thus, the MCP achieved an F1-score of 0.997 and near-perfect recall (0.999), demonstrating that the hybrid fusion detects almost all real anomalies with very few false negatives. The LightGBM model had been excellent in detecting discrete, event-based anomalies, while the LSTM Autoencoder provided strong temporal sensitivity. Integration of these two models into the MCP led to a robust mechanism of anomaly detection, which is further consistent with findings from other hybrid intrusion detection studies.

B. Experiment 2: Framework Resilience to Network Faults

The second experiment tested the robustness of the MCP against simulated network disturbances through Gaussian noise and packet loss in the Digital Twin environment. According to Fig. 3, at 20% total fault levels (10% noise and 10% packet loss), the MCP still had an F1-score above 0.94; thus, graceful degradation rather than failure took place. This gradual degradation indicates graceful performance decay rather than abrupt failure, which is a desirable property for resilient WSN deployments operating in unstable environments.

In this way, hybrid detection methods demonstrate their resilience compared with single models regarding environmental instability or data loss. This is the required robustness for sensors in Industry 5.0 scenarios operating under uncertain conditions.

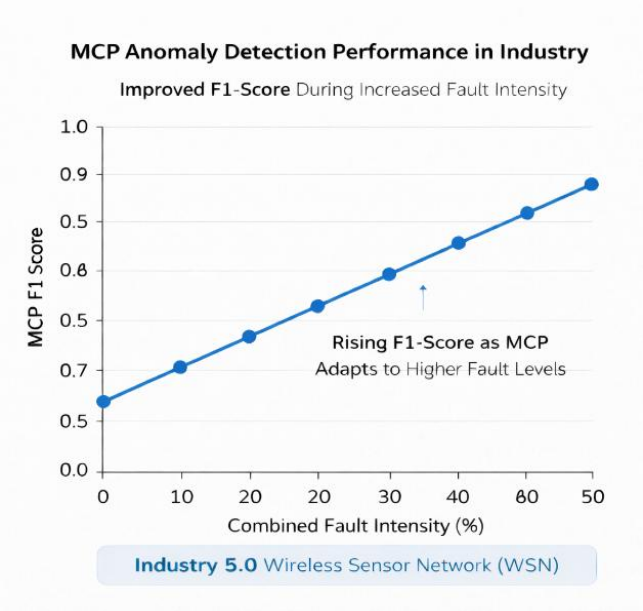


Fig. 3. MCP F1-Score degradation under injected noise and channel faults.

C. Experiment 3: Reputation System and Quarantine Validation

The third experiment focused on the trust adaptation of the Micro-Ledger with a designated faulty sensor node that always sent anomalous readings. Fig. 4 shows the degradation of the reputation score for the faulty sensor node over time until it reached the quarantine threshold ($R < 50$); eventually, the node automatically got isolated from the network.

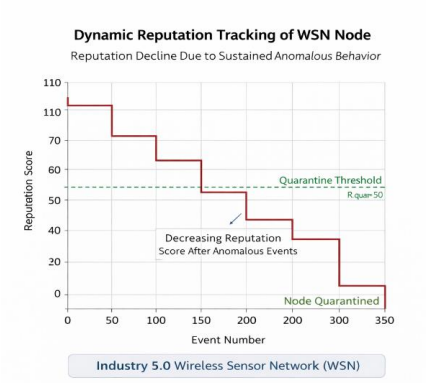


Fig. 4. Reputation score of the designated faulty sensor over time.

As the simulation unfolded, the node's reputation score gradually decreased due to sustained abnormal behavior, eventually crossing the quarantine threshold of 50. The node was launched into quarantine and demoted from active engagement with the network after 312 events. This was illustrated in Fig. 4, allowing us to conclude that the behaviorally driven reputation algorithm is effective, and its real-time action was also effective. The observed convergence toward quarantine reflects the effect of sustained abnormal behavior rather than isolated transient deviations. This time-to-quarantine (TTQ) value highlights the framework's ability to isolate unreliable nodes within a bounded number of observations, contributing to faster recovery and reduced energy waste.

The experiment demonstrated the validation of the metric TTQ and showed that, through the reputation-based system, unreliable nodes are effectively identified and isolated, preserving data integrity and energy efficiency. An adaptive reputation model in WSN environments can be designed with an improvement in the performance of self-healing networks.

D. Experiment 4: Network Lifetime and Efficiency Assessment

The observed network lifetime improvement is consistent with prior trust-aware WSN studies, where early isolation of unreliable nodes reduces redundant communication and unnecessary energy expenditure. Unlike approaches that rely solely on routing optimization, the proposed framework achieves energy savings through behavior-driven trust adaptation. A quantitative comparison of total energy consumption, network lifetime improvement, and Micro-Ledger storage overhead is summarized in Table II.

TABLE II. QUANTITATIVE COMPARISON OF TOTAL ENERGY CONSUMPTION, NETWORK LIFETIME IMPROVEMENT, AND MICRO-LEDGER STORAGE OVERHEAD

Metric	Value
Total Energy (Baseline System)	1465.7 Units
Total Energy (Our Framework)	1191.6 Units
Network Lifetime Improvement	18.7% Energy Saved
Blockchain Storage Overhead	98 KB

Using the framework improved network lifetime by 18.7% due early detection and quarantine of faulty nodes, which limited the number of redundancies. The Micro-Ledger even when being multi-sourced, is still very lightweight and minimal needed storage was approximately 98KB, which is in line with the design goals of energy-constrained WSN applications.

These indications support that a systems-based approach utilizing an aspect of hybrid AI detection integrated with context-based behavior-driven blockchain trust management framework has improved resilience and energy efficiency in practical WSN applications.

E. Discussion

The combined results of the experiments demonstrate both the effectiveness and scalability of the proposed framework. The hybrid MCP indicated statistical significance in detecting improvements compared to the other models, while the Micro-Ledger provides a lightweight, effective mechanism for evolving trust in decentralized WSN context.

The experimental findings outline three key benefits of the proposed framework:

- Detection Robustness: The hybrid MCP exhibits superior event-based and temporal anomaly detection when compared to existing individual ML and DL models. This characteristic of dual detection impacts a significant shortcoming of existing individual models.
- Autonomous Trust Management: The Micro-Ledger becomes capable of evolving trust continuously and autonomously. When it evolves and develops trust autonomously, the network can adapt and self-manage without human operation. This sets a stage for a substantial development in systems that are self-managing toward Industry 5.0.
- Energy Efficiency: The feedback between the MCP and the Micro-Ledger reduces redundancy of transmissions and optimizes battery resources, leading to observable lifetime improvements.

While the results demonstrate strong performance within the simulated environment, it is acknowledged that real-world deployments may introduce additional variability, such as hardware-induced noise or coordinated adversarial behavior. Nevertheless, the controlled evaluation provides valuable insight into the framework's resilience properties and establishes a solid foundation for future physical validation.

VI. CONCLUSION AND FUTURE WORK

A. Conclusion

This study presented a resilience-oriented framework for Wireless Sensor Networks that integrates hybrid AI-based anomaly detection with lightweight, behavior-driven trust management to address reliability and energy efficiency challenges in Industry 5.0 environments. Unlike traditional systems that analyze anomaly detection, data integrity, and trust management in isolation, the framework merges these properties into a seamless adaptive framework consisting of two primary elements:

- A Hybrid AI Anomaly Detection Engine — the Model Context Protocol (MCP) — that utilizes LightGBM and LSTM Autoencoder models to detect both event-based and sequential anomalies.
- A Lightweight Blockchain-Based Reputation Ledger (Micro-Ledger) that manages dynamic node trust through a Proof-of-Authority (PoA) consensus algorithm that optimizes security and energy consumption.

Through Digital Twin–based evaluation, the proposed framework achieved an anomaly detection F1-score of 0.997, isolated persistently unreliable nodes within a bounded number of events, and improved overall network lifetime by 18.7% compared to a baseline system without trust management. The associated Micro-Ledger maintained a low storage overhead of approximately 98 KB, demonstrating suitability for resource-constrained WSN deployments.

These results indicate that combining complementary detection models with adaptive trust evolution can yield system-level benefits beyond detection accuracy alone. By linking anomaly evidence to trust-aware isolation decisions, the framework reduces redundant communication and mitigates long-term energy drain caused by unreliable nodes.

From an Industry 5.0 perspective, the proposed framework aligns with the emphasis on resilient, human-centric, and sustainable cyber–physical systems by enabling autonomous monitoring and adaptive response without continuous human intervention. These directions aim to further enhance adaptability and robustness while preserving the lightweight nature of the proposed design.

This hybridized design also demonstrated that behavioral reputation tracking and AI based anomaly detection are not competing paradigms but rather complementary pillars of secure, sustainable IoT infrastructure.

B. Future Work

While the proposed framework demonstrates strong performance under controlled simulation conditions, several extensions can further improve adaptability and real-world applicability, many opportunities remain for future research and real-life implementation:

- Deployment on physical hardware: Future work includes deploying the framework on physical hardware platforms, such as Raspberry Pi or ESP32-based sensor clusters, to evaluate latency, power consumption, and operational robustness under real-world conditions.
- Adaptive algorithms for reputations: The present model uses fixed reward and penalty values for trust update calculations. Incorporating context-aware or decay-based reputation updates may allow the system to better distinguish transient faults from sustained abnormal behavior.
- Reintroduction of quarantined nodes: In the present implementation, quarantined nodes are isolated temporarily, and future work will further refine probation-based reintegration mechanisms. A revalidation phase of probation could allow quarantined nodes that have been rehabilitated to be reinstated back into the network after a period of observation based on recovery. Such mechanisms would support self-healing behavior without compromising long-term network integrity.
- Inter-cluster trust fabric: The micro-ledger can also be expanded to provide a secure communication pathway between clusters, allowing accordingly distributed action across multiple WSN clusters, which forms the basis for building a trust fabric collaboratively. This direction also opens opportunities for managing trust scalability in large-scale, multi-cluster WSN deployments.
- Cross-domain application: In addition to WSNs, the proposed hybrid AI–blockchain framework could be considered for other applications like industrial robotics, smart grids, or autonomous vehicle networks, where trust is critical for detecting anomalies in real-time.

These extensions aim to enhance robustness and scalability while preserving the lightweight and energy-aware nature of the proposed framework.

C. Closing Remarks

This work demonstrates that resilience in Wireless Sensor Networks can be effectively achieved by tightly coupling intelligent anomaly detection with adaptive, lightweight trust management.

Rather than treating security, reliability, and energy efficiency as isolated objectives, the proposed framework highlights the benefits of addressing them jointly through a feedback-driven design. This perspective is particularly relevant for emerging Industry 5.0 systems, where long-term sustainability and autonomous operation are key considerations.

The combination of interpretable learning components and transparent trust records also supports accountability and auditability in distributed sensing environments. Overall, the findings suggest that hybrid AI and trust-aware architectures provide a practical and extensible foundation for building resilient and sustainable sensor networks in future cyber–physical ecosystems.

ACKNOWLEDGMENT

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REFERENCES

[1] X. Xu, Y. Lu, B. Vogel-Heuser, and L. Wang, “Industry 4.0 and Industry 5.0 – Inception, Conception and Perception,” Journal of Manufacturing Systems, vol. 61, pp. 530–535, 2021.

[2] I. Butun, S. D. Morgera, and R. Sankar, “A Survey of Intrusion Detection Systems in Wireless Sensor Networks,” IEEE Communications Surveys & Tutorials, vol. 16, no. 1, pp. 266–282, 2014.

[3] Y. Zhang, N. Meratnia, and P. Havinga, “Outlier Detection Techniques for Wireless Sensor Networks: A Survey,” IEEE Communications Surveys & Tutorials, vol. 12, no. 2, pp. 159–170, 2010.

[4] M. A. Al-Garadi, A. Mohamed, A. K. Al-Ali, X. Du, I. Ali, and M. Guizani, “A Survey of Machine and Deep Learning Methods for Internet of Things (IoT) Security,” IEEE Communications Surveys & Tutorials, vol. 22, no. 3, pp. 1646–1685, 2020.

[5] M. Emeç and M. Ozcanhan, “A Hybrid Deep Learning Approach for Intrusion Detection in IoT Networks,” Advances in Electrical and Computer Engineering, vol. 22, no. 1, pp. 3–12, 2022.

[6] P. Malhotra, L. Vig, G. Shroff, and P. Agarwal, “Long Short Term Memory Networks for Anomaly Detection in Time Series,” Proceedings of ESANN, 2015.

[7] H. Zhang, Y. Wang, and Q. Han, “USTG: Multivariate Time Series Anomaly Detection via Unsupervised Spatial-Temporal Graph Learning,” 11th Int. Conf. on Behavioural and Social Computing (BESC), Harbin, China, 2024.

[8] M. Deng et al., “Lightweight Trust Management Scheme Based on Blockchain in Resource-Constrained Intelligent IoT Systems,” IEEE Internet of Things Journal, vol. 11, no. 15, pp. 25706–25719, 2024.

[9] D. Stefanescu, P. Galán-García, L. Montalvillo, A. Urbieta, and J. Unzilla, “A Systematic Literature Review of Lightweight Blockchain for IoT,” IEEE Access, vol. 10, pp. 122336–122357, 2022.

[10] S. Sahraoui and A. Bachir, “Lightweight Consensus Mechanisms in the Internet of Blockchained Things: Thorough Analysis and Research Directions,” Digital Communications and Networks, vol. 11, 2025.

[11] S. Awan, M. Sajid, S. Amjad, U. Aziz, M. U. Gurmani, and N. Javaid, “Blockchain-Based Authentication and Trust Evaluation Mechanism for Secure Routing in Wireless Sensor Networks,” Sensors, vol. 21, no. 14, 2021.

[12] G. Ke et al., “LightGBM: A Highly Efficient Gradient Boosting Decision Tree,” Advances in Neural Information Processing Systems 30 (NIPS), 2017.

[13] Y. Liu, J. Wang, Z. Yan, Z. Wan, and R. Jantti, “Blockchain-Based Trust Management for Internet of Things,” IEEE Internet of Things Journal, 2023.

[14] A. Al-Khatib, M. Balfaqih, and A. Khelil, “A Survey on Outlier Detection in Internet of Things Big Data,” IET Book Series on Big Data, 2019.

[15] Y. Lu, C. Liu, K. Wang, H. Huang, and X. Xu, “Digital Twin-Driven Smart Manufacturing: Connotation, Reference Model, Applications, and Research Issues,” Robotics and Computer-Integrated Manufacturing, vol. 61, 2019.

[16] R. Ojstersek, A. Javernik, and B. Buchmeister, “Optimizing Smart Manufacturing Systems Using Digital Twin,” Advances in Production Engineering & Management, vol. 18, no. 4, pp. 475–485, 2023.

[17] H. Liao, M. Z. Murah, M. K. Hasan, A. Aman, J. Fang, X. Hu, and A. U. R. Khan, "A Survey of Deep Learning Technologies for Intrusion Detection in Internet of Things," IEEE Access, 2024.

[18] E. F. Khairullah and N. Alsenani, "A Comprehensive Study of Deep Learning Models for Intrusion Detection in IoT Devices," Engineering, Technology & Applied Science Research, vol. 15, no. 2, pp. 21029–21036, Apr. 2025.

[19] J. Yang, S. He, Y. Xu, L. Chen, and J. Ren, "A Trusted Routing Scheme Using Blockchain and Reinforcement Learning for Wireless Sensor Networks," Sensors, vol. 19, no. 4, p. 970, 2019.

[20] P. Reddy, V. Pham, N. B. Prabadevi, N. Deepa, K. Dev, T. Gadekallu, R. Ruby, and M. Liyanage, "Industry 5.0: A Survey on Enabling Technologies and Potential Applications," Journal of Industrial Information Integration, vol. 26, 2021.

[21] G. Han, J. Jiang, L. Shu, and J. Niu, "Management and Applications of Trust in Wireless Sensor Networks: A Survey," Journal of Computer and System Sciences, vol. 80, no. 3, pp. 602–617, 2014.

[22] D. Airehrour and S. Ray, "SecTrust-RPL: A Secure Trust-Aware RPL Routing Protocol for Internet of Things," Future Generation Computer Systems, vol. 93, pp. 860–876, 2018.

[23] H. Mliki, A. Kaceam, and L. Fourati, "A Comprehensive Survey on Intrusion Detection Based on Machine Learning for IoT Networks," ICST Transactions on Security and Safety, vol. 8, no. 6, 2021.

[24] Y. Yang, L. Wu, G. Yin, L. Li, and H. Zhao, "A Survey on Security and Privacy Issues in Internet of Things," IEEE Internet of Things Journal, 2017.

[25] T. Booij, I. Chiscop, E. Meeuwissen, N. Moustafa, and F. den Hartog, "ToN-IoT: The Role of Heterogeneity and the Need for Standardization of Features and Attack Types in IoT Network Intrusion Data Sets," IEEE Internet of Things Journal, 2021.

[26] N. Maatallah, H. Mestiri, A. A. Mohamed, and M. Machhout, "Enhancing IoT Security for Sustainable Development: A Parity Checking Approach for Fault Detection in PRESENT Block Cipher," Engineering, Technology & Applied Science Research, vol. 15, no. 2, pp. 21982–21988, 2025.

MTML 1.0: A Novel Interlingua Knowledge Representation Model for Machine Translation

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***Abstract*—Machine translation is one of the major areas of both computational linguistics and artificial intelligence that employs computer algorithms to automatically translate text between different natural languages. At present, the advent of Large Language Models (LLMs) has revolutionized this field, marking a significant turning point in its evolution. Despite their impressive capabilities, LLMs still fall short of achieving human-like translation due to key limitations, namely lack of transparency, explainability, and interpretability, the production of non-deterministic outputs, and insufficient support for low-resource languages. To address these challenges, incorporating human-aided translation mechanisms that reflect how the human brain performs translation is effective. Therefore, from a computer science perspective, this motivates the development of a novel hybrid machine translation approach that integrates a rule-based approach with LLM-based methods. This study presents a novel rule-based interlingual knowledge representation model named MTML 1.0 that has been designed and implemented to accurately analyze source language input and systematically structure the resulting linguistic information to facilitate applications, including target language generation and question-answering systems. The MTML 1.0 system consists of four key modules, namely the preprocessing module, morphological analyzer module, syntax analyzer module, and semantic analyzer module. Furthermore, the system has been fully implemented as a web-based application using the Python programming language, with spaCy serving as the foundation for natural language processing tasks. Finally, the functionality of the system has been demonstrated through the development of a prototype question-answering system.**

Keywords*—Machine translation; knowledge representation; LLMs; rule-based approach; hybrid approach

I. Introduction

Machine translation is one of the major branches of natural language processing, and a subfield of computational linguistics as well as artificial intelligence. It refers to machine-aided systems that automatically translate text or speech from one natural language to another natural language without human intervention [1]. The history of machine translation dates to the ninth century when Arab cryptologists introduced methods such as frequency analysis, probability, statistical information, and cryptanalysis which later influenced modern translation systems. Subsequently, the idea of machine translation resurfaced in the 1920s, whereas in 1956, the first machine translation conference marked a significant milestone in this field of research. Since then, machine translation has evolved significantly with various approaches, including dictionary-based approach, rule-based approach, corpus-based approach, statistical approach, hybrid approach, and sophisticated neural network-based approaches [2].

Presently, the field of machine translation has undergone a profound transformation with the emergence of Large Language Models (LLMs) that have revolutionized the way machines understand, generate, and translate human languages. In contrast to neural machine translation (NMT) systems that are trained specifically for translation tasks, Large Language Models (LLMs) like GPT (OpenAI), PaLM (Google), LLaMA (Meta), and mBART are general-purpose deep neural network models which are trained on vast corpora of multilingual data. Moreover, these models can perform a wide range of natural language processing tasks, including machine translation. Therefore, unlike traditional NMT systems, LLMs can translate across multiple language pairs without the need for separate models for each language pair, with great scalability and versatility [3]. Also, LLM-based machine translation provides some promising advantages, such as multilingual capability, contextual understanding, and the ability to perform zero-shot and few-shot learning.

Large Language Models (LLMs) have demonstrated remarkable capabilities and advancements in machine translation, but they still fall short of achieving truly human-like translation due to several major limitations, such as a lack of transparency, explainability, and interpretability, a non-deterministic nature, and their limited support for low-resource languages. Accordingly, to address and potentially overcome these issues, a solution is proposed by considering the human-aided translation processes inspired by the functioning of the human brain [4]. Therefore, the solution is a novel hybrid machine translation approach that combines the strengths of both rule-based methods and large language model (LLM)-based translation systems paradigms to overcome the existing drawbacks of any single methodology. The core premise of this approach is that by judiciously integrating these two paradigms, it is possible to develop a translation system that achieves greater accuracy, fluency, robustness, and human-like performance across a broader range of language pairs and domains [5][6]. However, at present, significant research progress has been made in LLM-based translation; still, there is no proper rule-based machine translation model or a comprehensive interlingua representation model to successfully capture, structure, and represent the linguistic knowledge encoded within source language input.

The aim of this study is to present the design and implementation of a novel system named the MTML 1.0 model (Machine Translation Markup Language 1.0 model), which is a novel rule-based interlingua knowledge representation model specifically designed for machine translation using markup language techniques. The novelty of this system is that it is a universal model that can be applied to any human language. Furthermore, in the implementation of this system, English has been adopted as the source language, and the main advantage of this model is that it can be further applied in a variety of domains, including the generation of target language outputs, question-answering systems, and other natural language processing tasks. Besides, this model has the potential to address several key limitations inherent in modern LLM-based machine translation approaches.

The rest of the study is organized as follows: Section II briefly describes the proposed approach to knowledge representation in machine translation, while Section III and Section IV deeply review the English language and the existing knowledge representation models, respectively. Section V discusses one of the data structure models that is used to represent knowledge, namely XML. Moreover, Section VI presents the design of the MTML 1.0 system, and Section VII explains the working procedure of the developed system. Finally, Section VIII is reserved to conclude the study by presenting future works.

II. Proposed Approach to Knowledge Representation in Machine Translation

The proposed approach of this research is based on how human beings perform translation from one language to another language which is tightly connected with the human brain.

The human brain is the most complex organ in the human body that controls memory, thoughts, emotions, vision, touch, breathing, temperature, motor skills, and many other processes effectively by sending and receiving chemical and electrical signals throughout the human body [7]. Structurally, the brain is divided into three main regions, namely the cerebrum, cerebellum, and brainstem. Fig. 1 illustrates the major parts of the human brain.

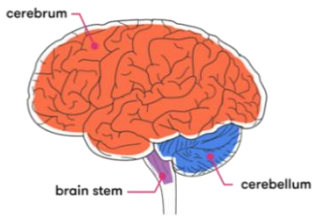


Fig. 1. Major parts of the human brain.

The cerebellum, or little brain, is located at the back of the head and performs maintaining posture, balance, and equilibrium, thinking, emotions, and social behavior. Secondly, the brainstem serves as a connection pathway between the cerebrum and the spinal cord. Thirdly, the cerebrum is the largest part of the brain that is divided into left and right hemispheres symmetrically by the longitudinal fissure. The outer part of the cerebrum is named as cerebral cortex, which is arranged as a collection of layers. This cortex is divided into fifty different functional areas named Brodmann's areas. Fig. 2 illustrates the Brodmann areas.

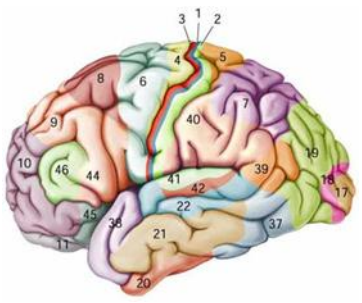


Fig. 2. Brodmann areas.

Brodmann areas were first introduced and systematically numbered in the early 20th century by the German anatomist Korbinian Brodmann based on the cytoarchitectural organization of neurons. Accordingly, Brodmann mapped the human brain and identified 52 distinct regions that were numbered from 1 to 52. These regions are associated with diverse functions such as motor control, cognition, and sensation. Notably, Brodmann area 22 is included in Wernicke's area, while areas 44 and 45 are located within Broca's area. Furthermore, both Wernicke's and Broca's areas are critical for language processing, although they perform entirely distinct functions [8]. From a translation perspective, humans must successfully comprehend and store linguistic information related to morphology, syntax, semantics, thematic roles, grammar rules, and language fluency. Achieving accurate and precise translation requires not only knowledge of grammar and linguistic structures but also language fluency, which is developed through frequent interaction and practice with the language. Within the human brain, Wernicke's area plays a key role in language fluency, while Broca's area is primarily responsible for processing grammatical rules. By simultaneously engaging both of these regions, humans are able to generate highly effective, correct, and contextually accurate translations [9].

Computationally, this scenario can be substituted with the aid of a hybrid machine translation approach that is a combination of a rule-based approach and an LLM-based translation approach. More specifically, the rule-based approach can be used to demonstrate the behavior of Broca's area, while the LLM-based translation approach can be used to demonstrate the behavior of Wernicke's area.

III. Overview of the English Language

English is the main global lingua franca that is widely used across the world in diverse domains such as communication, education, business, science and technology, tourism, trade, and the Internet. English originated in England and is currently recognized as the official or co-official language in more than fifty-nine (59) countries. Linguistically, it is classified as a West Germanic language within the Indo-European language family. The history of the English language dates back to the 5th century and is divided into four major eras, namely Old

English, Middle English, Early Modern English, and Modern English. Today, the form predominantly used worldwide is Modern English [10].

The English language comprises twenty-six (26) letters, including five (5) vowels. From a computational grammar perspective, English can be analyzed across four main areas such as grammatical units, word classes, phrases, and sentence elements. The grammatical units of English comprise words, phrases, clauses, and sentences, while the word classes (or parts of speech) are traditionally categorized into eight (8) groups, namely nouns, verbs, adjectives, adverbs, pronouns, prepositions, determiners, and conjunctions. Similarly, English phrases can be classified into five (5) types, namely noun phrases, verb phrases, adjective phrases, adverb phrases, and prepositional phrases, and finally, the sentence elements of English include the subject, verb, object, complement, and adverbial [11]. From a machine translation perspective, the English language can be systematically analyzed by considering its core linguistic elements, namely morphology, syntax, and semantics. A brief description of each of these elements is provided below.

A. English Language Morphology

Morphology is one of the major areas in linguistics that refers to the scientific study of the internal structure of words with respect to stems, root words, prefixes, and suffixes. English language morphology can be classified into four main groups such as noun morphology, adjective morphology, verb morphology, and adverb morphology. In the English language, nouns play a significant role as subjects, direct objects, indirect objects, and in various other syntactic positions. Morphologically, English nouns participate in both inflection and derivation. Inflection generates different grammatical forms of the same word, whereas derivation produces entirely new words [12]. Furthermore, based on inflectional patterns, English nouns can be classified into regular nouns and irregular nouns. Overall, English nouns conform to ten key morphological rules, which are summarized in Table I [13].

TABLE I. MORPHOLOGICAL RULES FOR ENGLISH NOUNS

Grammar	Morphology		
	Base form	***Add***	***Remove***
Singular	Noun	-	-
Plural	Noun	s	-
Plural	Noun	es	-
Plural	Noun	ies	y
Plural	Noun	ves	fe
Singular Possessive	Noun	‘s	-
Plural Possessive	Noun	s’	-
Singular	Verb	er	-
Plural	Verb	ers	-
Singular	Verb	ment	-
Plural	Verb	ments	-

Secondly, verbs in the English language exhibit five (5) primary morphological forms, such as the simple present tense, the third-person singular form, the simple past tense, the present participle, and the past participle. In addition, five major morphological rules govern the formation and transformation of English verbs, and these rules are summarized in Table II.

TABLE II. MORPHOLOGICAL RULES FOR ENGLISH VERBS

Grammar	Morphology		
	Base form	***Add***	***Remove***
Infinitive	Verb	-	-
Simple present	Verb	s	-
Present Participle	Verb	ing	-
Past	Verb	ed	-
Past Participle	Verb	ed	-

As the next morphological categories of English language, English adjective morphology shares 13 rules that are shown in Table III.

TABLE III. MORPHOLOGICAL RULES FOR ENGLISH ADJECTIVES

Grammar	Morphology		
	Base form	***Add***	***Remove***
(Positive) Adjective	Adjective	-	-
(Positive) Adjective	Noun	ish	-
(Positive) Adjective	Verb	ful	-
(Positive) Adjective	Verb	less	-
(Positive) Adjective	Noun	en	-
(Positive) Adjective	Verb	active	-
(Positive) Adjective	Verb	able	-
(Comparative) Adjective	Adjective	er	-
(Comparative) Adjective	Adjective	r	-
(Comparative) Adjective	Adjective	ier	y
(Superlative) Adjective	Adjective	est	-
(Superlative) Adjective	Adjective	st	-
(Superlative) Adjective	Adjective	iest	y

Finally, adverbs are used to provide additional information about a verb, an adjective, or another adverb. In English, many adverbs are formed by adding the suffix -ly to adjectives. Beyond this common pattern, adverbs also serve to explain aspects such as how something happens, as well as when, where, in what way, and to what extent an action occurs. Examples of these relationships are summarized in Table IV, which illustrates the connections between verbs and their corresponding adverbs.

TABLE IV. CONNECTIONS BETWEEN VERBS AND ADVERBS

Verb	Adverb	Example
When?	early	She arrives early in the morning
How?	carefully	She drives carefully
Where?	everywhere	They go everywhere together
In what way?	slowly	She walks slowly
To what extent?	slowly	It is slowly hot

B. Syntax of the English Language

The architecture of English syntax is a multifaceted domain that integrates principles of hierarchical structure, constituent arrangement, and transformational operations to govern sentence formation. Fundamentally, syntax examines how words are systematically organized to form phrases and sentences. Consequently, it encompasses key grammatical aspects such as word order, sentence structure, sentence complexity, and grammar rules. In the case of English, five basic syntactic rules can be identified, along with seven major syntactic patterns that represent the standard word order of sentences and clauses [14][15]. These are summarized in Table V and Table VI, respectively.

TABLE V. SYNTACTIC RULES IN THE ENGLISH LANGUAGE

Syntactic Rule	Description
Rule 1	All sentences need a subject and a verb, except imperative sentences.
Rule 2	In a sentence, the subject comes first, and the verb comes second. When the sentence has an object, it comes third after the verb.
Rule 3	A single sentence must contain one main idea. When a sentence contains two or more ideas, it needs to be broken up into multiple sentences.
Rule 4	Dependent clauses need a subject and a verb.
Rule 5	Adjectives and adverbs are placed in front of the appropriate words. When there are multiple adjectives describing the same noun, one needs to use the proper adjective order, known as royal order.

TABLE VI. MAJOR SYNTACTIC PATTERNS IN THE ENGLISH LANGUAGE

Pattern Type	Pattern
Pattern 1	Subject → Verb
Pattern 2	Subject → Verb → Direct Object
Pattern 3	Subject → Verb → Subject Complement
Pattern 4	Subject → Verb → Adverbial Complement
Pattern 5	Subject → Verb → Indirect Object → Direct Object
Pattern 6	Subject → Verb → Direct Object → Object Complement
Pattern 7	Subject → Verb → Direct Object → Adverbial Complement

C. Semantics of the English Language

Semantics is another major branch of linguistics that focuses on the study of meaning in language. It primarily examines how expressions are constructed across different layers of language, such as words, clauses, sentences, and texts, and how the meanings of these elements interact with and influence one another. Semantics can be viewed from two main perspectives, namely the internal side and the external side. The internal side concerns the relationship between words and mental phenomena, such as conceptual representations and ideas, while the external side investigates how words correspond to objects in the real world and the conditions under which a sentence can be judged as true or false. Furthermore, semantics can be divided into several subfields, including lexical semantics, phrasal semantics, sentence-level semantics, and paragraph-level semantics [16].

Lexical semantics is the study of lexical relations between words. The aim of lexical semantics is to analyze words in depth, as words may have multiple meanings. Lexical semantics can be divided into two approaches such as semasiology and onomasiology. The semasiology approach starts with words and examines their meanings, while onomasiology goes from meaning to word. Secondly, phrase-level semantics are used to bridge the gaps between lexical semantics and sentence-level semantics. Thirdly, sentence-level semantics are used to study the meaning of a sentence by analyzing how words and phrases combine to form meaningful statements. Moreover, thematic relationships or semantic roles are used to build the meaning of a sentence by considering the relationship between phrases presented in a sentence. Table VII shows the semantic roles of a sentence. Finally, paragraph-level semantics takes the context to contribute to meaning by analyzing the complete knowledge of each sentence in a paragraph.

TABLE VII. MAJOR SEMANTIC ROLES OF A SENTENCE

Relationship	Description
Agent	The entity that acts intentionally
Experiencer	The entity that experiences a state or sensation
Patient	The entity that is affected by the action or undergoes a change of state
Theme	The entity that will not be affected because of an action
Instrument	The means by which an action is performed, often with the help of a tool or object
Force	Mindlessly performs the action.
Location	Where the action occurs
Goal	The endpoint or destination of an action or movement
Recipient	The entity that receives something as a result of an action
Source	Where the action originated
Time	The time at which the action occurs
Beneficiary	The entity for whose benefit the action occurs
Manner	The way or method by which an action is performed
Purpose	The reason for which an action is performed
Cause	The reason why an action or state occurs

IV. KNOWLEDGE REPRESENTATION TECHNIQUES IN MACHINE TRANSLATION

Knowledge representation in machine translation is a pivotal area that focuses on developing formalisms to represent information in ways that machines can effectively process and thereby bridge the gap between different languages. Knowledge representation involves encoding human knowledge into machine-readable formats that capture meaning, context, and linguistic nuances. Furthermore, these representations enable machine translation systems to perform complex tasks requiring reasoning, inference, and understanding [17] [18]. From a machine translation point of view, knowledge representation not only maps words from one language to another, but also models morphology, syntax,

semantics, and discourse-level information and provides a foundation for reasoning, inference, and disambiguation capabilities that go beyond simple word-to-word translation. There are several major knowledge representation techniques related to machine translation, such as lexicons or bilingual dictionaries, frames, semantic networks, ontologies, interlingua representations, feature structures, and logical representations. A brief description of each of these techniques is presented below [19].

A. Lexicon

A lexicon or bilingual dictionary serves as a fundamental knowledge representation tool in machine translation, which is a structured list of word-level entries for one or more languages. It is widely employed across different MT paradigms such as the rule-based approach, hybrid approach, and neural approach. A lexicon typically consists of source-language words, their target-language equivalents, and associated linguistic information such as part-of-speech categories, morphological features, and semantic roles. It supports machine translation by enabling word lookup to find equivalent terms in the target language, facilitating disambiguation by selecting the correct sense of a word based on part of speech or context, and handling morphology effectively by adjusting word forms to match tense, number, gender, and other grammatical features. Furthermore, it supports different machine translation approaches, such as a rule-based approach as the core component that is deeply integrated with grammar rules, a hybrid approach as statistical or neural models to improve accuracy, and a neural approach as embeddings. Therefore, lexicons offer several advantages, such as providing clear word mappings, supporting low-resource languages, and enabling fine-grained control over translation. However, they have some limitations, including the time-consuming effort required for their development and maintenance, as well as difficulties in handling idiomatic expressions and context-dependent translations [20].

B. Frames

A frame is a structured knowledge representation technique introduced by Marvin Minsky in 1975. In the context of machine translation, frame representation is employed to capture semantic structures as it organizes knowledge in a way that mirrors human cognitive processes. The structure of the frame contains three components, namely frame name (the type of the concept), slots/roles (key components of the concept), and fillers (actual values in a sentence). It supports machine translation in different ways, such as facilitating semantic role labeling to identify semantic roles in a sentence, disambiguation by resolving meanings, generating target language sentences, and cross-lingual mapping. Furthermore, it supports different machine translation approaches, such as an interlingua-based approach by representing interlingual meaning using frames, a hybrid approach by combining frame semantics with statistical or neural components, and a neural approach by improving translation accuracy. Therefore, frame representation offers several advantages, such as handling variations in word order, providing better translation of idiomatic and context-rich expressions, and supporting rich semantic reasoning. However, it also has some limitations, including structural complexity, susceptibility to errors during frame extraction, and the requirement for large annotated corpora to function effectively [21].

C. Semantic Networks

Semantic networks are graph-based knowledge representation models in which concepts or words are represented as nodes and the semantic relationships between them are represented as edges. In machine translation systems, semantic networks are commonly used to support tasks such as lexical disambiguation, word sense disambiguation to identify the correct sense of a polysemous word, and synonym replacement to improve fluency by selecting contextually appropriate synonyms during target language generation. Besides, it supports different machine translation approaches, such as rule-based approaches by supporting semantic level transfer and disambiguation, a hybrid approach by improving translation fluency and accuracy via contextual knowledge, and a neural approach as an external knowledge base to enhance model understanding. Therefore, semantic networks offer several benefits, including maintaining semantic coherence, supporting meaning preservation across structurally different languages, and handling synonyms, antonyms, and context-sensitive words. Nevertheless, they also have some drawbacks, such as being labor-intensive to construct, having limited coverage across different domains, and struggling with idiomatic expressions [22].

D. Ontologies

Ontologies are formal and structured representations of knowledge that facilitate understanding the meaning of a language by accurately modeling real-world knowledge and the semantic roles associated with words. The structure of an ontology consists of five key elements such as class/concept (a category or type of thing), instance (a specific object of a class), property or attribute (describes a feature or relationship), relation (links between concepts), and axioms/ rules (constraints or logic). Ontologies support various machine translation tasks such as semantic understanding, word sense disambiguation, and cross-lingual mapping that aligns equivalent concepts across different languages to achieve more accurate translations. Moreover, it supports different machine translation approaches, such as rule-based approaches to enhance rule creation and semantic interpretation, an interlingua-based approach to define interlingual concepts to map source language input to target language output, a hybrid approach to improve context handling, and a neural approach to guide the translation via fine-tuning using external ontologies. Accordingly, ontologies offer some benefits such as improving semantic and contextual accuracy, enabling domain-specific translations, facilitating concept alignment across languages, and supporting intelligent reasoning and inference. However, it has some drawbacks, such as a labor-intensive process of creation and maintenance, limited coverage in low-resource languages, and the difficulty of integrating them with end-to-end neural models without specialized techniques [23].

E. Interlingua Representation

Interlingua serves as a universal pivot language in interlingual-based machine translation systems that enables translation across multiple source and target languages without the need for direct pairwise mappings. Interlingua captures the

deep semantic content of the source text and performs more flexible and scalable multilingual translation by abstracting away from the grammatical and lexical structures of individual languages. Primarily, an interlingua is composed of three key elements such as concepts, which represent language-independent notions; semantic roles, which define relationships between concepts; and attributes, which describe their properties. Also, it supports a rule-based approach by enabling semantic abstraction to capture meanings of source or target language grammar, context handling to represent roles and relationships, disambiguation to resolve ambiguities, and modularity to decouple language analysis from language generation. Furthermore, the interlingua approach offers several advantages, including language independence, preservation of meaning across languages, scalability through the reduction of required translation modules, and reusability as a single interlingua can support multiple target languages. However, it also presents certain drawbacks such as high complexity and domain sensitivity, high computational cost and resource intensity, and limited flexibility when compared to modern data-driven models [24].

F. Feature Structure

Feature structure is a formal framework that provides a robust mechanism for representing linguistic information through attribute–value pairs that are commonly referred to as features. This approach enables a structured and hierarchical organization of linguistic features by representing the grammatical, syntactic, and semantic properties of sentences, which are essential for effective machine translation. Fundamentally, this knowledge representation approach is employed to maintain morphological and syntactic consistency, enforce agreement rules, and support transfer rules in structural mapping between source and target languages. Furthermore, it supports different machine translation approaches, such as rule-based approaches by acting as a core component for grammar-based parsing and generation, and a hybrid approach by combining feature-based rules with statistical or neural techniques. Moreover, feature structures offer several advantages, including high expressiveness, suitability for morphologically rich languages, support for linguistic constraints and agreement checking, and facilitation of language-neutral parsing and transfer. However, they also present notable drawbacks such as structural complexity, high computational cost, limited scalability, and the need for extensive manual rule creation [25].

G. Logical Representation

Logical representation is a proper method for expressing the meaning of sentences through logic-based expressions, including propositional logic, predicate logic, and temporal logic. In machine translation, logical representation is primarily used to capture the underlying meaning of sentences at a semantic level. The structure of logical representation comprises five key elements, such as a predicate that represents properties or relationships, arguments that denote the entities involved in an action, quantifiers to express universal or existential statements, connectives that serve as logical operators, and tense, which is represented using formal logical expressions. Moreover, logical representation serves different roles in machine translation, including facilitating semantic analysis, supporting inference and reasoning, enabling disambiguation, and assisting in cross-linguistic mapping. In addition, logical representation supports various machine translation approaches, such as rule-based approaches to perform pattern matching and structure inference, an interlingua-based approach to serve as a language-neutral representation, and in hybrid or neural approaches to perform semantic annotation, evaluation, or control. Consequently, it offers some advantages, including high precision, universality, and support for reasoning. However, it also presents drawbacks such as structural complexity, high resource requirements, data scarcity, and limited suitability for idiomatic or metaphorical expressions.

V. Extensible Markup Language (XML)

Extensible Markup Language, commonly abbreviated as XML, is a markup language that has been designed to store, transport, and structure data in a platform-independent and human-readable format. Therefore, XML contains a set of rules to encode documents in a proper format that is both human-readable and machine-readable. The main purpose of this language is serialization, which involves storing, transmitting, and reconstructing arbitrary data. Generally, XML labels, categorizes, and structurally organizes information using tags. Furthermore, these tags define the data structure and contain metadata. Fundamentally, XML is used to facilitate various areas such as web services, including SOAP and RESTful services, linguistics and NLP to annotate corpora and feature structures, knowledge representation to encode ontologies, frames, and dictionaries, and different machine translation systems. There are some major features in XML, such as extensible, hierarchical, human-readable, machine-readable, and platform-independent. Moreover, XML has four key components, such as elements that can be described as a data container with opening and closing tags, attributes that store metadata inside the start tag, the root element, which is the main parent element of the XML tree, and nested elements that are elements inside other elements [26].

XML offers several benefits, such as being easy to understand and edit, highly portable and interoperable, widely supported by programming languages and tools, including Java, Python, and C#, and standardized across many domains. However, it also has notable drawbacks, including verbosity, slower parsing compared to binary formats, and inefficiency for real-time data transmission over networks.

VI. Design of the MTML Model

The Machine Translation Markup Language (MTML) 1.0 model is a novel universal rule-based interlingual knowledge representation model specifically designed for machine translation tasks using markup language techniques. The primary objective of this model is to represent and store all the linguistic knowledge extracted from the source language input, which can then be utilized to generate output in any target language. To achieve this, the system deeply analyzes the source language input by following the machine translation pyramid that is shown in Fig. 3 with respect to key linguistic levels such as morphology, syntax, and semantics.

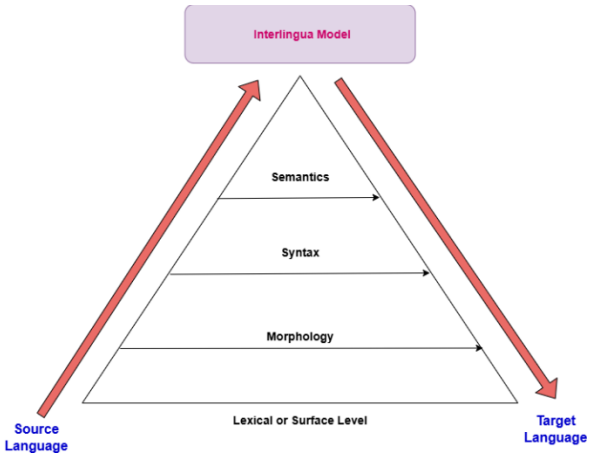


Fig. 3. Machine translation pyramid.

The extracted knowledge is subsequently represented and stored in a well-structured format, which is named as an MTML script that is a combination of XML and frame-based representation. The main advantage of this model lies in its versatility; it can be employed not only for generating target language output but also for supporting applications such as question-answering systems and other natural language processing tasks. Moreover, by following a rule-based approach, MTML 1.0 has the potential to overcome several limitations inherent in modern LLM-based machine translation approaches. Fig. 4 shows the pipeline of the MTML 1.0 model. Fig. 5 illustrates the design of the MTML 1.0 model, and the brief description of the design is provided below:



Fig. 4. Pipeline of the MTML 1.0 model.

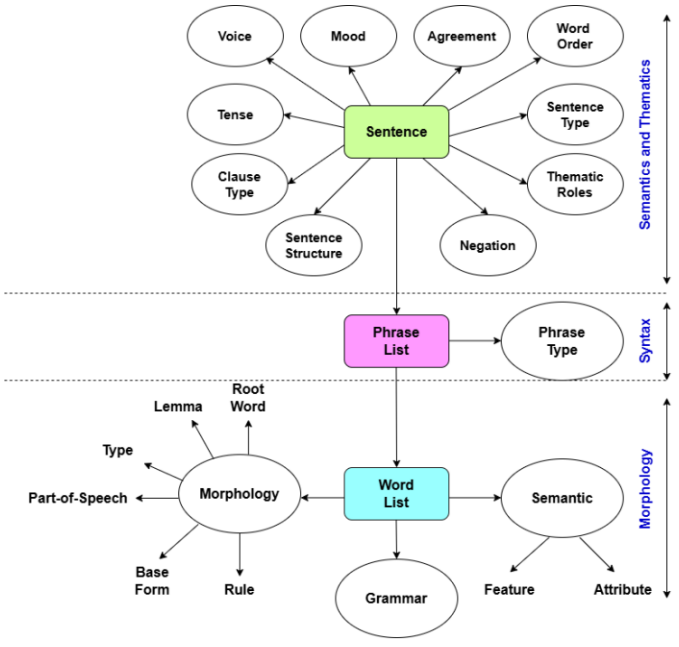


Fig. 5. Design of the MTML 1.0 model.

The MTML 1.0 model has been designed considering the common grammatical structure that is applied for any language. Furthermore, this system follows a top–down approach in its analysis. First of all, it begins with an English sentence as input and sequentially processes it through ten key linguistic properties that characterize English sentences, namely sentence structure, clause type, tense, voice, mood, agreement, word order, sentence type, negation, and thematic/semantic roles as follows:

1) Sentence structure – The model first identifies the four main structural components, namely subject, predicate, object, and modifiers.

2) Clause type – It then determines whether the sentence contains an independent clause, a dependent clause, or a relative clause.

3) Tense – The model detects the major tense (present, past, future) and further specifies the appropriate sub-tense.

4) Voice – It classifies the sentence as being in the active voice or passive voice.

5) Mood – The model identifies the speaker's intention by detecting moods such as indicative, imperative, or subjunctive.

6) Agreement – It verifies grammatical subject–verb agreement and noun–pronoun agreement.

7) Word order – The system checks if the sentence follows the standard Subject–Verb–Object (SVO) order or an inverted order (commonly used in questions).

8) Sentence type – It categorizes the sentence as declarative, interrogative, imperative, or exclamatory.

9) Negation – The model detects whether the sentence contains a negation property.

10) Thematic/semantic roles – Finally, it assigns semantic roles to constituents, including agent, experiencer, patient, theme, instrument, force, location, direction/goal, recipient, source, time, beneficiary, manner, purpose, and cause.

After completing this first stage of analysis, the model proceeds to the second stage, where it identifies and segments the sentence into five major phrase types, such as noun phrases, verb phrases, adjective phrases, adverb phrases, and prepositional phrases. These are further analyzed syntactically using a parse tree. Furthermore, in the third stage, the detected phrases are tokenized into words, and each word undergoes morphological analysis to examine its internal structure and grammatical features.

The architecture of the MTML 1.0 system is structured into four key modules, namely the Preprocessing Module, Morphological Analyzer Module, Syntactic Analyzer Module, and Semantic Analyzer Module. The overall system architecture is illustrated in Fig. 6, and a brief description of each module is provided below.

A. Preprocessing Module

This module serves as the foundational step in the MTML 1.0 system, where it accepts an English sentence as input and converts it into a structured and standardized form by functioning as a filter. Specifically, it eliminates unnecessary elements from the input sentence that are not relevant to the

analysis process, such as special characters, extra white spaces, unreadable symbols, and abbreviations. Once refined, the module produces a processed output, which is then passed to the second key component of the system, named the morphological analyzer module.

B. Morphological Analyzer Module

The morphological analyzer module is the second major module of the MTML 1.0 system, which takes the output generated by the preprocessing module as its input. The primary function of this module is to perform morphological analysis of the source sentence and identify the morphological features of each word. To achieve this, the module consists of five sub-modules, namely the tokenizer, part-of-speech tagger, morphological parser, feature extractor, and morphological output generator. At first, the tokenizer splits the sentence into individual words, which are then passed to the part-of-speech tagger to map them to their base forms with corresponding tags. Secondly, the morphological parser applies morphological rules to decompose inflected words into morphemes, and in the third step, the feature extractor identifies additional linguistic attributes such as root word, number, and word type. Finally, the morphological output generator produces the analyzed output that is enriched with structured morphological tags.

C. Syntax Analyzer Module

This module is the third major component of the MTML 1.0 system, consisting of two sub-modules, namely the syntactic parser and the syntax output generator. The primary function of the syntax analyzer module is to analyze the structure of the input sentence by searching all the phrases available in the input. In syntactic parsing, two main approaches are commonly used, namely dependency parsing and constituency parsing. For this system, a constituency parser is employed to construct the syntactic structure of the sentence. This parser detects various phrase types present in the input, such as noun phrases, verb phrases, adjective phrases, adverb phrases, and prepositional phrases. Once the parsing process is completed, the syntax output generator produces a structured representation of the sentence by visualizing its syntactic organization through a predefined tag set.

D. Semantic Analyzer Module

The semantic analyzer module is the final module of the MTML 1.0 system. Its primary responsibility is to interpret the meaning of the source language sentence and ensure that the extracted meaning is accurately preserved for subsequent applications, such as generating target language output or answering questions in a Q&A system. This module consists of three sub-modules, namely the semantic role labeler module, grammar identification module, and semantic output generator. The semantic role labeler identifies the thematic relationships present in the input sentence, while the grammar identification module handles complex grammatical tasks such as sentence structure, clause type, tense, voice, mood, agreement, word order, and sentence type. Finally, the semantic output generator produces a structured representation of the sentence's semantic features organized through a predefined tag set.

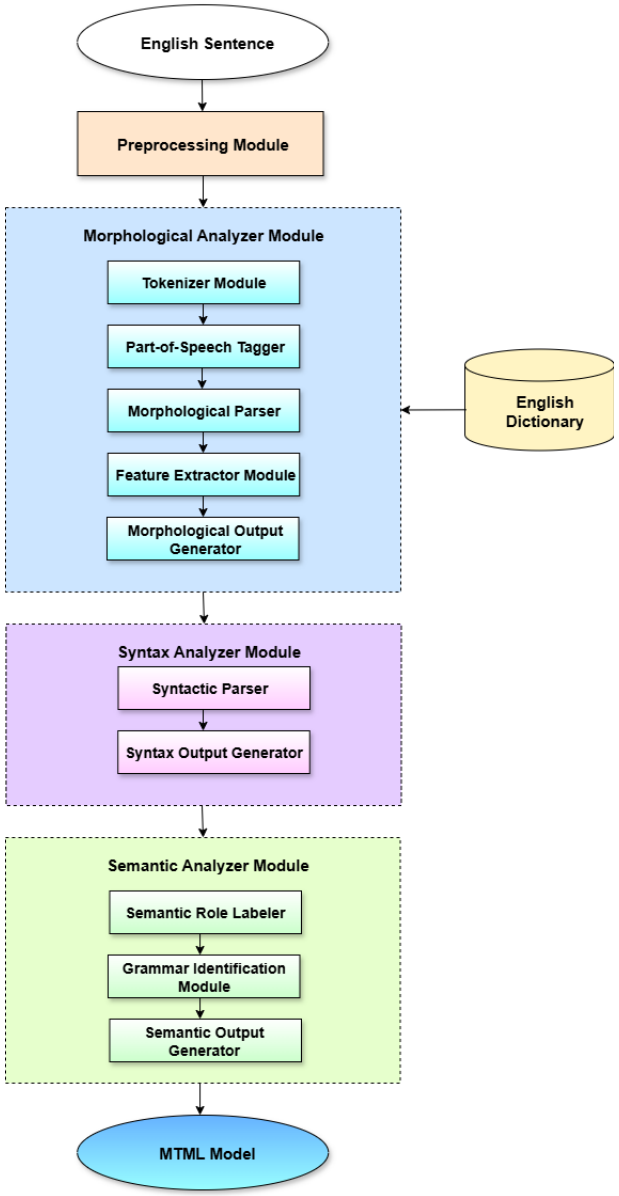


Fig. 6. Architecture of the MTML 1.0 system.

E. MTML 1.0 Model

MTML (Machine Translation Markup Language) 1.0 model represents the final output of the system that is produced after a deep analysis of the source language sentence. It can be introduced as a novel frame-based knowledge representation model specifically designed for machine translation tasks through markup language techniques. Essentially, this model represents and stores all linguistic information and knowledge contained in the source text using a structured set of tags that are automatically filled during the analysis process. The significance of this model lies in its role as a successful interlingua representation, which can be applied to various tasks such as the generation phase of machine translation systems, as well as the design and development of Q&A systems.

VII. MTML 1.0 System in Action

This section provides a brief overview of the working procedure of the MTML 1.0 system. The system has been implemented as a web-based application using the Python programming language. Furthermore, all the natural language processing (NLP) tasks within the system are modeled using spaCy, which is an advanced open-source NLP library. Unlike the Natural Language Toolkit (NLTK), which is widely adopted for educational and research purposes, spaCy is primarily designed to support NLP tasks within deep learning workflows and is well-suited for both research and industrial applications. Built on Thinc as its backend, spaCy offers a range of robust features including tokenization, part-of-speech (POS) tagging, named entity recognition (NER), dependency parsing, lemmatization, sentence segmentation, word vectors, language models, and rule-based matching, etc. Fundamentally, the MTML 1.0 system consists of two Graphical User Interfaces (GUIs) that are shown in Fig. 7 and Fig. 8, respectively.

The first graphical user interface (GUI) of the system, shown in Fig. 7, allows the user to input an English sentence. This interface includes three buttons such as "Generate", "Clear", and "Next". The "Generate" button produces the MTML script representing the linguistic knowledge extracted from the given input sentence. This script is then downloaded as an XML file, which can be utilized for further applications. The "Clear" button erases the entered input, while the "Next" button navigates the user to the second GUI, as shown in Fig. 8.

The second GUI has been designed to demonstrate a Q&A system that uses the MTML script as input to answer common questions about English sentences. In this interface, users can upload the previously generated MTML script and query the system to test its performance. Specifically, the system can respond to ten predefined questions related to English sentence analysis as follows:

1) Who did this?
2) What did you do?
3) To whom was this done?
4) When did it happen?
5) Where did it happen?
6) Why did it happen?
7) How did it happen?
8) What is the subject of the sentence?
9) What is the verb of the sentence?
10) What is the object of the sentence?



Fig. 7. GUI No. 1 of the MTML 1.0 system.

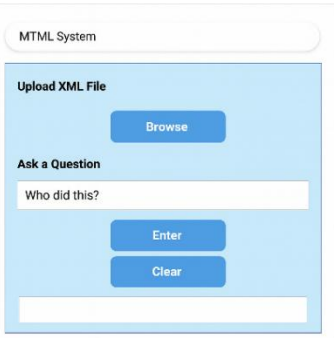


Fig. 8. GUI No. 2 of the MTML 1.0 system.

VIII. Conclusion and Future Works

This study presented the design and implementation of a novel rule-based knowledge representation model for machine translation, namely the MTML 1.0 system. The primary objective of this model is to integrate with existing LLM-based machine translation approaches in order to develop a hybrid system that more closely simulates human cognitive translation processes. The novelty of this model is that it is a universal interlingua model that can be used to analyze any natural language. In the implementation process, the model has been developed for the English language. The architecture of the MTML 1.0 system consists of four core modules, namely the preprocessing module, the morphological analyzer module, the syntax analyzer module, and the semantic analyzer module. The system has been successfully implemented as a web-based application using the Python programming language with all NLP-related tasks modeled through the spaCy library. Furthermore, the functionality of the system has been demonstrated through a prototype Q&A application, which highlights its potential for broader applications in natural language understanding and generation.

As the next stage of this research, the existing MTML 1.0 system will be extended into MTML 2.0, with the capability to address tasks that are challenging for LLM-based approaches, such as the effective handling of idiomatic expressions in the English language. In addition, the performance of the upgraded system will be systematically tested and evaluated within a controlled laboratory environment using human evaluators to ensure reliability and practical applicability.

References

[1] H. Mercan, Y. Akgün, and M. C. Odacioğlu, "The Evolution of Machine Translation: A Review Study," Int. J. Lang. Transl. Stud., vol. 4, no. 1, pp. 104–116, 2024, [Online]. Available: https://dergipark.org.tr/tr/pub/lotus.

[2] M. S. H. Ameur, F. Meziane, and A. Guessoum, "Arabic Machine Translation: A survey of the latest trends and challenges," Comput. Sci. Rev., vol. 38, p. 100305, Nov. 2020, doi: 10.1016/J.COSREV.2020.100305.

[3] S. Han, M. Wang, J. Zhang, D. Li, and J. Duan, "A Review of Large Language Models: Fundamental Architectures, Key Technological Evolutions, Interdisciplinary Technologies Integration, Optimization and Compression Techniques, Applications, and Challenges," Electron. 2024, Vol. 13, Page 5040, vol. 13, no. 24, p. 5040, Dec. 2024, doi: 10.3390/ELECTRONICS13245040.

[4] W. Li et al., "TACTIC: Translation Agents with Cognitive-Theoretic Interactive Collaboration," 2025, [Online]. Available: http://arxiv.org/abs/2506.08403.

[5] H. W. Xuan, W. Li, and G. Y. Tang, "An advanced review of hybrid machine translation (HMT)," Procedia Eng., vol. 29, pp. 3017–3022, 2012, doi: 10.1016/j.proeng.2012.01.432.

[6] A. Anugu and G. Ramesh, "A Survey on Hybrid Machine Translation," E3S Web Conf., vol. 184, pp. 1–6, 2020, doi: 10.1051/e3sconf/202018401061.

[7] K. A. Maldonado and K. Alsayouri, "Physiology, Brain," StatPearls, Mar. 2023, Accessed: Sep. 02, 2025. [Online]. Available: https://www.ncbi.nlm.nih.gov/books/NBK551718/.

[8] K. Zilles, "Brodmann: a pioneer of human brain mapping — his impact on concepts of cortical organization," pp. 3262–3278, 2018, doi: 10.1093/brain/awy273.

[9] O. Articles, "Bidirectional Connectivity Between Broca ' s Area and Wernicke ' s Area During Interactive Verbal Communication," vol. 12, no. 3, pp. 210–222, 2022, doi: 10.1089/brain.2020.0790.

[10] F. Sharifian, "English as an international language: An overview," English as an Int. Lang. Perspect. Pedagog. Issues, pp. 1–18, 2009, doi: 10.21832/9781847691231-004.

[11] R. Hogg and D. Denison, A history of the english language. 2006.

[12] Z. Altan, "the Role of Morphological Analysis in Natural Language Processing," Anadolu Univ. J. Sci. Technol., vol. 3, no. January 2002, pp. 59–76, 2002.

[13] "Study Morphological Complexity of Non-Related Languages to Build a Universal Morphological Model for Machine Translation," Int. J. Comput. Appl. Technol. Res., Nov. 2024, doi: 10.7753/IJCATR1311.1010.

[14] "What Is Syntax? Definition, Rules, and Examples | Grammarly." https://www.grammarly.com/blog/grammar/syntax/ (accessed Sep. 02, 2025).

[15] A. Kulmizev and J. Nivre, "Schrödinger ' s tree — On syntax and neural language models."

[16] L. Rissman and A. Majid, "Thematic roles: Core knowledge or linguistic construct?," Psychon. Bull. Rev., vol. 26, no. 6, pp. 1850–1869, 2019, doi: 10.3758/s13423-019-01634-5.

[17] R. Zou, W. Chang, S. Gao, and S. Qin, "Strategies for improving the quality of computer-assisted translation based on internet," Int. J. Adv. Acad. Stud., vol. 4, no. 4, pp. 156–158, Oct. 2022, doi: 10.33545/27068919.2022.V4.I4C.890.

[18] C. Deng, X. Ji, C. Rainey, J. Zhang, and W. Lu, "Integrating Machine Learning with Human Knowledge," iScience, vol. 23, no. 11, p. 101656, Nov. 2020, doi: 10.1016/J.ISCI.2020.101656.

[19] G. Mast, B. Hettige, and B. Amrr, "Understanding Knowledge Representation Concepts in Machine Translation: A Review," Int. J. Comput. Appl., vol. 186, no. 58, pp. 35–44, Dec. 2024, doi: 10.5120/IJCA2024924343.

[20] B. T. S. Atkins, "Bilingual dictionaries: Past, present and future," Euralex 96 Proc., pp. 515–545, 1996, [Online]. Available: http://www.euralex.org/elx_proceedings/Lexicography and Natural Language Processing/B.T.S. Atkins - Bilingual Dictionaries Past, Present and Future.pdf.

[21] B. J. Kuipers, "A Frame for Frames: Representing Knowledge for Recognition," Representation and Understanding. 1983.

[22] S. Peters and H. E. Shrobe, "Using semantic networks for knowledge representation in an intelligent environment," Proc. 1st IEEE Int. Conf. Pervasive Comput. Commun. PerCom 2003, no. November, pp. 323–329, 2003, doi: 10.1109/percom.2003.1192756.

[23] R. Stevens, C. A. Goble, and S. Bechhofer, "Ontology-based knowledge representation for bioinformatics.," Brief. Bioinform., vol. 1, no. 4, pp. 398–414, 2000, doi: 10.1093/bib/1.4.398.

[24] H. M. Elsherif and T. R. Soomro, "Perspectives of arabic machine translation," J. Eng. Sci. Technol., vol. 12, no. 9, pp. 2315–2332, 2017.

[25] G. Penn and K. Shi, "Feature Structures in the Wild: A Case Study in Mixing Traditional Linguistic Knowledge Representation with Neural Language Models," Proc. ESSLLI 2021 Work. Comput. Semant. with Types, Fram. Relat. Struct., pp. 53–59, 2021, [Online]. Available: https://aclanthology.org/2021.cstfrs-1.6.

[26] L. Papaleo, Introduction to XML and its applications, no. September. 2013.

Safety Helmet Wear Detection Algorithm Based on ASG-YOLOv8s

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***Abstract*—In the field of industrial safety, the standardised wearing of safety helmets by workers constitutes a core protective measure against head injuries. However, in industrial settings, multi-scale background interference arising from variations in monitoring distance renders traditional detection models ineffective at capturing the contour features of small-sized helmets. This study, therefore, proposes the ASG-YOLOv8s safety helmet detection network, based on YOLOv8s, to address the challenge of complex scene background interference. First, the AKC-SCAM unit is introduced within the YOLOv8 backbone network to replace certain standard convolutions. This module dynamically adjusts the sampling shape of convolutional kernels, enhancing the extraction of multi-scale defect features. Secondly, a cross-scale interaction architecture (Slim-neck) is constructed in the Neck section, employing GSConv instead of conventional convolutions. This combines with a cross-level feature pyramid to achieve cross-scale interaction between deep semantic features and shallow details. Finally, GAM attention is embedded before the multi-scale output for head detection, establishing a dual-stream attention mechanism that synergistically optimises feature response intensity for low-quality candidate boxes, while suppressing background noise interference. Experimental results demonstrate that the enhanced ASG-YOLOv8s achieves improvements of 2.54%, 2.94%, and 3.16% over the original model in Precision (P), Recall (R), and mean average precision (mAP), respectively, on the SHWD dataset.**

***Keywords*—YOLOv8; safety helmet wearing detection; slim-neck; attention mechanism**

I. Introduction

In industrial production environments, complex and hazardous work types such as elevated operations and concurrent tasks frequently occur. Among these, incidents involving falling objects, impact collisions, and collapses often result in severe property damage and casualties. Statistics indicate that within the construction industry, accidents caused by falls, collisions, and collapses account for over 50% of all annual incidents [1]. The correct wearing of approved protective equipment represents the most direct and effective method to prevent such losses. However, in practical working environments, personnel frequently neglect wearing protective gear for various reasons. Consequently, monitoring the use of protective equipment by on-site workers is an effective means of ensuring construction safety. Currently, methods for monitoring the wearing of safety helmets within industrial sites primarily include the following: manual inspections, sensor-based detection, traditional image processing recognition, and deep learning-based target recognition methods. Early approaches primarily relied on sensors to detect helmet wear. For instance, Kelm et al. [2] developed an RFID-based system to monitor personal protective equipment compliance as personnel passed through security gates at construction site entrances. Dong et al. [3] employed pressure sensors embedded within protective gear to determine whether workers were wearing it. Traditional detection methods have gradually been phased out due to their complexity in both wearability and detection.

With the advancement of image processing technology, traditional image processing algorithms have gradually been applied to the detection of workers' safety equipment usage. Zhu et al. [4] proposed a rapid and stable algorithm for identifying safety helmets within substations. This approach first detects pedestrians within the substation; then, based on human body geometric features, locates the head position among pedestrians; finally, utilising the characteristic of minimal deformation in safety helmets, employs template matching to identify helmets, thereby determining whether the worker is wearing one. Jia et al. [5] proposed an algorithm for safety helmet detection. This approach utilises a deformable part model to generate block-based local binary pattern histograms, thereby recovering information lost when solely employing gradient direction histograms as features. However, these methods demand high image clarity and involve complex computations, resulting in low efficiency and recognition accuracy. Consequently, they prove unsuitable for complex and diverse industrial environments.

In recent years, deep learning technology has advanced rapidly. Object recognition networks based on deep learning are increasingly applied in practical scenarios due to their excellent real-time performance. Deep learning-based object detection primarily falls into two categories: two-stage networks and one-stage networks. The former primarily consists of two layers: the first layer extracts candidate regions, while the second layer classifies and precisely localises these regions. Representative models include Faster R-CNN [6]. The latter comprises a single layer, integrating classification and localisation into a unified implementation. Representative models include the SSD [7] and YOLO [8] series. Due to their superior detection efficiency and real-time performance, single-stage networks are extensively employed in practical research. Zhang et al. [9] proposed a novel helmet detection algorithm based on an enhanced YOLOv5 framework. This approach redesigns bounding box sizes using the K-Means++ algorithm, matching them to corresponding feature layers, and incorporates a multispectral channel attention module. This enhances the network's ability to distinguish foreground from background and improves overall detection performance. Su et

al. [10] proposed a helmet detection algorithm based on an enhanced YOLOX-s framework. This approach strengthened the model's feature representation capabilities by incorporating a small object detection head and integrating methods such as the SIoU loss function and CA attention mechanism. Han et al. [11] introduced an attention-based helmet-wearing status detection model, optimising it through a bidirectional multi-layer connection fusion feature pyramid network to enhance accuracy. Most recently, Yang et al. [12] designed an epistemic feature enhancement module to construct the backbone feature extraction network. They proposed a dual-scale feature fusion module to acquire and amplify local epistemic feature information of occluded targets, thereby improving detection accuracy for partially obscured objects. In the same year, Ding et al. [13] employed deeper convolutions to replace the small residual network in DeepSORT, enhancing appearance information extraction capabilities. Simultaneously, they added a query head to the decoupled head section to bolster detection performance. Although these approaches optimised algorithms to achieve certain improvements in model accuracy, they still suffer from issues such as high parameter counts and slow detection speeds, failing to meet edge computing requirements. Therefore, further refinements are necessary to enable models to deliver superior detection performance in complex small-object scenarios.

To address the aforementioned issues, this study proposes an enhanced safety helmet detection network, ASG-YOLOv8s, based on YOLOv8s to achieve efficient and precise safety management at the edge. The primary research contributions include:

- Introducing the AKC-SCAM module into the YOLOv8 backbone network. By dynamically adjusting the sampling shape of convolutional kernels, this enhances the extraction capability of multi-scale helmet features.
- Constructing the cross-scale interaction architecture Slim-neck within the feature fusion module. This replaces standard convolutions with GSConv and combines cross-level feature pyramids to facilitate effective interaction between deep semantic information and shallow detail features.
- Embedding the GAM attention mechanism before the multi-scale prediction layer for head detection. This establishes a dual-stream attention structure coordinating both channel and spatial attention to enhance effective feature responses while suppressing background noise.

II. Model Introduction

A. ASG-YOLOv8s Model

In the task of safety helmet detection, the YOLOv8s [14] model emerges as an ideal choice due to its lightweight design and high-efficiency performance. Compared to smaller-scale models such as YOLOv8n, YOLOv8s enhances feature reuse capabilities through its C2f [15] module. Combined with a decoupled head architecture that separates classification and regression tasks, it significantly improves detection accuracy for small-scale safety helmets. Compared to larger models like YOLOv8 l/x, it achieves a compact model size of 22-25MB by streamlining parameters and computational complexity. This strikes an efficient balance between accuracy and efficiency in industrial settings, making it well-suited for resource-constrained real-time detection requirements.

To enhance the detection performance of the YOLOv8 model in complex industrial settings, we first propose the AKC-SCAM module within the YOLOv8 backbone network to replace certain standard convolutional layers. This module integrates Adaptive Kernel Convolution (AKConv) with a Spatial Context-Aware Module (SCAM), dynamically adjusting the sampling shape of convolutional kernels to strengthen multi-scale defect feature extraction. This enhances the ability to capture edge textures of small-sized safety helmets worn by workers during bending operations. Secondly, a Slim-neck module is constructed within the Neck section, employing GSConv to replace conventional convolutions. This combines with a cross-hierarchical feature pyramid to achieve cross-scale interaction between deep semantic features and shallow-level details. Finally, a GAM module is embedded prior to the multi-scale outputs of the detection head, establishing a dual-stream attention mechanism for channels and spatial domains. This dynamically optimises the feature response intensity of low-quality candidate boxes, effectively mitigating missed detections in scenarios with dense occlusions. The overall architecture of the enhanced YOLOv8 network model is illustrated in Fig. 1.

B. AKC-SCAM Module

Whilst YOLOv8's backbone architecture enhances detection efficiency through multi-scale feature fusion and lightweight design, its core components still exhibit two pressing limitations requiring resolution: Firstly, the fixed kernel size of traditional 3×3 convolutions results in a static receptive field, rendering it ill-suited to dynamically adapt to the geometric deformation characteristics of irregular objects encountered in industrial inspection scenarios. Secondly, the consecutive stacking of Bottleneck structures within the C2f module induces parameter redundancy and a surge in computational complexity. To mitigate this phenomenon, this study proposes embedding the AKC-SCAM module—comprising AKConv (Adaptive Kernel Convolution) and SCAM (Spatial Context-Aware Module)—into the Bottleneck residual path of the C2f module, replacing the original 3×3 convolutional layer. This approach reduces model parameters while adaptively adjusting kernel sizes to extract features at different scales, thereby enhancing multi-scale feature extraction capabilities.

The core concept of the AKConv [16] module lies in efficiently extracting features through a convolutional kernel that dynamically adjusts both the number of parameters and the sampling shape, thereby enhancing network performance. The structural diagram of the AKConv module is shown in Fig. 2.

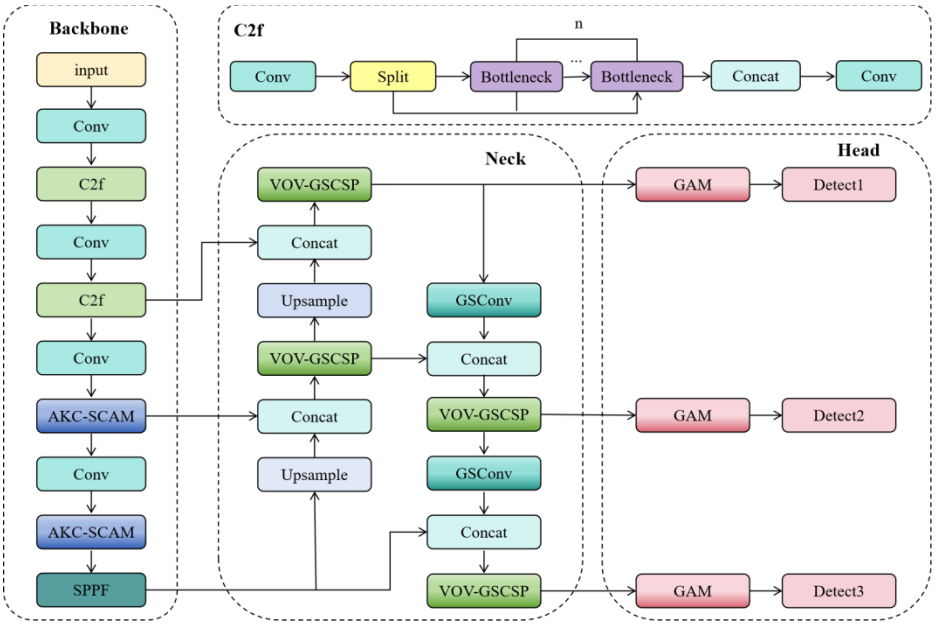


Fig. 1. The architecture of the ASG-YOLOv8s.

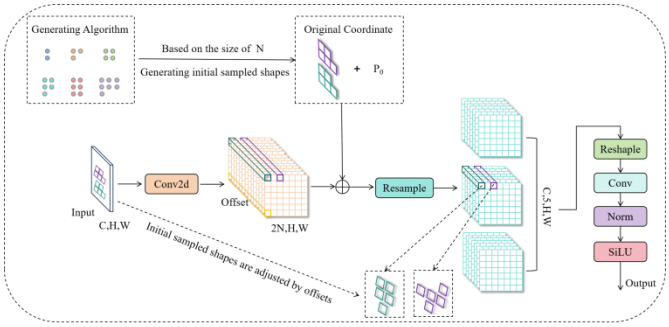


Fig. 2. Structure of the AKConv module.

In the diagram, the input to the AKConv module is a feature map with dimensions (C, H, W), where C denotes the number of channels, and H and W represent the height and width, respectively. The module first generates an initial sampling structure for the convolutional kernel using an initial sampling shape. It then performs a standard convolution operation on the feature map via Conv2d (two-dimensional convolution). Learned offsets dynamically adjust the initial sampling shape; this adaptive property enables the convolutional kernel to flexibly accommodate the spatial distribution of the feature map. The adjusted sampling shape further drives a resampling operation on the feature map to obtain a more optimal local feature representation.

SCAM [17] comprises a channel attention mechanism and spatial-channel reconstruction units. It first decomposes global pooling into horizontal pooling (X Avg Pool) and vertical pooling (Y Avg Pool), thereby effectively capturing long-range spatial interactions with precise positional information. The pooled feature maps undergo concatenation (Concat), convolution (Conv), and splitting (Split) operations to enhance the accuracy of feature representation. Furthermore, the Spatial Reconstruction Unit (SRU) and Channel Reconstruction Unit (CRU) introduced in SCConv perform sequential spatial and channel-wise restructuring on input feature maps. The SRU converts spatial features into spatial weight information, applying thresholds to differentiate weight values. Subsequently, two sets of weighted information are applied to the original feature map to obtain non-redundant and redundant feature maps. These are split and interleaved, producing a spatially reorganised feature map of identical scale to the original. This process refines the spatial information.

Following spatial reorganisation, the feature map employs CRU to restructure channel information, partitioning the input feature map channels into two segments. One portion of the channel features serves as a carrier for rich information, while the other functions as a carrier for secondary information. Distinct convolutional operations are applied to each segment, yielding a feature map refined from the channel information. At this stage, the original feature map undergoes spatial and channel information reorganisation through the SRU and CRU, reducing redundancy within the features. Subsequently, the feature maps restructured by the SRU and CRU are concatenated with the reweighted feature map. This approach enhances the accuracy of feature representation while maintaining lightweight processing, minimises redundant information within the features, and effectively improves model performance. The SCAM architecture is illustrated in Fig. 3.

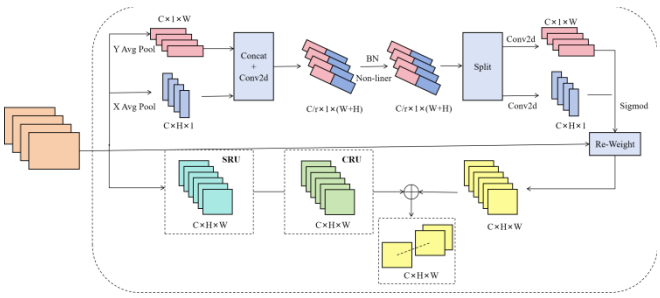


Fig. 3. Structure of the SCAM module.

C. Slim-neck Module

The neck network of YOLOv8 relies on dense convolutional operations during feature fusion, resulting in high parameter counts and computational complexity. To address this issue, this study proposes introducing the Slim-neck [18] module into the neck section. The Slim-neck module incorporates lightweight structures derived from GS bottleneck and VOV-GSCSP upon the foundation of GSConv [19] (Global Sparse Convolution), reducing model complexity while maintaining detection accuracy. GSConv represents a novel, lightweight convolution technique that enhances detection accuracy while reducing computational burden, differing from traditional approaches that increase accuracy by deepening network architecture and amplifying computational load. The GSConv architecture, illustrated in Fig. 4, processes input features through standard convolutional layers followed by depth-wise separable convolutions applied independently to each channel. Output features are then concatenated and rearranged via a shuffle operation to enhance inter-feature information flow. The GS bottleneck architecture further optimises GSConv, enhancing the network's feature processing capabilities. VOV-GSCSP [20] employs a one-time aggregation strategy, optimising certain module designs to improve feature utilisation efficiency and overall coherence.

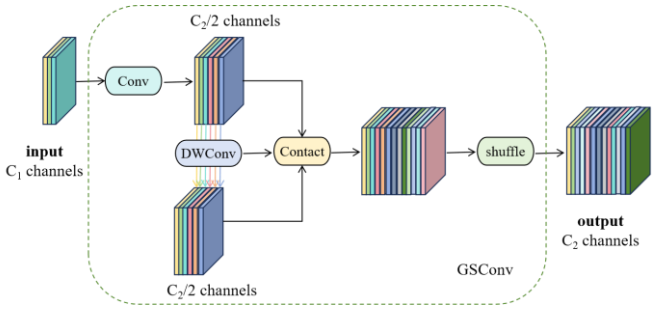


Fig. 4. Structure of the GSConv module.

D. GAM Attention Mechanism

To enable the model to adaptively focus on key regions within the input data while enhancing robustness and reducing computational complexity, this study incorporates a Global Attention Mechanism (GAM) module [21] before each detection head in YOLOv8. By integrating dual mechanisms of channel attention and spatial attention, GAM collaboratively captures key features across channel, spatial, and feature dimensions, achieving global context modelling of input data. Its primary structure is illustrated in Fig. 5. Specifically, the channel attention module extracts channel importance weights through Global Average Pooling (GAP) and Global Max Pooling (GMP), then employs a shared Multi-Layer Perceptron (MLP) to generate channel weight vectors, thereby reinforcing key semantic features, as depicted in Fig. 5(a). The spatial attention module generates spatial saliency maps through parallel global pooling and 7×7 convolutions, focusing on the spatial distribution information of target regions, as depicted in Fig. 5(b). Subsequently, the two weight types interact through element-wise multiplication to achieve multidimensional feature interaction, ultimately outputting an optimised feature representation. Compared to the conventional Convolutional Attention Module (CBAM) [22], GAM further incorporates a dynamic weight allocation strategy. This enhances the perception of fine-grained features in complex scenes while reducing redundant computational overhead through lightweight design, thereby improving model performance.

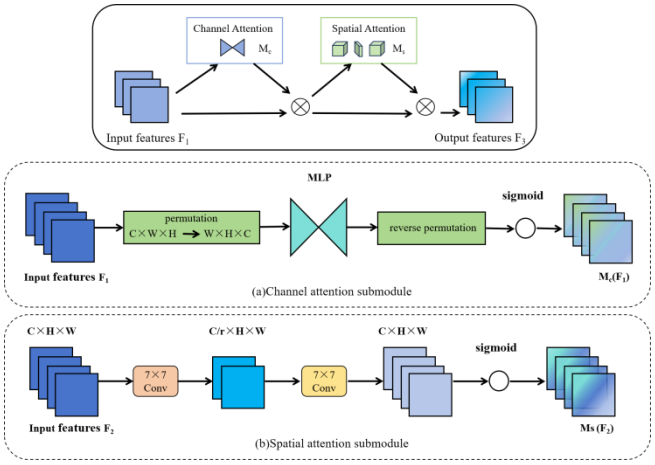


Fig. 5. Structure of the GAM module.

III. Experimental Data and Analysis

A. Datasets and Evaluation Metrics

The dataset employed herein should encompass construction sites across different seasons and complex weather conditions to fulfil the experimental requirements of this study. The dataset utilised in this experiment was created by refining the publicly available Safety-Helmet-Wearing-Dataset (SHWD). This involved removing unsuitable images and substantially augmenting the dataset with additional construction site scenarios, resulting in the SHWD-T construction site helmet dataset comprising 21,480 images. The dataset was randomly partitioned into training, validation, and test sets in an 8:1:1 ratio to facilitate subsequent data processing and analysis. All experiments were conducted without loading pre-trained weights.

To evaluate the model's performance and the accuracy of helmet detection, this study employs three metrics: Precision (P), Recall (R), and Mean Average Precision (mAP). The corresponding equations are presented in Eq. (1) to Eq. (3):

$$P = \frac{TP}{TP + FP} \tag{1}$$

$$R = \frac{TP}{TP + FN} \tag{2}$$

$$\text{mAP} = \frac{1}{N}\sum_{i=1}^{N} AP_i \tag{3}$$

In the equation: TP (True Positive) denotes the number of predicted boxes matching actual boxes; FP (False Positive) denotes the number of predicted boxes differing from actual boxes; FN (False Negative) denotes the number of objects contained within images that were not correctly detected during prediction; N represents the number of categories delineated in this study.

B. Ablation Experiment

To validate the effectiveness of the algorithmic improvement strategy proposed herein, eight sets of ablation experiments were conducted on the SHWD-T dataset based on the YOLOv8 baseline. The experimental results obtained from various experimental models are presented in Table I.

TABLE I. ABLATION EXPERIMENT RESULTS

AKC-SCAM	*Slim-neck*	*GAM*	*P/%*	*R/%*	*mAP/%*
-	-	-	87.26	80.52	83.62
√	-	-	88.07	81.22	84.30
-	√	-	88.92	81.88	85.16
-	-	√	88.44	82.73	84.41
√	√	-	89.07	81.65	84.83
√	-	√	88.49	82.07	85.29
-	√	√	89.09	82.50	85.63
√	√	√	89.80	83.46	86.78

Experiments reveal that incorporating the AKC-SCAM backbone network yields an 0.86% improvement in mAP compared to YOLOv8, demonstrating that the AKC-SCAM module effectively enhances the model's object recognition accuracy and strengthens its feature representation capabilities. Following the integration of the Slim-neck module, the model's mAP value increased by 1.84%, demonstrating that this lightweight neck design optimises feature propagation and enhances detection performance without significantly increasing computational overhead. The combined approach of YOLOv8 + AKC-SCAM + Slim-neck + GAM elevated the P value to 89.80%, the R value to 83.46%, and the mAP to 86.78%. This demonstrates that the synergistic interaction among these three components can substantially enhance the model's comprehensive detection capabilities.

Overall, the refined algorithm demonstrably enhances the model's comprehensive detection capabilities compared to YOLOv8, particularly by achieving a comprehensive improvement in detection accuracy while maintaining model lightness. This validates the effectiveness and superiority of the proposed methodology.

C. Contrast Experiment

To comprehensively evaluate the performance of the improved YOLOv8 network in helmet detection tasks, comparative experiments were conducted on the SHWD-T dataset against several classical object detection networks and state-of-the-art algorithms. As shown in Table II, the proposed ASG-YOLOv8s model demonstrates significantly superior detection accuracy compared to other methods.

TABLE II. CONTRAST EXPERIMENT RESULTS

Model	Experimental parameters		
	P/%	*R/%*	*mAP/%*
ASG-YOLOv8s	89.80	83.46	86.78
RFBNet	82.6	73.4	75.60
YOLOv5	86.40	78.60	82.70
YOLOv8	87.26	80.52	83.62
SSD	86.30	76.70	82.20
DAAM-YOLOv5	86.70	78.60	83.30
YOLOv7	87.98	84.21	85.76
YOLOv3-tiny	79.87	75.89	78.65
SSD	79.91	70.34	77.65
Faster RCNN	80.35	71.26	78.14
MEM-YOLOv8	87.50	76.60	83.20

D. Experimental Results Analysis

To validate the performance of the ASG-YOLOv8s model in practical detection scenarios, this study tests images captured across various complex construction site environments. Fig. 6 presents detection results from both the ASG-YOLOv8s and YOLOv8s models across distinct scenarios: Fig. 6(a) depicts a scene with background interference, Fig. 6(b) shows a densely populated target scenario, and Fig. 6(c) illustrates an occlusion scenario. The left column presents detection results from the YOLOv8s model, while the right column shows results from the ASG-YOLOv8s model. Comparing these outcomes enables an assessment of performance differences between the two models in diverse environments. It is evident that the YOLOv8s model is prone to both missed detections and false positives in complex environments, exhibiting lower detection accuracy. Conversely, the ASG-YOLOv8s model demonstrates superior performance, accurately detecting small objects within intricate settings.



(a) Scenes with background interference.



(b) Dense Target Scenario.



(c) Occlusion of Target Scenes.

Fig. 6. Comparison of model detection results in different job scenarios.

IV. Conclusion

To address the issues of delayed response times in manual industrial safety monitoring and high false detection rates for small targets such as safety helmets due to dynamic changes in monitoring distance, this study proposes the ASG-YOLOv8s enhanced algorithm. Firstly, the AKC-SCAM module is introduced into the backbone network to replace some standard convolutional layers in the conventional backbone. Secondly, a Slim-neck module is constructed in the Neck section, employing GSConv to substitute traditional convolutional kernels. Finally, a GAM module is embedded prior to the multi-scale outputs of the detection head. Experimental results demonstrate that the proposed ASG-YOLOv8s model achieves improvements of 2.54%, 2.94%, and 3.16% in Precision, Recall, and mAP, respectively, over the original model on the SHWD-T dataset. This indicates that the ASG-YOLOv8s algorithm exhibits superior detection accuracy, with significant enhancements in detecting occluded and small targets, rendering it well-suited for safety helmet detection applications.

References

[1] TANG K, CHEN L, ZHANG Z J, et al.Statistical analysis and countermeasures of production safety accidents i n my country's construction industry[J]. Construction Saf ety, 2020, 35(09): 40-43.

[2] Kelm A ,Laußat L ,Meins-Becker A , et al.Mobile passive Radio Frequency Identification (RFID) portal for automated and rapid control of Personal Protective Equipment (PPE) on construction sites[J].Automation in Construction,2013,36:38-52.

[3] DONG S , HE Q , LI H ,et al. Automated PPE Misuse Identification and Assessment for Safety Performance Enhancement[M]//ICCREM 2015. 2015: 204-214.

[4] ZHU F Y, DAI X L, FU J, et al. Research on safety helmet detection algorithm in substation based on video surveillance[J]. Power System and Clean Energy, 2018, 34(12): 71-76.

[5] JIA J S, BAO Q J, TANG H M. Safety helmet wearing detection based on deformable component model[J]. Journal of Computer Application Research, 2016, 33(03): 953-956.

[6] SHAOQING R ,KAIMING H ,ROSS G , et al.Faster R- CNN: Towards Real-Time Object Detection with Region Proposal Networks.[J]. IEEE transactions on pattern analysis and machine intelligence, 2017, 39(6): 1137-1149.

[7] LIU W ,ANGUELOV D ,ERHAN D, et al. Ssd: Singles hot multibox detector[C]//Computer Vision–ECCV 2016: 14th European Conference,

Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part I 14. Springer International Publishing, 2016: 21-37.

[8] REDMON J ,DIVVALA K S ,GIRSHICK B R , et al. You only look once: Unified, real-time object detection[C]//Proceedings of the IEEE conference on computer vi sion and pattern recognition. 2016: 779-788.

[9] ZHANG J, QU P Q, SUN C, et al. Helmet wearing detection algorithm based on improved YOLOv5[J]. Journal of Computer Applications, 2022, 42(04): 1292-1300.

[10] SU P, LIU M, MA S Q. Safety helmet detection based on improved YOLOX-s[J]. Computer Systems and Applications, 2023, 32(07): 145-154.

[11] HAN F T,LIU Y Q,FANG Y D ,et al.Detection model for wearing status of safety helmet based on attention mechanism[J].Journal of Safety Science and Technology, 2024,20(08):196-202.

[12] YANG G L, HONG X F, SHENG Y Y ,et al.A helmet detection algorithm based on appearance feature enhance ment and fusion[J/OL].Computer Engineering and Applications,1-12[2024-09-29].

[13] Ding L, Miao X R, Hu J F, et al.Improved Miner Chin Strap Detection and PersonnelTracking with YOLOv8s and DeepSORT[J].Computer Engineering and Applications,2024,60(5):328-335.

[14] Wang Y ,Yang H,Gao L, et al.Research on Target Detection Algorithm for Sea Surface Oil Spill Recognition in SAR Image on YOLOS-Taking Improved YOLOv8 as an Example[J].IAENG International Journal of Computer Science,2025,52(12):

[15] Ai S ,Li J ,Li Y .MDC-YOLO: an enhanced steel plate surface defect detection algorithm based on YOLOv8[J].Engineering Research Express,2025,7(4):0452a5-0452a5.DOI:10.1088/2631-8695/AE2237.

[16] Feng S ,Niu X .Vehicle Detection in Aerial Drone Overhead Images based on YOLOv8[J].International Core Journal of Engineering,2025,11(5):147-156.

[17] Jenipher N V ,Radhika S .Lung tumor cell classification with lightweight mobileNetV2 and attention-based SCAM enhanced faster R-CNN[J].Evolving Systems,2024,15(4):1381-1398.DOI:10.1007/S12530-023-09564-3.

[18] Chen Z ,Fang Y ,Yin J , et al.A novel lightweight YOLOv8-PSS model for obstacle detection on the path of unmanned agricultural vehicles[J].Frontiers in Plant Science,2024,151509746-1509746.

[19] Ancha K V ,Gonuguntla V ,Vaddi R .GSS-YOLO: an improved YOLOV5 prediction head with slim-neck for defect detection in printed circuit board assembly[J].Signal, Image and Video Processing,2025,19(11):915-915.DOI:10.1007/S11760-025-04511-Y.

[20] Song L ,Lu S ,Tong Y , et al.YOLOv8s-GSW: a real-time detection model for hexagonal barbed wire breakpoints[J].The Journal of Supercomputing,2024,81(1):222-222.DOI:10.1007/S11227-024-06738-X.

[21] Yu Q ,Ouyang X,Su B, et al.Vehicle Detection Algorithm in Complex Scenes Based on Improved YOLOv8[J].IAENG International Journal of Computer Science,2025,52(4).

[22] Sayem S ,Sanny I S S ,Nabil R H .Hybrid CNN Model with CBAM for Malaria Disease Classification: Enhanced Feature Extraction[J].Biomedical Materials & Devices,2025,(prepublish):1-15.DOI:10.1007/S44174-025-00607-8.

A Comparative Review of AI, IoT, and Big Data in Healthcare: Towards a Data-Centric Approach for Enhanced Data Quality and Contextual Adaptability

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***Abstract*—The convergence of Artificial Intelligence (AI), the Internet of Things (IoT), and Big Data is revolutionizing healthcare by enabling predictive diagnostics, real-time monitoring, and personalized treatment through data-driven analytics and intelligent decision-making. Despite these advancements, the effectiveness of such systems is significantly hindered by poor data quality, including issues such as missing values, noise, bias, and inconsistencies. This study presents a systematic and comparative review of recent research at the intersection of AI, IoT, and Big Data in healthcare, highlighting critical gaps in data quality that undermine model performance and real-world reliability. In response, we introduce the Data-Centric AI (DCAI) paradigm as a promising approach focused on systematic data improvement rather than model complexity. We examine the application of the METRIC framework for assessing data quality dimensions such as completeness, consistency, fairness, and timeliness. Furthermore, we propose future research directions to improve scalability and trustworthiness in AI-driven healthcare, integrating advanced AI techniques such as generative AI and multimodal frameworks with DCAI principles for more ethical AI applications. This work serves as both a comparative synthesis of existing literature and a conceptual foundation for future experimental validation through a case study integrating context-aware data modeling and real-time decision support.**

***Keywords*—Data-Centric AI; IoT; Big Data Analytics; healthcare informatics; data quality; bias mitigation; privacy; predictive analytics; machine learning; disease prediction**

I. Introduction

The convergence of Artificial Intelligence (AI), Big Data, and the Internet of Things (IoT) is reshaping modern healthcare by enabling real-time monitoring, predictive diagnostics, and personalized treatment pathways. These technologies promise improved patient outcomes, operational efficiency, and data-driven clinical decision-making. However, the performance and reliability of such systems are not solely dependent on advanced algorithms—they are fundamentally tied to the quality and integrity of the underlying data.

Healthcare data, particularly from heterogeneous IoT environments, is often plagued by issues such as missing values, noise, demographic bias, and inconsistencies, which compromise clinical accuracy and fairness [1]. Additionally, challenges around interoperability, privacy, and regulatory compliance continue to impede scalable AI adoption in real-world healthcare settings [2], [3].

Traditional approaches have predominantly focused on model-centric AI (MCAI), prioritizing algorithmic optimization while assuming static, clean datasets. This focus has resulted in unreliable predictions, biased treatment recommendations, and limited generalizability across diverse patient populations [4]. In healthcare—where errors can be life-threatening—this paradigm is no longer sustainable. The increasing complexity of multimodal healthcare data, combined with real-time demands and stringent privacy constraints, requires a shift in focus: from model optimization to systematic data enhancement. As recent findings emphasize that improvements in data quality can often outperform equivalent enhancements in model complexity, especially in critical settings like clinical diagnostics or patient monitoring [5], [6], and that poor data quality, like mislabeled samples, can propagate errors throughout the AI lifecycle, leading to unsafe or inequitable medical decisions[5], [7]. The result is a growing consensus that high-quality, well-curated data must be central to AI development.

Despite widespread research on AI and IoT integration in healthcare, there remains no unified framework that systematically addresses how data quality, fairness, and interoperability should be prioritized to enable robust, ethical AI systems. Data-Centric AI (DCAI) —a paradigm that prioritizes the systematic curation, preprocessing, and contextual enrichment of data to improve AI model performance and fairness— has emerged as a promising approach to filling this void [8], [9]. However, its application within healthcare remains underexplored and unstandardized.

This study offers a conceptual and comparative synthesis of existing AI-IoT-Healthcare literature through the lens of DCAI. While no experimental implementation is conducted, our aim is to theoretically map how DCAI principles can address persistent data quality limitations in healthcare systems. We seek to bridge that gap by comparing twenty-three AI-IoT-Healthcare studies and analyzing DCAI's theoretical and practical potential to enhance data quality. We explore a structured conceptual framework that maps DCAI principles to recurring healthcare challenges—specifically related to data noise, bias, missing values, and contextual inconsistency—, offering pathways toward more scalable, interpretable, and trustworthy AI solutions. Additionally, we identify future directions, including emerging techniques such as generative AI, multimodal integration, and advanced data recovery techniques as promising complements to DCAI in clinical contexts. This study sets the

foundation for future empirical validation through real-world case studies or clinical datasets.

Fig. 1 illustrates the layered integration of IoT, Big Data, and AI within smart healthcare systems. IoT devices serve as the primary data acquisition layer, collecting real-time physiological and behavioral data. This raw data is then aggregated and processed through Big Data infrastructures, which handle high-volume, high-velocity data streams for storage, cleaning, and transformation. The processed data feeds AI algorithms at the decision layer, where predictive models generate insights for diagnostics, risk stratification, and personalized care. This pipeline enables closed-loop feedback mechanisms, supporting adaptive, context-aware healthcare while ensuring scalability, data integrity, and privacy compliance.

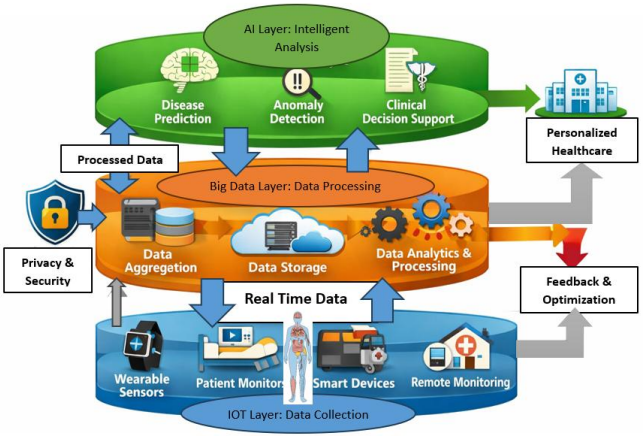


Fig. 1. Integration of AI, IoT, and Big Data in smart healthcare systems.

The remainder of this study is organized as follows: Section II presents related work and the structured literature review methodology. Section III details the technological and operational challenges in AI-driven healthcare. Section IV introduces DCAI concepts and applications. Section V maps DCAI to persistent data quality issues. Section VI outlines relevant data quality metrics. Section VII discusses study limitations. Section VIII explores future research directions, and Section IX concludes with reflections on ethical, scalable AI in healthcare.

II. Background and Related Work

A. Literature Review and Methodology

AI, Big Data, and IoT have driven major advances in healthcare, facilitating predictive diagnostics, real-time monitoring, and data-driven decision-making. Despite the technical sophistication of these systems, their real-world effectiveness is frequently compromised by persistent challenges—including poor data quality, heterogeneity, lack of standardization, and privacy concerns. These issues threaten the reliability, fairness, and scalability of AI applications in healthcare environments.

Data-Centric AI (DCAI) has recently emerged as a promising paradigm to tackle these challenges by emphasizing the quality, structure, and contextual integrity of data over algorithmic complexity. Yet, dedicated review studies that explore DCAI's practical implications in healthcare settings are scarce. This work addresses that gap by conducting a structured review of both foundational DCAI literature and application-oriented studies that highlight real-world limitations in AI, Big Data, and IoT for healthcare.

To ensure scientific rigor, the review process followed a structured literature selection methodology that allows our work to reflect the contributions of prior research on IoT, AI, and Big Data in healthcare, while also incorporating foundational studies on DCAI principles and data quality metrics. Our goal is to highlight the ongoing shift from model-centric to data-centric approaches and to underscore the growing relevance of DCAI-based solutions in healthcare AI.

1) Search strategy and data sources: The literature search was conducted using a multi-database strategy to encompass a broad range of both technical and medical research publications, ensuring comprehensive coverage of both theoretical AI/IoT research and practical healthcare applications. The following academic databases were selected:

- IEEE Xplore
- Scopus
- Web of Science
- PubMed
- ScienceDirect
- Google Scholar

Our search queries combined key terms related to AI, IoT, Big Data, and healthcare, for the selection of the 23 articles such as: "Artificial Intelligence", "Machine Learning", "Deep Learning", "Internet of Things", "Healthcare IoT", "Big Data Analytics", "Context-Aware Systems", and "Smart Healthcare".

Boolean operators were applied to refine results [e.g., ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("Internet of Things" OR "Healthcare IoT") AND ("Big Data Analytics" OR "Smart Healthcare" OR "Real-time Monitoring") AND ("Context-Aware Systems" OR "Privacy" OR "Interoperability" OR "Clinical Decision Support Systems")]. The search was limited to the 2016–2025 publication window. Manual adjustments were made to avoid duplicated retrievals across platforms.

2) Eligibility criteria: The search was conducted on publications between 2016 and 2025, and duplicates were removed. The citation management tool Rayyan was used to facilitate collaborative screening, inclusion/exclusion filtering, and conflict resolution during selection. In Table I, our chosen eligibility criteria that were applied to the various screening steps of our selection process of the twenty-three peer-reviewed application-oriented studies are listed.

3) Selection and analysis process: An initial screening based on titles and abstracts was performed, followed by a full-text review of eligible articles. Twenty-three studies were ultimately selected as representative of prevailing practices and

challenges in AI, IoT, and Big Data-driven healthcare systems for prediction, monitoring, and decision-making.

TABLE I. ELIGIBILITY CRITERIA APPLIED TO THE SCREENING AND FULL-TEXT ASSESSMENT PROCESSES

Criterion	
Inclusion	Peer-reviewed journal articles or chapter book or conference papers
	Publications between 2016 and 2025 published in **English**
	Studies addressing healthcare applications of AI, IoT, and/or Big Data for predictions of diseases or monitoring or real word application
	Articles discussing at least one of the following: challenges related to data quality, context awareness, interoperability, scalability, privacy, Healthcare diagnostics, monitoring, decision support using AI/IoT or Real-time systems.
Exclusion	Non-peer-reviewed sources, editorials, or opinion pieces
	Studies unrelated to healthcare applications
	Works focused exclusively on algorithms without consideration of data characteristics or system-level integration
	Redundant or overlapping publications

To bridge the gap between these practical challenges and the conceptual framework of DCAI, the tool Rayyan was used to facilitate collaborative screening, conflict resolution, and exclusion tagging. This process resulted in the selection of:

- Seven Foundational DCAI Publications outlining data-centric concepts, lifecycle frameworks, data-centric design principles, and metrics for evaluating data quality
- Twenty-Three Application-Oriented Studies demonstrating real-world applications and challenges in AI-IoT-Big Data healthcare systems.

A PRISMA-style flow diagram (Fig. 2) outlines the article selection workflow, culminating in the inclusion of twenty-three peer-reviewed studies focused on AI and IoT applications in healthcare. These articles were analyzed using a unified comparison framework emphasizing data sources, modeling techniques, evaluation outcomes, and reported limitations. This methodology enabled a systematic comparative analysis and the extraction of key limitations, forming a solid foundation for identifying research gaps addressed by the Data-Centric AI (DCAI) paradigm.

To enhance analytical depth and provide objective insights, a quantitative content analysis was also performed. Each selected study was reviewed to extract explicitly stated limitations related to data quality, scalability, interoperability, privacy, and integration. These issues were then categorized by frequency, allowing the construction of a visual summary of common challenges (see Fig. 3). This process not only highlighted recurring barriers but also emphasized the relevance of DCAI as a unifying approach to overcome these limitations.

Table II presents an organized summary of the core literature reviewed in this study, categorized by focus and contribution.

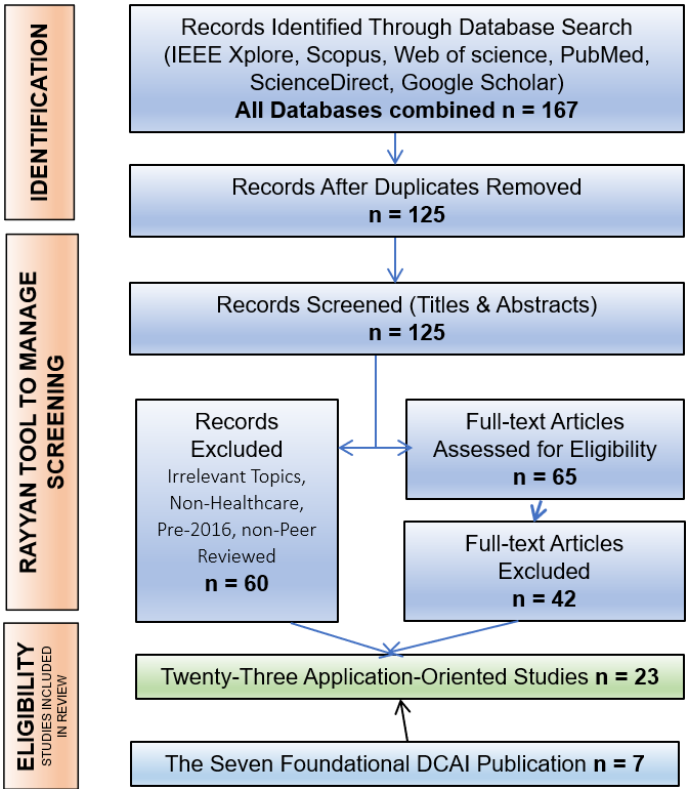


Fig. 2. PRISMA-style flow diagram illustrating the article selection process. A total of 167 records were initially identified from six academic databases. After removal of duplicates and exclusion based on titles and abstracts, 65 full-text articles were reviewed. Finally, 23 articles were selected as application-oriented studies in healthcare AI, IoT, and Big Data and added to 7 foundational DCAI publications. Rayyan was used to manage and streamline the screening process.

TABLE II. SUMMARY OF KEY ARTICLES USED IN THIS STUDY

Category	Article	Focus/Key Contribution
Foundational Articles	[4] Bhatt et al. (2024)	Techniques for data-centric deep learning improvement
	[9] Malerba & Pasquadibisceglie (2024)	DCAI philosophy: prioritizing data refinement over model tuning
	[1] Schwabe et al. (2024)	METRIC framework for healthcare data quality evaluation
	[15] Zha et al. (2023) - A Survey	Taxonomy and automation levels in DCAI
	[5] Jin et al. (2024)	DCAI lifecycle: data operations across AI stages
	[6] Nieberl et al. (2024)	DCAI implementation patterns and research gaps
	[7] Zha et al. (2023) - Perspectives	Strategic challenges in DCAI for training, inference, and deployment
Application-Oriented Articles	[16] Zonayed et al. (2025)	Narrative synthesis of AI models in chronic disease prediction; highlights key trends and challenges in healthcare ML
	[17] Šajnović et al. (2024)	IoT and Big Data analytics in preventive healthcare; synthesizes enablers, gaps, and interoperability issues
	[18] Charfare et al. (2024)	Survey on AI-IoT integration in healthcare; identifies performance trends and system-level limitations
	[19] Alsabah et al. (2025)	Comprehensive review of smart healthcare IoT architectures; technical challenges and future directions
	[10] Zon et al. (2023)	Context-aware data optimization in healthcare systems
	[11] Chung et al. (2020)	Deep learning for context-driven health risk prediction
	[13] Saranya & Fatima (2022)	Context-aware data fusion for IoT patient monitoring.
	[20] Kishor & Chakraborty (2021)	AI-IoT integration for remote health monitoring
	[21] Ghazal et al. (2021)	ML applications in smart city healthcare
	[12] Kim & Chung (2020)	Adaptive health context prediction models
	[22] Kaur (2021)	Heart disease prediction using ML and IoT
	[2] Banerjee et al. (2020)	Big Data and IoT trends in healthcare
	[3] Meraj et al. (2021)	IoT for monitoring infectious diseases
	[23] Vijayalakshmi et al. (2021)	Disease prediction using Big Data tools
	[24] Verma et al. (2019)	Hybrid IoT-cloud architecture for diagnosis
	[25] Aceto et al. (2020)	Personalization through Industry 4.0 healthcare IoT
	[14] Aborokbah et al. (2018)	Context-aware decision systems for chronic diseases.
	[26] Castro et al. (2017)	IoT wearables for activity recognition
	[27] Chui et al. (2019)	Behavior monitoring via Big Data and IoT
	[28] Ngiam & Khor (2019)	ML applications for healthcare analytics
	[29] Shah et al. (2018)	IoT-based systems for monitoring disorders
	[30] Tian et al. (2019)	IoT-cloud platforms for smart healthcare
	[31] Yin et al. (2016)	Overview of IoT use cases in healthcare

A. Comparative Analysis of AI, IoT, and Big Data Healthcare Studies

To assess the state of healthcare applications involving AI, IoT, and Big Data, we conducted a comparative analysis of the 23 peer-reviewed studies published between 2016 and 2025. Based on the defined inclusion and exclusion criteria, these studies were selected for their relevance to disease prediction, patient monitoring, smart healthcare systems, and healthcare infrastructure. Our objective was to extract common practices, recurring challenges, and methodological gaps that inform the need for a shift toward the emerging data-centric paradigm.

1) Categories of reviewed studies: To move beyond a structured descriptive synthesis, the selected 23 articles were classified into four primary domains based on their methodological focus and healthcare application scope. Within each category, we explicitly compare approaches, data dependencies, and reported limitations to identify recurring patterns and systemic gaps.

a) Context-aware systems and adaptive intelligence: Several studies underscore the importance of integrating environmental, behavioral, and physiological context for more accurate and responsive healthcare interventions. In [10], Zon et al underscored the lack of context-aware medical systems, which limits adaptability to patient conditions, addressing the difficulty of integrating context-aware medical systems due to heterogeneous healthcare data, highlighted the lack of a structured understanding of medical contexts, and identified key medical contexts for AI adaptation. Similarly, in [11], Chung et al. proposed an ambient context-based deep neural network that leverages contextual health data for health risk

assessment in patients with chronic diseases, improving prediction accuracy but facing issues with heterogeneous and noisy input IoT data. In [12], Kim & Chung advanced this area by developing a neural network-based adaptive context prediction model for ambient intelligence, which enhanced patient care personalization. Their approach demonstrated an enhanced ability to predict and adapt to various patient states, leading to better patient care, though the systems required further validation due to data integration complexity. In [13], Saranya & Fatima tackled data heterogeneity in IoT-based patient monitoring by developing an improved context-aware data fusion model that enhances security and optimizes data integration from multiple sensors, achieving high precision in real-time health monitoring. In [14], Aborokbah et al. proposed an adaptive computing paradigm that utilizes machine learning techniques, which improved chronic disease management but required further validation for diverse populations.

While all studies acknowledge context as a critical factor, most approaches treat context as an auxiliary feature rather than a first-class data entity. None adopts a systematic data-centric strategy to validate, curate, or standardize contextual information, leading to scalability and robustness limitations.

b) Disease prediction and monitoring: IoT-enabled models for real-time monitoring and diagnosis are prominently featured. In [13], Saranya & Fatima proposed a fusion model for wearable data that achieved 97.9% accuracy in patient monitoring but faced issues of sensor reliability and cybersecurity. The need for real-time disease prediction was explored by Kishor & Chakraborty in [20], who integrated IoT with machine learning classifiers, obtaining high accuracy but encountering real-time processing constraints. Meanwhile, in [22], Kaur investigated the increasing prevalence of heart diseases and the need for predictive models that can provide timely warnings and applied IoT and machine learning for heart disease prediction, demonstrating high accuracy but struggling with data privacy and completeness. Similarly, in [3], Meraj et al reviewed IoT-based infectious disease detection, emphasizing the need for real-time outbreak prediction, though sensor noise and lack of data remained challenges. In [26], Castro et al. focused on wearable-based human activity recognition using IoT and developed a machine learning-based system that classified physical activities, achieving improved movement detection accuracy, but environmental noise remained a limiting factor. In [29], Shah et al. conducted a case study on IoT-based sensing for healthcare applications, focusing on detecting narcolepsy episodes and implemented machine learning classifiers to identify sleep disorder patterns, demonstrating that IoT sensors could effectively improve sleep disorder diagnosis and patient monitoring. Additionally, in [28], Ngiam & Khor reviewed the challenges and opportunities of applying machine learning algorithms in healthcare and emphasized the importance of high-quality data preprocessing and ethical considerations in AI-driven healthcare systems, demonstrating that integrating AI could enhance prediction and diagnostic accuracy while raising concerns about data bias, data labeling, annotation inconsistencies and privacy. The study [16] is a more recent contribution by Zonayed et al. that comprehensively synthesizes the advancements, challenges, and future directions of integrating Machine Learning (ML) and the Internet of Things (IoT) in healthcare. This integration facilitates real-time health monitoring and the analysis of intricate medical datasets, yielding insights that support evidence-based clinical decision-making. The review highlights the high predictive accuracy (85%–95%) achieved by models like CNNs and XGBoost, particularly in diagnostics and chronic disease management. Challenges remain concerning data security, interoperability, and ethical transparency, scalability, and the need for explainable AI to foster clinical trust and ethical transparency. Future direction must prioritize robust security, standardization, and effective human-AI collaboration to fully realize the potential of Healthcare 5.0. Finally, in [30], Tian et al. analyzed the potential of smart healthcare technologies, including IoT, AI, and Big Data, in making medical care more efficient and personalized and identified key areas where smart healthcare solutions could improve hospital management and patient engagement, highlighting the necessity of integrating intelligent systems for optimizing healthcare operations.

Across this category, models are predominantly model-centric, focusing on algorithm selection and accuracy optimization, while data quality issues are treated as secondary concerns. This imbalance limits real-world generalization despite strong experimental results.

c) Big Data analytics and infrastructure challenges: In [23], Vijayalakshmi et al. introduced a Big Data-driven model to enhance disease forecasting using machine learning techniques and leveraged Big Data analytics for chronic disease prediction, improving classification accuracy but struggling with data sparsity and labeling errors. Respectively, a broader examination of IoT and Big Data analytics in biomedical healthcare was conducted by Banerjee et al in the chapter [2], who highlighted standardization challenges in wearable device data processing, where latency remained a key limitation. Both noted substantial improvements in data-driven decision-making, but also highlighted latency issues, sparse data, and infrastructural limitations. In [21], Ghazal et al. applied machine learning for smart healthcare infrastructure, optimizing medical resource allocation, but still faced data quality issues. In [29], Šajnović et al. conducted a large-scale synthetic review that analyzes 2272 publications from the Scopus database on the intersection of the Internet of Things (IoT) and Big Data Analytics in preventive healthcare, observing exponential literature growth since 2012, peaking in 2023. The study identifies eight key themes, including the role of AI in personalized medicine (genetics/genomics) and risk prediction, and the use of big data in public health and epidemiology, alongside critical challenges concerning data security, privacy, interoperability, ethical concerns, and the high cost of the IoMT system. In the comprehensive survey [18], Charfare et al. examine the integration of IoT and AI technologies in healthcare applications. The study reviews 28 AI/ML models across diverse applications, including disease detection (COVID-19, diabetes), patient monitoring, athletic performance tracking, and elderly care. Top-performing models

include LightGBM (99.23% accuracy for activity recognition) and LSTM (99% for fall detection). Key challenges identified include data security, computational constraints, energy efficiency, and interoperability issues. The study emphasizes future research directions in federated learning, adaptive algorithms, and multi-modal data fusion for enhanced healthcare delivery. In [19], Alsabah et al. conducted a comprehensive analysis of IoT-based smart healthcare systems, focusing on the interplay between edge computing, cloud services, and data analytics. They examine AI/ML applications in smart healthcare, analyzing studies covering disease diagnosis (glaucoma, diabetic foot ulcers, skin diseases), medical image encryption, and IoT security. Key technologies include CNNs, deep learning, federated learning, and blockchain-based privacy protection. Models demonstrate enhanced diagnostic accuracy, early disease detection, and secure data transmission. Applications span medical imaging, remote health monitoring, and intrusion detection. Their review highlights technical challenges such as system scalability, latency, and real-time decision-making, particularly when handling massive healthcare datasets. They also underscore the need for high-throughput infrastructure capable of managing heterogeneous medical data while ensuring interoperability and low-latency processing. In [27], Chui et al. focused on patient behavior monitoring using IoT and Big Data analytics and developed a framework to analyze patient movement patterns and predict potential health risks, providing valuable insights for caregivers, improving patient safety, and reducing hospital readmissions.

While Big Data enables broader population-level insights, the absence of standardized data pipelines and quality control mechanisms limits scalability and reproducibility—issues that are not addressed by model improvements alone.

d) Privacy, security, and interoperability: The integration of IoT and AI has exposed healthcare systems to data privacy risks and interoperability hurdles. In [25], Aceto et al. examined the role of IoT and Big Data in Healthcare 4.0, improving data fusion for personalized medical services, while highlighting privacy concerns. Similarly, in [31], Yin et al. provided an overview of the Internet of Things in healthcare, summarizing its applications, challenges, and future directions, and discussed the importance of data security, interoperability, and regulatory considerations in IoT-based healthcare systems, emphasizing the need for robust security frameworks to ensure patient data protection. In [24], Verma et al. developed a hybrid secure cloud IoT framework for disease prediction and diagnosis, which improved data security and accuracy of disease diagnosis but raised concerns regarding scalability and privacy.

These studies clearly demonstrate that privacy and interoperability are not peripheral concerns, but structural constraints. However, they remain loosely coupled to AI model design, reinforcing the need for an integrated data-centric framework.

2) Key observations and emerging gaps: These studies converge on a critical insight: while model-centric innovations have improved local accuracy, they often neglect systemic issues related to data quality and governance. Few solutions prioritize data refinement as a strategic goal, dataset representativeness, noise reduction, or robust data integration—gaps which DCAI directly addresses. As shown in Table III, the reviewed studies highlight recurring limitations (e.g., noisy data, lack of standardization, sensor faults, and unstructured inputs) that underscore the need for a paradigm shift toward DCAI methodologies.

To consolidate the expanded comparative insights derived from the 23 reviewed studies, we performed an updated quantitative synthesis of the key limitations reported in AI-, IoT-, and Big Data-driven healthcare systems. As illustrated in Fig. 3, privacy concerns remain the most dominant challenge, cited in 10 studies (43.5%), reflecting persistent issues related to patient data protection, regulatory compliance, and trust in large-scale digital health infrastructures. Data heterogeneity follows closely, reported in 9 studies (39.1%), highlighting the ongoing difficulty of integrating heterogeneous data sources such as IoT sensors, EHRs, and unstructured clinical data. Noisy data was identified in 6 studies (26.1%), underscoring the impact of sensor inaccuracies, transmission errors, and real-world data variability on model reliability. A second tier of limitations includes security risks and integration challenges, same as noisy data limitation each reported in 6 studies (26.1%), indicating that secure data exchange and seamless system interoperability remain unresolved barriers. Real-time processing constraints, data sparsity, and scalability limitations were each mentioned in five studies (21.7%), reflecting the computational and infrastructural challenges of deploying AI systems in dynamic clinical environments. Missing values were cited in 4 studies (17.4%), pointing to data incompleteness issues arising from sensor failures and fragmented health records. Lower-frequency yet significant concerns include standardization issues and sensor faults (same as missing values limitation every four studies, 17.4%), as well as contextual inconsistencies, bias, ethical concerns, and labeling errors (each reported in two to three studies, ~8.7–13%). Collectively, these findings demonstrate that many of the most critical obstacles are fundamentally data-centric rather than model-centric, reinforcing the necessity of Data-Centric AI (DCAI) approaches that prioritize data quality, governance, interoperability, and scalability as prerequisites for trustworthy and effective healthcare AI deployment.

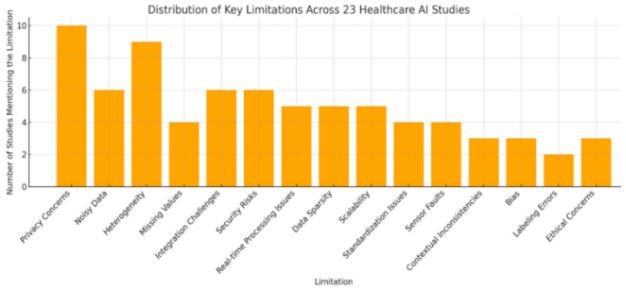


Fig. 3. Distribution of key limitations mentioned across 23 reviewed healthcare AI studies. Privacy, noise, and data heterogeneity emerge as the most cited barriers, underscoring the need for robust data quality and governance frameworks.

3) Summary of comparative insights

a) IoT-based healthcare solutions: Many studies emphasize real-time patient monitoring but lack context-aware and adaptive AI models to dynamically adjust to patient conditions [3], [10].

b) AI for predictive healthcare: AI models demonstrate strong disease prediction capabilities, but their accuracy is often limited by poor data quality, missing values, and a lack of contextual understanding [11], [23].

c) Security and privacy concerns: IoT-driven healthcare systems are highly vulnerable to cyber threats, necessitating secure data-sharing and privacy-preserving [13], [24].

d) Interoperability issues: The absence of standardized data formats and frameworks inhibits seamless integration between healthcare systems and IoT devices, creating barriers to efficient data exchange [25], [31].

These studies demonstrate the growing impact of IoT, AI, and Big Data in modern healthcare, particularly in areas such as real-time monitoring, predictive diagnostics, and personalized treatment. However, most adopt a model-centric approach that prioritizes algorithm performance over data integrity. Persistent data issues continue to undermine scalability, fairness, and reliability. In response, this study advocates for the DCAI paradigm, which prioritizes high-quality, standardized, and context-aware datasets as the foundation for trustworthy and adaptive healthcare systems.

TABLE III. COMPARATIVE ANALYSIS OF HEALTHCARE AI-IOT STUDIES

Ref	Model Used	Application	Data Type & Source	Metrics for Evaluation	Results of the Study	Limitations
[10] Zon et al. (2023)	Various Context-Aware Systems (The study primarily reviews various context-aware models used in healthcare applications, without focusing on a specific single model)	Context-aware healthcare applications that utilize user location, demographic information, activity level, time of day, phone usage patterns, lab/vital metrics, and patient history data.	Healthcare IoT & Sensor Data from 25 peer-reviewed articles found in databases	Accuracy, Sensitivity	Identified key medical contexts for AI adaptation, Improved patient-centered healthcare	Context heterogeneity affects reliability and lack of details on methods for determining contexts and on the systems currently used.
[11] Chung et al. (2020)	Deep Neural Networks	Context-basedHealth risk alert system for chronic disease patients	Electronic Medical Record (EMR), Personal Health Record (PHR) & Public Health Data (PHD) & Open API Data (OAD) (Korean Health & Nutrition Survey data)	Root Mean Square Error (RMSE) and comparison of prediction accuracy rates	Improved risk prediction accuracy, Effective ambient context pattern detection	Limited number of data set scope and integration issues, possibly affecting the reliability of predictions.
[13] Saranya & Fatima (2022)	Improved Context-aware Data Fusion (ICDF) and Enhanced Recursive Feature Elimination (ERFE) Model	IoT-Based Patient Monitoring	Biometrics and health data collected from IoT devices and sensors, including RFID sensors	Accuracy, Precision, , recall, F1-score, True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) rates	Enhanced real-time monitoring, reduced false alerts (97.9% accuracy)	Challenges in data integration, potential cyber vulnerabilities in IoT systems, reliance on the accuracy of sensor data, need for regular battery replacements, and scalability challenges
[20] Kishor & Chakraborty (2021)	Machine Learning Classifiers that employ seven classification algorithms: Decision Tree, Support Vector Machine, Naïve Bayes, Adaptive Boosting, Random Forest, Artificial Neural Network, and K-	The early and accurate prediction of various diseases including heart disease, diabetes, breast cancer, hepatitis, liver disorder, dermatology, thyroid issues, surgery data, and spect heart conditions.	IoT Data, Electronic Health Record (HER) , UCI Health datasets	Accuracy, sensitivity, specificity, and area under the curve (AUC).	The Random Forest classifier achieved an accuracy of 97.62%, sensitivity of 99.67%, specificity of 97.81%, and AUC of 99.32%.	Limitations related to the quality of data collected through IoT sensors & Real-time processing issues

	Nearest Neighbor.					
[21] Ghazal et al. (2021)	Machine Learning (From the selected existing studies)	Smart Healthcare Systems , Smart Cities & Patient Monitoring	Discussing the use of Big Data and IoT Sensor Data (biodata transmitted in real-time and historical health records from various healthcare settings)	Efficiency, Prediction Accuracy	Enhanced patient monitoring, Improved diagnostic methods through centralized device monitoring + Potential for decentralized care, especially beneficial in underserviced areas	Potential downsides of smart city technologies, such as privacy and security concerns relating to IoT integration in healthcare
[12] Kim & Chung (2020)	Neural Network-Based Adaptive Context Model	Ambient Intelligence (Adaptive Context Prediction for Health Monitoring)	Heterogeneous data such as medical big data, bio big data, lifelog data, and various health-related contexts from personal health devices, IoT devices, environmental data and structured and unstructured medical data.	F1-score, Recall , RMSE, error rate	The neural-network based similarity weight method achieved the highest prediction accuracy when implemented with the specified parameters & Potential in improving healthcare delivery and quality of life through context predictions.	Potential fairness concerns due to contextual inconsistencies and limited scope of data, potential challenges in accurately predicting changes in context and health conditions and the necessity of substantial advanced data integration techniques to handle large volumes of heterogeneous data effectively.
[22] Kaur (2021)	IoT Framework + Machine Learning from various research findings	Heart Disease Prediction (Remote patient monitoring, medical data analysis, and decision support systems)	IoT Wearables, Patient Data (clinical records, medical images, and structured and unstructured sensor data)	Accuracy, Precision & Recall	High prediction accuracy for cardiac risks	Security concerns around patient data privacy and the potential for data leaks can affects model generalization
[2] Banerjee et al. (2020)	Not a specific model but a acknowledging of Big Data Analytics	Book chapter about IoT & AI in Healthcare for Smart Cities & Healthcare Integration	Wearable Devices, Sensor Networks	Data Efficiency, Latency	Improved data standardization for healthcare analytics, disease detection rates and patient outcomes	The chapter does not detail specific limits but identifies challenges concerning the quality of data in developing countries like Wearable device latency issues , Infrastructure-dependent implementation
[3] Meraj et al. (2021)	IoT Sensor Analysis of real-time surveillance systems	Infectious Disease Detection particularly in pandemic contexts	IoT Sensors, Public Health Data	Outbreak Prediction Accuracy	Enabled early outbreak warnings, Improved infectious disease detection rates and healthcare responses, better real-time care management.	IoT infrastructure for continuous large -scale monitoring, potential for data issues
[23] Vijayalakshmi et al. (2021)	Big Data Analytics	Chronic Disease Prediction and Real-time patient monitoring	Data would likely come from healthcare systems such as electronic medical records (EMRs) / EHR, Medical Reports	Classification Accuracy	Improved long-term disease predictions , clinical outcomes and decision-making processes in healthcare through real-time data analysis	Acknowledging challenges related to data quality and the implementation of IoT systems in certain contexts, Data sparsity limits precision, issues with unstructured data processing
[24] Verma et al. (2021)	Hybrid Secure Cloud IoT Model (Hybrid Encryption & Optimization (HEE, GFI-GWALO))	Disease Prediction & Diagnosis in IoT-based Healthcare	IoT Data, Cloud Computing, including structured, semi-structured and unstructured medical records	Security, Accuracy, encryption time, decryption time	Enhanced secure cloud-based diagnosis , Achieved 100% accuracy, encryption time of 80ms, addressing the challenges of managing health data in IoT-based healthcare systems	Privacy concerns in cloud-based storage, data quality issues and integration challenges
[25] Aceto et al. (2020)	Not a specific model but combining	Personalized Healthcare and	Systematic literature review, secondary data	Literature synthesis	Identified challenges & benefits of Industry 4.0 in healthcare , Improved	Privacy concerns limit implementation (Regulatory and transparency concerns)

	research from IoT, cloud computing, Industry 4.0 and big data analytics to assess their impact on healthcare systems	healthcare service delivery	(Smart Devices, Cloud Data with the use of a "snowball" method to analyze the available research)	(Integration Efficiency)	data fusion for patient management and improved clinical and public health operations through better data analysis and decision-making)	+ the challenges of error-free big data analysis and the management of large amounts of medical data
[14] Aborokbah et al. (2018)	Context-Aware Decision Systems (Support Vector Machines (SVM))	Chronic Disease Management (Cardiac Disease Risk Prediction in Smart cities)	Wearable Devices, IoT Data (Physiological sensor data)	Decision Accuracy	Adaptive healthcare decision support , Effective real-time monitoring of heart failure risk	Contextual inconsistencies in patient data, Limited dataset size, Quality of data collected and generalizability of results.
[26] Castro et al. (2017)	IoT-Based Human Activity Recognition (Bayesian & C4.5 Decision Trees)	Health Monitoring , Human Activity Recognition (HAR)	Wearable Sensor Data (HR, acceleration, respiration)	Pattern Recognition Accuracy, classification rate	Improved activity-based patient monitoring (95.83% accuracy for activity recognition)	Small dataset, limited activity categories, potential of environmental noise affects precision
[27] Chui et al. (2019)	ML + Big Data & IoT	Patient Behavior Monitoring and cardiovascular disease detection in healthcare	Healthcare Institution Data (Wearable & implantable sensors)	Anomaly Detection Rate , Sensitivity, specificity	Better patient behavior analytics , Reduced hospital readmissions, improved health outcomes.	Lack of real case studies, Data heterogeneity affects standardization, Privacy concerns in patient monitoring
[28] Ngiam & Khor (2019)	Deep Learning, Neural Networks + Big Data & ML	AI in Healthcare (medical diagnostics, predicting disease risks, analyzing medical images, and supporting clinical decision-making)	EHR, IoT Data, lab results, textual physician notes, Demographic data, imaging data	Prediction Accuracy, precision, recall	Comprehensive survey on AI applications (High predictive accuracy in clinical settings and better personalization of treatments)'	Ethical concerns in AI adoption, potential challenges in data preprocessing and inaccurate labeling
[29] Shah et al. (2018)	IoT Sensing Systems + SVM , KNN and RF	Healthcare Monitoring, Sleep Disorder Detection (Narcolepsy) and other human activities	Wearable Sensors, IoT Networks (Radar-based Band-S signals)	Reliability, Sensitivity , Classification accuracy	Improved remote patient monitoring (90%+ accuracy in detecting sleep disorders), better care for narcolepsy patients through early detection of sleep episodes, reduction of accidents related to sleep attacks.	Issues in reliability for sleep disorder tracking, Small sample size (the study may be limited by the quality of the data collected due to multipath interference and the need for specialized equipment)
[30] Tian et al. (2019)	AI & IoT-based Smart Healthcare from the reviewed studies	Medical Intelligence (Smart Hospitals), AI-assisted Diagnosis, chronic disease management, patient monitoring and treatment personalization.	EHR, IoT Sensors (Clinical trial datasets, literature reviews)	System Efficiency , Qualitative benefits assessment	Enhanced real-time AI-driven healthcare, Smart healthcare systems improve the efficiency of care, enable faster treatment and reduce costs while improving patients' quality of life.	Privacy concerns in real-time applications, Scalability of AI integration in healthcare
[31] Yin et al. (2016)	IoT-Based Healthcare Framework from the reviewed studies (not a specific model)	IoT in Medical Systems to improve remote patient monitoring and personalized rehabilitation services	Big Data, EHR, datasets from various sources such as hospitals, home-care, rehabilitation centers	Adoption Rate, System interoperability, real-time updates	Overview of IoT applications in healthcare, Improved patient tracking & remote monitoring	Integration challenges remain, Security and data privacy challenges, the complexity of managing big data
[16] Zonayed et al. (2025)	Narrative review of studiens that uses (KNN, SVM, Random	A comprehensive narrative review - Detection and prediction of	Healthcare datasets from UCI and hospital-based EHRs	Qualitative synthesis of existing research	Identified current trends, challenges, Key finding: KNN achieved 100% (breast cancer), RF 96.6%	Feature selection, model interpretability, data imbalance, lack of real-time adaptability, Data security,

	Forest, XGBoost, AdaBoost, CNN, En-RfRsK, HFSDLF)	chronic diseases: breast cancer, diabetes, hepatitis, Alzheimer's, lung cancer			(heart), LR 93.18% (hepatitis), AdaBoost highest in Alzheimer's, CNN+XGBoost 97.43% (lung)	patient privacy ,Scalability , data heterogeneity interoperability issues, context-aware access control and ethical
[29] Šajnoví et al. (2024)	Not applicable (review paper)	Preventive healthcare via IoT and Big Data Analytics	Synthetic review of 2272 papers from Scopus between 1985 and June 10, 2024., including real-world IoT health data and big data systems	Not empirical; thematic synthesis used	Identified major research trends, technologies, and enablers (IoT devices, data lakes, wearable sensors); proposed future directions for intelligent preventive systems	Lack of standardization in data collection, ,heterogeneous data, need for interoperability among IoMT devices.privacy concerns, data integration challenges, limited real-world validation
[18] Charfare et al. (2024)	Multiple AI techniques (e.g., deep learning, ML algorithms) integrated with IoT platforms	Broad spectrum of healthcare applications including remote monitoring, predictive diagnostics, elderly care, and emergency response	Literature-based review of current deployments and innovations across real-world IoT-healthcare systems	Qualitative synthesis (no experimental metrics provided)	Presents a synthesized landscape of IoT-AI convergence, highlighting current innovations, benefits, and key healthcare domains highest performance (LightGBM for HAR (99.23%) and LSTM for fall detection (99%))	Lack of experimental data; challenges discussed include latency, security vulnerabilities, data heterogeneity, insufficient interoperability and need for real-time adaptability
[19] Alsabah et al. (2025)	Not a single model; comprehensive review of IoT architectures integrated with AI, Big Data analytics, edge/fog computing, and cloud platforms	Smart healthcare systems including remote patient monitoring, disease diagnosis, hospital management, emergency response, and personalized healthcare services	Secondary data from peer-reviewed IoT-based healthcare studies, including sensor data, EHR/EMR data, wearable data, and cloud-based medical datasets	Qualitative evaluation based on system scalability, latency, interoperability, data processing efficiency, security, and reliability	Identified key enabling technologies and architectural patterns for smart healthcare; highlighted the role of AI and Big Data in enhancing decision-making, real-time monitoring, and service personalization; provided a consolidated view of technical challenges and future research directions	Challenges remain in scalability, heterogeneity, interoperability, privacy preservation, noisy data, real-world deployment costs and the need of explainable ethical Ai models

III. Challenges in Integrating AI, Big Data, and IoT in Healthcare

Despite the transformative potential of AI, Big Data, and IoT in healthcare, their integration faces substantial barriers that impact reliability, scalability, and ethical deployment. A recurring limitation is data quality, particularly in real-time environments driven by sensor-generated streams.

Challenges stem from noise, missing data, inconsistencies, interoperability issues, privacy concerns, and bias, all of which hinder AI reliability and scalability in healthcare. Sensor noise, such as movement artifacts or calibration errors in ECG devices, distorts predictions and triggers false alarms [13]. Missing data further weakens AI models, leading to biased and unreliable decision-making, as gaps in patient records degrade deep learning performance [1]. Inconsistencies across IoT devices, caused by variations in data formats and protocols, complicate seamless integration, requiring standardized frameworks [21]. Without robust standardization, data fusion from disparate sources remains a technical bottleneck. Bias in IoT-generated datasets, often due to demographic imbalances or inconsistent labeling, results in inequitable AI predictions that disproportionately impact underrepresented populations [12]. Additionally, privacy risks, such as data anonymity and pseudonymization, affect dataset usability and AI predictive accuracy, making privacy governance essential in AI applications [1]. Scalability and real-time adaptability remain obstacles, with many AI models struggling to dynamically adjust to changing patient conditions [12]. Furthermore, interoperability issues between IoT devices, AI models, and hospital systems create siloed environments that restrict data sharing and hinder holistic patient care [30], [31].

Poor data quality in AI-driven healthcare systems can lead to severe outcomes, including misdiagnosis, inequitable care delivery, and loss of clinical trust. According to Jin et al. in [5], imperfections such as incorrect labels, missing values, and anomalies not only degrade model performance but risk overfitting and undermine generalizability—particularly critical in healthcare where model predictions influence life-altering decisions. In [6], Nieberl et al. emphasize that data cascades, which occur when initial quality issues propagate through the pipeline, are a hidden yet profound threat to AI reliability.

Building on our literature-driven hypothesis, we propose that Data-Centric AI (DCAI) offers a viable pathway to overcoming these challenges by emphasizing data quality, fairness, security, and standardization, ensuring more reliable AI-driven healthcare outcomes [4], [9]. Fig. 4 illustrates the major data-related challenges encountered in the integration of AI, Big Data, and IoT for Healthcare.

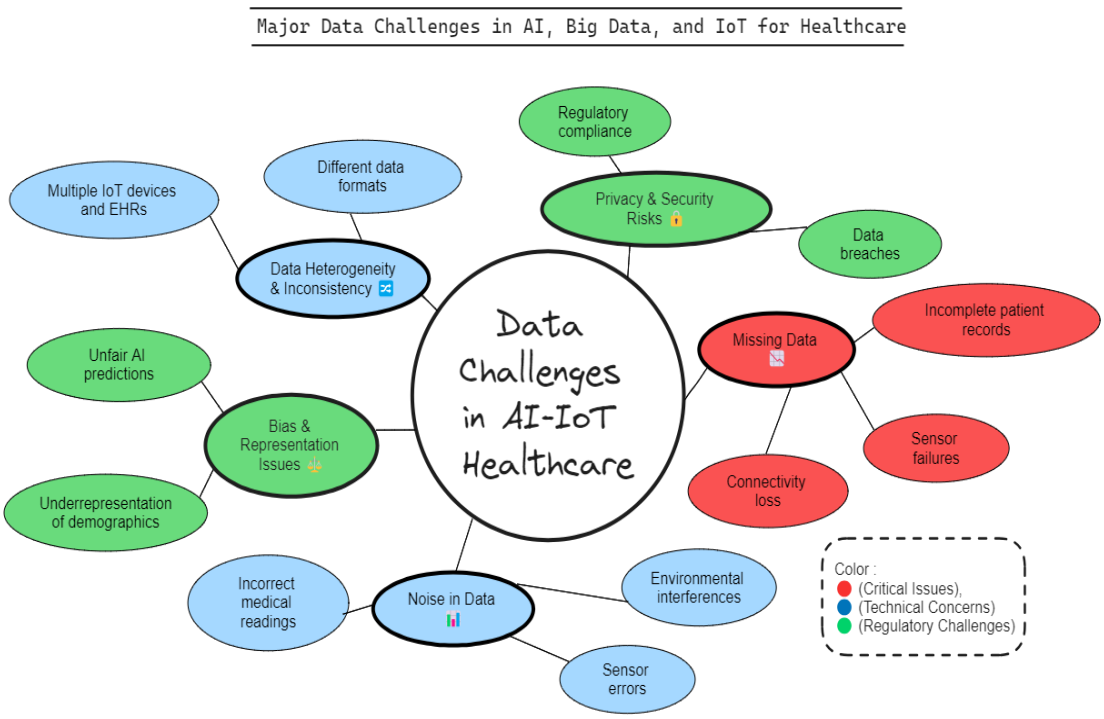


Fig. 4. Major data challenges in AI, Big Data, and IoT for healthcare.

IV. Data-Centric AI: A Paradigm for Addressing Data Challenges in Healthcare

As highlighted in the previous section, the core contribution of our study lies in positioning Data-Centric Artificial Intelligence (DCAI) as a foundational paradigm for addressing longstanding challenges in healthcare AI systems—specifically, issues related to data quality, context-awareness, standardization, and ethical scalability. Recent advances highlight that high-quality, well-annotated, and context-rich data can outperform more complex models trained on flawed datasets, reshaping our understanding of what drives AI success. Unlike traditional AI methodologies, which focus on hyperparameter tuning and deep learning architectures, Data-Centric AI (DCAI) enhances model reliability through systematic data curation [4] (see Table IV).

Despite this shift, few studies have comprehensively mapped how DCAI principles can be applied to healthcare-specific challenges, particularly in the context of IoT-generated data and Big Data analytics. As Jin et al. in [5] argue, a unified, structured synthesis of DCAI methodologies tailored to healthcare is lacking, especially one that considers clinical interoperability, fairness, and regulatory constraints. In healthcare, where the stakes of predictive errors are high and datasets are often noisy, incomplete, heterogenous or biased, DCAI-driven methodologies offer a critical corrective and provide robust solutions to mitigate these challenges [9]. By ensuring high-quality, well-labeled, and diverse datasets, DCAI enables AI systems to generalize effectively across different populations and healthcare environments. As Bhatt et al. in [4] demonstrate that smaller models trained on high-quality datasets can outperform larger models trained on flawed data. Similarly, Malerba et al. in [9] argue that DCAI methodologies—ranging from noise filtering and imputation to data augmentation and bias mitigation—are key to building scalable and ethical healthcare AI.

TABLE IV. Comparison of Data-Centric AI (DCAI) and Model-Centric AI in Healthcare AI

Aspect	Model-Centric AI	Data-Centric AI (DCAI)
Primary Focus	Optimizing AI models and algorithms [4]	Improving data quality, completeness, and fairness [1]
Approach to AI Performance	Improves performance by refining model architecture and hyperparameters [4]	Enhances performance by refining datasets rather than just improving models [1]
Data Handling	Assumes data is fixed and optimizes models to extract insights [9]	Systematic preprocessing, data augmentation, and bias mitigation [4]
Model Complexity	Requires complex models to compensate for suboptimal data [1]	Simpler models trained on high-quality data perform as well as or better than complex models [4]
Scalability	Limited scalability due to dependency on large models and retraining [9]	Highly scalable as data improvements generalize across different models [1]
Bias Mitigation	Bias correction is applied post hoc through model adjustments [1]	Bias is addressed at the dataset level, ensuring fairer and more representative AI outputs [4]
Challenges	Sensitive to data drift, requires frequent model updates, struggles with unreliable data [1]	Requires investment in systematic data collection, labeling, cleaning, and augmentation [4]

DCAI facilitates the standardization and structuring of IoT-generated health data, improving interoperability between AI models, IoT devices, and hospital infrastructures to reduce healthcare system fragmentation. High-quality data is essential for accurate diagnostics, equitable treatment recommendations, and compliance with ethical and regulatory standards. To improve data integrity and to address persistent issues in healthcare, DCAI integrates techniques such as bias detection, noise filtering, and data augmentation [1]. By treating data as a dynamic, evolving infrastructure, DCAI ensures AI systems remain fair, trustworthy, and effective. As highlighted by Zha, Bhat, Lai, Yang, Jiang, Zhong & Hu in [15], DCAI emphasizes continuous data improvement throughout the AI lifecycle, transforming data from a static input into a dynamic, strategic asset. Additionally, real-time adaptive AI models leveraging DCAI principles can dynamically adjust to context-aware decision-making, enhancing patient monitoring and disease prediction by utilizing high-quality labeled datasets that reflect dynamic changes in patient states.

Our study seeks to map recurring limitations identified in AI-IoT healthcare studies we previously discussed, such as inconsistency, bias, and lack of contextual adaptation, to specific DCAI techniques and solutions. We emphasize that issues like heterogeneity, fairness, and reliability are not solely technical but deeply tied to data design. By applying frameworks such as the METRIC framework [1], developers can evaluate healthcare datasets across dimensions like completeness, consistency, timeliness, and contextual fit. This paradigm shift is particularly critical in healthcare, where reliable AI-driven decisions directly impact patient safety and system credibility. Furthermore, robust decision-making relies on high-quality health data to generate consistent and evidence-based insights. By shifting the emphasis from algorithmic optimization to data integrity, interoperability, and real-time adaptability, this study explores the theoretical potential of Data-Centric AI (DCAI) to transform AI-driven healthcare systems into more scalable, ethical, and efficient solutions. Although our work does not empirically validate DCAI interventions, we propose that its principles are particularly well-suited for dynamic, context-aware, real-time healthcare environments, such as remote monitoring or emergency diagnostics. Crucially, DCAI supports the development of adaptive, context-aware AI systems that can respond dynamically to evolving patient conditions using continuously curated and context-rich datasets. This is particularly vital in applications such as remote monitoring and emergency diagnostics, where decision-making must be both rapid and reliable. By reframing the development pipeline around data quality, our study positions DCAI as a catalyst for building more ethical, transparent, scalable, and resilient AI systems in healthcare.

V. Addressing Data Quality Challenges Through Data-Centric AI (DCAI)

DCAI provides a structured framework for overcoming the previously outlined persistent data quality issues in healthcare AI systems. By prioritizing the curation, augmentation, and governance of data over merely tuning models, DCAI supports the development of more accurate, fair, and context-aware AI tools. For instance, bias mitigation is achieved through dataset audits, augmentation strategies, and synthetic data generation, as seen in [4], where underrepresented populations were better included in disease prediction models. Likewise, missing data—often resulting from sensor failures or transmission gaps in IoT-based health monitoring—is addressed through statistical and machine learning-based imputation techniques. In [9], Malerba et al. showcased robust hybrid approaches for managing data gaps, especially in critical use cases like glucose level monitoring.

Furthermore, to tackle noise and inconsistency in heterogeneous healthcare data, DCAI recommends pipelines for standardization and noise filtering, as highlighted by Bhatt et al in [4]. These processes enhance model robustness across diverse data sources and clinical settings. While privacy and security are not traditionally part of data quality metrics, they are integral to data usability and regulatory compliance. In [1], Schwabe et al. underscore that privacy should be treated as a governance concern, though technical solutions like federated learning and differential privacy can still support secure AI deployment. Taken together, these DCAI methods form a foundational toolkit for building scalable, ethical, and effective AI systems in healthcare—aligning data practices with real-world demands for transparency, interoperability, and patient-centered decision-making.

VI. Key Metrics for Evaluating Data Quality in Healthcare AI

The foundational literature on Data-Centric AI (DCAI) offers critical insights into data quality metrics and governance dimensions essential for trustworthy AI systems in healthcare. These include completeness, consistency, accuracy, bias mitigation, and timeliness, alongside data management principles such as privacy, documentation, and alignment with Findable, Accessible, Interoperable, and Reusable (FAIR) principles (see Fig. 5). These metrics are central to developing reliable, ethical, and high-performing healthcare AI systems. In [4], Bhatt et al. highlight the importance of data preprocessing and augmentation in reducing bias and improving dataset robustness. In [1], Schwabe et al. introduce the METRIC framework, which formalizes the assessment of data quality in medical AI applications, particularly in medical imaging and electronic health records (EHRs). In [9], Malerba et al. emphasize standardization, integration, and privacy-preserving AI techniques as foundational to secure and reliable healthcare AI models.

A. Core Data Quality Metrics

- Completeness ensures datasets are comprehensive, preventing unreliable predictions due to missing vitals or sensor gaps, with Schwabe et al. in [1] advocating for imputation techniques to address these issues.
- Consistency focuses on standardizing data formats across heterogeneous sources, as Malerba et al. in [9] emphasize normalization techniques to improve interoperability.
- Accuracy is critical in avoiding errors from faulty sensor readings, with Bhatt et al. in [4] recommending noise filtering methods like Kalman filters to enhance data reliability.

- Bias detection mitigates demographic imbalances in datasets, where techniques such as GAN-based synthetic data generation help improve fairness [4].
- Timeliness ensures real-time decision-making in critical care scenarios, with Schwabe et al. in [1] promoting edge computing to minimize delays.

B. Data Governance and Security Considerations

Though not typically framed as "quality" metrics, data privacy, security, and documentation are crucial for regulatory compliance and patient protection for ethical deployment of healthcare AI. In [9], Malerba et al. emphasize the need for:

- Federated learning to enable secure model training without centralizing sensitive data.
- Differential privacy to ensure anonymity and protect patient confidentiality during analysis and model deployment.

Together, these factors shape trustworthy, high-performance AI systems, ensuring data-driven healthcare solutions are reliable, fair, and efficient. These governance mechanisms are essential for legal compliance (e.g., GDPR, HIPAA), fostering patient trust and ensuring ethical alignment of AI solutions.

C. Standardized Frameworks: The Role of METRIC

The METRIC framework, introduced by Schwabe et al. in [1], provides a structured approach to evaluate medical datasets across key dimensions—completeness, consistency, timeliness, relevance, interoperability, and contextual fit. This framework is particularly useful for multi-source, privacy-sensitive environments like EHR systems and remote IoT monitoring platforms.

Our study underscores the need for standardized, interpretable, and scalable evaluation frameworks such as METRIC, particularly in multi-source, privacy-sensitive healthcare environments. They form the backbone of resilient healthcare AI systems capable of delivering equitable, transparent, and patient-centered outcomes. However, deploying a DCAI Framework in clinical settings is not without challenges—cost, data governance gaps, and system interoperability all pose real-world implementation barriers (see Section VIII (B).

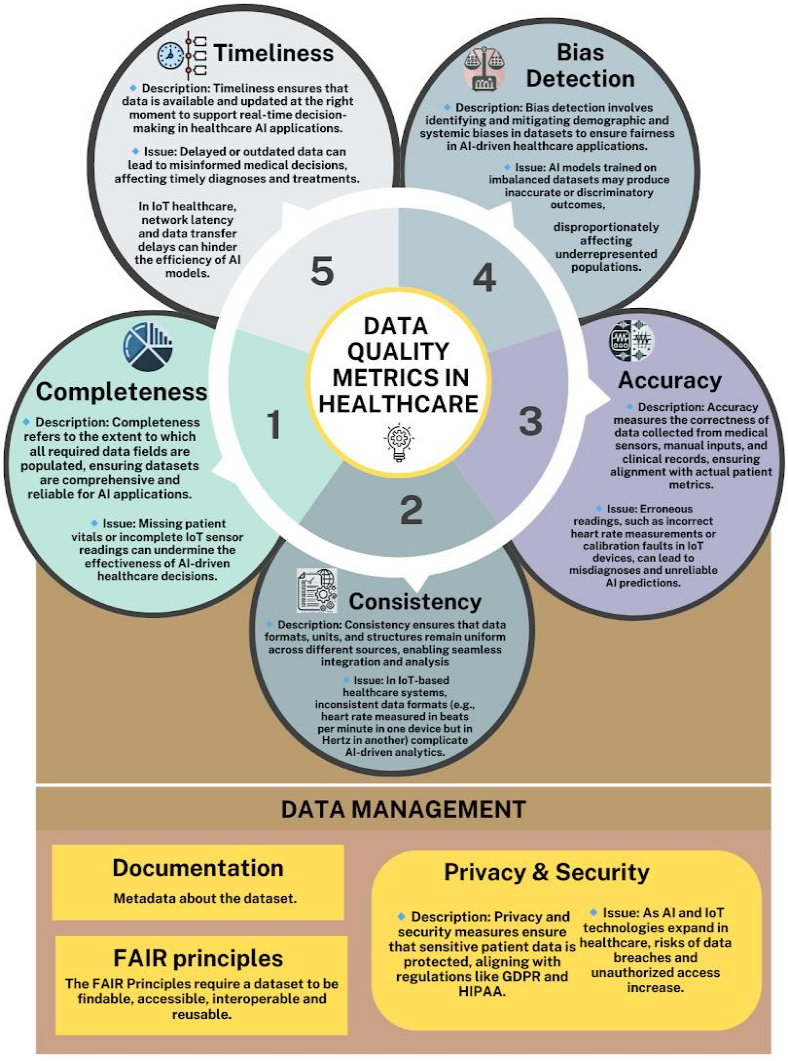


Fig. 5. Data quality metrics in healthcare AI (from the METRIC framework).

D. Summary: Core Principles of DCAI in Healthcare

- Enhancing Data Completeness and Consistency
- Ensure no missing values in critical health datasets and maintain consistency across diverse healthcare sources.
- Mitigating Bias and Ensuring Fairness.
- Promote diverse and well-balanced datasets and eliminate demographic bias in AI-driven medical decision-making.
- Standardizing Healthcare Data and Enabling Interoperability.
- Harmonize heterogeneous data formats and support seamless integration of multiple IoT sources and clinical data to facilitate smooth data exchange.
- Strengthening Data Security and Privacy.
- Apply robust privacy-preserving mechanisms to protect sensitive patient information to ensure confidentiality and prevent unauthorized access or exposure of sensitive medical information.

VII. Challenges and Limitations

Despite the potential of Data-Centric AI (DCAI) to improve healthcare AI systems, several challenges and limitations must be addressed to ensure scalability, fairness, and trustworthiness. These issues stem from both technical and systemic barriers within healthcare data ecosystems.

First, quantifying fairness in AI systems remains inherently complex due to demographic disparities across global healthcare environments. Biased training data can lead to inequitable outcomes, particularly for underrepresented populations, and current bias metrics often fail to capture these nuances accurately.

Second, data variability and quality continue to pose significant hurdles. Real-time data streams from IoT devices require constant monitoring to ensure consistency, contextual relevance, and timeliness. However, as Schwabe et al in [1] highlight, pervasive data issues—including noise, missing values, and inconsistency across heterogeneous sources—complicate integration and reliability of AI models.

Third, privacy and regulatory constraints (e.g., HIPAA, GDPR) restrict access to comprehensive patient data, hindering bias detection and correction. While privacy-preserving methods such as federated learning and differential privacy provide alternatives [9], their implementation is still limited by technical and legal challenges.

Fourth, computational overhead poses another challenge, as evaluating data quality at scale demands significant resources, especially in large IoT and Big Data systems [4].

Fifth, explainability and trust in AI-driven decisions remain critical for clinical adoption, as healthcare professionals require interpretable models and datasets with documentation, annotation, and data provenance for decision support.

Lastly, real-world deployment presents practical barriers. Integrating AI systems with existing hospital IT infrastructure, obtaining regulatory approvals, and ensuring seamless interoperability across data sources all remain major impediments to widespread adoption.

Importantly, while our study synthesizes findings from foundational DCAI literature and healthcare-focused research, it does not incorporate empirical experimentation or advanced AI techniques (e.g., generative AI, self-supervised learning, explainable AI). These promising areas are earmarked for future exploration.

- Key Findings and Gaps
  - Persistent Data Quality Issues: Noise, missing values, and bias remain critical obstacles to reliable healthcare AI.
  - Limited Implementation of DCAI: Although promising, DCAI is rarely applied systematically in healthcare settings.
  - Lack of Standardized Evaluation Metrics: Inconsistent metrics across studies hinder cross-model comparisons and benchmarking.
  - Interoperability Challenges: Diverse data sources (e.g., EHRs, IoT, imaging) often lack harmonization, limiting seamless AI integration.
  - Difficulty Quantifying and Mitigating Bias: Demographic disparities in data create systemic bias that is difficult to measure and correct.
  - Limited Multimodal Integration: Many current models fail to combine diverse healthcare data types (e.g., clinical text, images, sensor streams), reducing contextual awareness and diagnostic performance.

VIII. Future Work

As healthcare AI systems evolve, Data-Centric AI (DCAI) practices—such as data augmentation, bias mitigation, and context-aware preprocessing—are becoming essential for developing ethical, interpretable, and adaptive solutions [6], [15]. While this review provides a conceptual synthesis of DCAI principles, bridging foundational literature and application studies through a structured methodology, significant research opportunities remain. These involve both enhancing core DCAI practices and integrating emerging technologies to improve scalability, fairness, real-time adaptability, and clinical trustworthiness.

A. Key Future Research Directions

Below, we outline key future research directions to extend the impact and applicability of DCAI in AI-driven healthcare systems:

1) Generative AI for data augmentation: Explore the use of generative models such as GANs (Generative Adversarial Networks) and VAEs (Variational Autoencoders) to create realistic synthetic healthcare data. This approach could reduce data scarcity, correct demographic imbalances, and improve model fairness and generalizability.

2) Multimodal AI frameworks: Investigate the integration of diverse data modalities—including EHRs, IoT sensor streams, medical imaging, and genomics—to build comprehensive and context-rich patient profiles. Evaluate their impact on diagnostic accuracy, clinical decision support, and patient stratification.

3) Advanced bias mitigation techniques: Develop and validate fairness-aware training strategies and bias auditing tools that operate across the entire AI pipeline. This includes addressing hidden biases in data collection, labeling, and model inference stages.

4) Transformer-based and hybrid AI models: Assess the role of cutting-edge architectures such as transformers and graph neural networks (GNNs) in modeling relational and temporal dependencies in complex healthcare environments, particularly where patient data is sparse, noisy, or interconnected.

5) Context-aware and self-adaptive AI systems: Design AI systems capable of dynamically adjusting to patient-specific contexts and environmental changes in real-time. Such models could enhance remote patient monitoring, emergency diagnostics, and chronic disease management by incorporating adaptive decision logic.

6) Explainable and trustworthy AI (XAI): Integrate explainability mechanisms into DCAI workflows to improve clinical interpretability and transparency. This involves applying interpretable models or post-hoc explanation tools (e.g., SHAP, LIME) to enhance clinician trust and facilitate regulatory approval.

7) Privacy-preserving AI methods: Implement and empirically validate federated learning, homomorphic encryption, and differential privacy to ensure regulatory compliance (e.g., HIPAA, GDPR) while maintaining model utility and protecting sensitive patient data.

8) Standardized IoT interoperability: Advance the development of universal communication protocols and interoperability standards for integrating heterogeneous IoT devices and healthcare platforms. This is essential for real-time data sharing, multi-system alignment, and scalable deployment.

B. Practical Considerations and Conclusion of the Section

While Data-Centric AI (DCAI) offers a promising path to improving fairness, accuracy, and scalability in healthcare AI, its implementation is hindered by practical barriers such as high resource requirements, lack of data governance structures, and limited interoperability in clinical settings. Many hospitals operate with fragmented IT systems, unstructured data silos, and unclear data ownership, which complicate systematic data curation and annotation workflows required for DCAI adoption [1], [5]. Implementing privacy-preserving techniques like federated learning or synthetic data generation demands not only technical expertise but also legal and institutional coordination, which may be lacking in resource-constrained environments [4], [9]. Moreover, most DCAI frameworks are designed for static datasets and are not easily adaptable to dynamic, real-time healthcare scenarios where context, data quality, and ethical oversight must constantly evolve. Addressing these challenges requires interdisciplinary collaboration, scalable governance models, and cost-effective toolkits tailored for healthcare infrastructure, ensuring that DCAI moves from conceptual promise to real-world impact.

IX. Conclusion

This study positions Data-Centric Artificial Intelligence (DCAI) as a transformative paradigm for advancing trustworthy, scalable, and ethical AI-driven healthcare systems. Unlike traditional model-centric approaches that emphasize algorithmic optimization, DCAI redirects focus toward systematic improvements in data quality—enhancing completeness, consistency, standardization, fairness, and interoperability. Through our literature-based analysis of twenty-three AI-IoT healthcare studies and foundational DCAI works, we identified persistent challenges related to noise, missing values, demographic bias, contextual inconsistency, and privacy concerns. DCAI addresses these limitations by integrating practical techniques such as data augmentation, noise filtering, bias mitigation, and standardized preprocessing, while frameworks like METRIC offer structured tools for evaluating data quality across key dimensions. Although our study is theoretical in nature, it establishes a foundational synthesis linking DCAI principles to healthcare-specific data challenges. Future directions should focus on integrating DCAI principles with cutting-edge technologies such as explainable AI (XAI), generative AI, and multimodal learning, while also advancing real-time, context-aware AI–IoT convergence in smart healthcare environments. Such integration will enable adaptive systems capable of continuous learning, secure data handling, and interpretable decision support—crucial for delivering equitable and high-quality care at scale.

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References

[1] D. Schwabe et K. Becker, « The METRIC-framework for assessing data quality for trustworthy AI in medicine: a systematic review | npj Digital Medicine », NPJ Digital Medicine, vol. 7, no 203, 2024, Consulté le: 28 octobre 2024. [En ligne]. Disponible sur: https://www.nature.com/articles/s41746-024-01196-4

[2] A. Banerjee, C. Chakraborty, A. Kumar, et D. Biswas, « Chapter 5 - Emerging trends in IoT and big data analytics for biomedical and health care technologies », in Handbook of Data Science Approaches for Biomedical Engineering, vol. 5, V. E. Balas, V. K. Solanki, R. Kumar, et M. Khari, Éd., Academic Press, 2020, p. 121-152. doi: 10.1016/B978-0-12-818318-2.00005-2.

[3] M. Meraj, S. A. M. Alvi, M. T. Quasim, et S. W. Haidar, « A Critical Review of Detection and Prediction of Infectious Disease using IOT Sensors », in 2021 Second International Conference on Electronics and Sustainable Communication Systems (ICESC), août 2021, p. 679-684. doi: 10.1109/ICESC51422.2021.9532992.

[4] N. Bhatt, N. Bhatt, P. Prajapati, V. Sorathiya, S. Alshathri, et W. El-Shafai, « A Data-Centric Approach to improve performance of deep learning models », Sci Rep, vol. 14, no 1, p. 22329, sept. 2024, doi: 10.1038/s41598-024-73643-x.

[5] W. Jin et al., « DCAI: Data-centric Artificial Intelligence », in Companion Proceedings of the ACM Web Conference 2024, Singapore Singapore: ACM, mai 2024, p. 1482-1485. doi: 10.1145/3589335.3641297.

[6] M. Nieberl, A. Zeiser, et H. Timinger, « A Review of Data-Centric Artificial Intelligence (DCAI) and its Impact on manufacturing Industry: Challenges, Limitations, and Future Directions », in 2024 IEEE Conference on Artificial Intelligence (CAI), Singapore, Singapore: IEEE, juin 2024, p. 44-51. doi: 10.1109/CAI59869.2024.00018.

[7] D. Zha, Z. P. Bhat, K.-H. Lai, F. Yang, et X. Hu, « Data-centric AI: Perspectives and Challenges », 4 avril 2023, arXiv: arXiv:2301.04819. doi: 10.48550/arXiv.2301.04819.

[8] M. H. Jarrahi, A. Memariani, et S. Guha, « The Principles of Data-Centric AI », Commun. ACM, vol. 66, no 8, p. 84-92, août 2023, doi: 10.1145/3571724.

[9] D. Malerba et V. Pasquadibisceglie, « Data-Centric AI | Journal of Intelligent Information Systems », Journal of Intelligent Information Systems, vol. 39, no 4, 2024, Consulté le: 28 octobre 2024. [En ligne]. Disponible sur: https://link.springer.com/article/10.1007/s10844-024-00901-9

[10] M. Zon, G. Ganesh, M. J. Deen, et Q. Fang, « Context-Aware Medical Systems within Healthcare Environments: A Systematic Scoping Review to Identify Subdomains and Significant Medical Contexts », International Journal of Environmental Research and Public Health, vol. 20, no 14, Art. no 14, janv. 2023, doi: 10.3390/ijerph20146399.

[11] K. Chung, H. Yoo, et D.-E. Choe, « Ambient context-based modeling for health risk assessment using deep neural network », J Ambient Intell Human Comput, vol. 11, no 4, p. 1387-1395, avr. 2020, doi: 10.1007/s12652-018-1033-7.

[12] J.-C. Kim et K. Chung, « Neural-network based adaptive context prediction model for ambient intelligence », J Ambient Intell Human Comput, vol. 11, no 4, p. 1451-1458, avr. 2020, doi: 10.1007/s12652-018-0972-3.

[13] S. S. Saranya et N. S. Fatima, « IoT-Based Patient Health Data Using Improved Context-Aware Data Fusion and Enhanced Recursive Feature Elimination Model», IEEE Access, vol. 10, p. 128318-128335, 2022, doi: 10.1109/ACCESS.2022.3226583.

[14] M. M. Aborokbah, S. Al-Mutairi, A. K. Sangaiah, et O. W. Samuel, « Adaptive context aware decision computing paradigm for intensive health care delivery in smart cities—A case analysis », Sustainable Cities and Society, vol. 41, p. 919-924, août 2018, doi: 10.1016/j.scs.2017.09.004.

[15] D. Zha et al., « Data-centric Artificial Intelligence: A Survey », 13 juin 2023, arXiv: arXiv:2303.10158. doi: 10.48550/arXiv.2303.10158.

[16] M. Zonayed et al., « Machine learning and IoT in healthcare: Recent advancements, challenges & future direction », Advances in Biomarker Sciences and Technology, vol. 7, p. 335-364, 2025, doi: 10.1016/j.abst.2025.08.006.

[17] U. Šajnović, H. B. Vošner, J. Završnik, B. Žlahtič, et P. Kokol, « Internet of Things and Big Data Analytics in Preventive Healthcare: A Synthetic Review », Electronics, vol. 13, no 18, p. 3642, sept. 2024, doi: 10.3390/electronics13183642.

[18] R. H. Charfare, A. U. Desai, N. N. Keni, A. S. Nambiar, et M. M. Cherian, « IoT-AI in Healthcare: A Comprehensive Survey of Current Applications and Innovations », IJRCS, vol. 4, no 3, p. 1446-1472, août 2024, doi: 10.31763/ijrcs.v4i3.1526.

[19] M. Alsabah et al., « A comprehensive review on key technologies toward smart healthcare systems based IoT: technical aspects, challenges and future directions », Artif Intell Rev, vol. 58, no 11, p. 343, août 2025, doi: 10.1007/s10462-025-11342-3.

[20] A. Kishor et C. Chakraborty, « Artificial Intelligence and Internet of Things Based Healthcare 4.0 Monitoring System », Wireless Personal Communications, vol. 127, p. 1615-1631, 2021, doi: 10.1007/s11277-021-08708-5.

[21] T. M. Ghazal et al., « IoT for Smart Cities: Machine Learning Approaches in Smart Healthcare—A Review », Future Internet, vol. 13, no 8, Art. no 8, août 2021, doi: 10.3390/fi13080218.

[22] B. Kaur, « IOT Framework for Heart Diseases Prediction Using Machine Learning », IJATCSE, vol. 10, no 3, p. 2036-2041, juin 2021, doi: 10.30534/ijatcse/2021/781032021.

[23] S. Vijayalakshmi, A. Saini, A. Srinivasan, et N. K. Singh, « Disease prediction over big data from healthcare institutions », in 2021 International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), mars 2021, p. 914-919. doi: 10.1109/ICACITE51222.2021.9404567.

[24] A. Verma, G. Agarwal, A. K. Gupta, et M. Sain, « Novel Hybrid Intelligent Secure Cloud Internet of Things Based Disease Prediction and Diagnosis », Electronics, vol. 10, no 23, Art. no 23, janv. 2021, doi: 10.3390/electronics10233013.

[25] G. Aceto, V. Persico, et A. Pescapé, « Industry 4.0 and Health: Internet of Things, Big Data, and Cloud Computing for Healthcare 4.0 », Journal of Industrial Information Integration, vol. 18, p. 100129, juin 2020, doi: 10.1016/j.jii.2020.100129.

[26] D. Castro, W. Coral, C. Rodriguez, J. Cabra, et J. Colorado, « Wearable-Based Human Activity Recognition Using an IoT Approach », Journal of Sensor and Actuator Networks, vol. 6, no 4, Art. no 4, déc. 2017, doi: 10.3390/jsan6040028.

[27] K. T. Chui, R. W. Liu, M. D. Lytras, et M. Zhao, « Big data and IoT solution for patient behaviour monitoring », Behaviour & Information Technology, vol. 38, no 9, p. 940-949, sept. 2019, doi: 10.1080/0144929X.2019.1584245.

[28] K. Y. Ngiam et I. W. Khor, « Big data and machine learning algorithms for health-care delivery », The Lancet Oncology, vol. 20, no 5, p. e262-e273, mai 2019, doi: 10.1016/S1470-2045(19)30149-4.

[29] S. A. Shah et al., « Internet of Things for Sensing: A Case Study in the Healthcare System », Applied Sciences, vol. 8, no 4, Art. no 4, avr. 2018, doi: 10.3390/app8040508.

[30] S. Tian, W. Yang, J. M. L. Grange, P. Wang, W. Huang, et Z. Ye, « Smart healthcare: making medical care more intelligent », Global Health Journal, vol. 3, no 3, p. 62-65, sept. 2019, doi: 10.1016/j.glohj.2019.07.001.

[31] Y. Yin, Y. Zeng, X. Chen, et Y. Fan, « The internet of things in healthcare: An overview », Journal of Industrial Information Integration, vol. 1, p. 3-13, mars 2016, doi: 10.1016/j.jii.2016.03.004.

A Bibliometric Analysis of Blockchain Applications in E-Commerce: Trends and Research Directions

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***Abstract*—Blockchain technology has emerged as a transformative force within the e-commerce industry, offering significant potential to address longstanding issues such as data security, transaction transparency, and customer trust. Despite its growing relevance, the academic exploration of blockchain applications in e-commerce remains fragmented and lacks a cohesive research agenda. This study conducts a comprehensive bibliometric analysis to map the intellectual landscape of blockchain applications in e-commerce, identifying influential publications, key authors, prominent journals, and major thematic trends. Using data extracted from the Scopus database between 2014 and 2024, the study employs bibliometric tools such as VOSviewer and Biblioshiny for performance analysis and science mapping. The analysis reveals a steady increase in research interest, with dominant themes including trust, smart contracts, supply chain management, and secure payments. Furthermore, the findings indicate that most research is concentrated in technologically advanced countries, and collaborations among scholars remain limited. By interpreting these patterns, the study uncovers critical gaps in the literature and proposes future research directions focusing on consumer behavior, regulatory frameworks, cross-border challenges, and integration with emerging technologies like AI and IoT. The results contribute to a clearer understanding of the evolution of blockchain research in e-commerce and provide a foundation for academics and practitioners to develop more secure, efficient, and user-centric digital commerce systems.**

***Keywords*—Blockchain; e-commerce; bibliometric analysis; smart contracts; digital transformation**

I. Introduction

The Fourth Industrial Revolution (4IR) is transforming the globe and altering how people interact with each other, their jobs, and their personal lives. The 4IR is a series of shifts in the creation, exchange, and distribution of economic, political, and social value that have been synchronized to occur globally in the digital sphere and impact both businesses and livelihoods [1]. According to the literature, because e-commerce platforms record and process every transaction that takes place on them, they must deal with enormous volumes of sensitive data, including banking information, personal information, and customer preferences [2]. Errors, fraud, and forgeries may arise because current e-commerce systems calculate and store customer data on a centralized cloud server [3]. Security is an issue because so few e-commerce companies have implemented blockchain [4].

It is suggested that e-commerce difficulties are complex, with some requiring the attention of the company in addition to individuals. Limited credit card adoption, a high percentage of technological illiteracy, worries about logistics, internet access and use, bandwidth prices, a lack of ICT infrastructure, trust, and security are some of the individual problems [5]. As blockchain technology has developed, more researchers have focused on leveraging it to boost the trust of e-commerce platforms [6]. The literature [7] claims that while artificial intelligence may be used to improve the search engine, recommendation system, and transaction monitoring of e-commerce platforms, blockchain technology may improve the security, data transparency, and trust of these platforms. The blockchain-based "decentralized authentication" model, which is the new authentication technology proposed in the paper [2], can significantly increase the security and credibility of e-commerce platforms for luxury brands. The use of blockchain technology in e-commerce platforms is the main topic of the study, which focuses on enhancing supply chain management, boosting trust, optimizing data management, and enhancing security [8]. A framework for trade facilitation for blockchain-based e-commerce platforms was developed in the literature with the goals of protecting consumer privacy, streamlining transaction procedures, and enhancing data management [9]. A smart contract for managing e-commerce that can consistently capture and validate transaction records and automatically execute e-commerce transactions is constructed using blockchain technology in the literature [10]. To solve the present data security issues in e-commerce platforms, a novel blockchain-based data encryption technique is offered [11]. By combining the distributed, tamper-evident, and decentralized characteristics of blockchain, this technique improves the data security of e-commerce platforms [12].

Logistics, a lack of qualified workers to develop e-commerce platforms, weak internet security, insufficient legal frameworks, misalignment between business, IT, and operational units, stakeholder engagement, a lack of funding and top management support, and the costs of advertising and payment gateways are some of the organizational challenges [13]. The ability to trace an item's origins through contract identification, data exchange, and system protection is considered an aspect of security [14]. The security issue in e-commerce is said to be resolved by using blockchain technology [14]. Blockchain technology is predicted to drastically alter a variety of corporate applications and processes, with substantial ramifications for e-commerce [15]. The use of blockchain has been the subject of numerous studies, including the following: e-commerce, tourism and hospitality, operations management, supply chain, and agriculture [16].

Smart contracts that enable supply chain automation, record management, payment applications, traceability support, and other business interactions are made possible by blockchain, a decentralized, distributed directory [17]. By using blockchain track and trace capabilities, a blockchain-based e-commerce strategy will ensure authenticity [12]. Additionally, the decentralized and encrypted core technology of blockchain enables track and trace capabilities [18]. This technology creates a distributed database that is inaccessible to unauthorized users by encrypting and storing data in a chain of back-linked information blocks, ensuring data integrity and accountability.

When analyzing blockchain technology, three factors need to be considered: technical, business, and legal. Blockchain technology's technological component is a database that keeps an entirely transparent distributed ledger. A peer-to-peer network for trading assets, value, and transactions makes up the business component. Finally, the legal component replaces previously trusted entities by validating transactions [12]. Blockchain technology's main benefits include the decentralized and transparent storage of transaction information, the database's operation by a network of computers known as nodes, which eliminates a single point of failure, real-time access to information, and the elimination of the need for middlemen to complete transactions, which lowers transaction costs [19]. Blockchain could improve e-commerce in addition to security [12]. First, by eliminating the need for middlemen, blockchain transactions on a single network enable faster speeds and lower costs [20]. Second, blockchain improves supply chain management by storing and recording product information. This enables the tracking of every product's life cycle, including who made it, what resources were utilized, where it came from, where it was stored, who bought it, and who completed the transaction [21]. Lastly, because each transaction is recorded on a shared ledger and cannot be altered, blockchain technology encourages trust and transparency in payments [12].

The primary research topics in the area of blockchain in e-commerce are mapped out with the use of the bibliometric technique. Important topics like the evolution of e-commerce and its uses in the Industry 4.0 era have been the subject of studies [22]. By identifying regions that have been thoroughly investigated and those that need more inquiry, this can help direct future studies. As was already indicated, the second limitation is that, despite the topic's ongoing and growing development, no study publication has been deemed sufficiently thorough. By examining the references, one can learn about the most referenced papers, prestigious publications, and the general influence of this field's study. This can aid in comprehending the importance and scope of different investigations. A number of methodological experts have stressed the necessity of a systematic review procedure to arrive at more impartial conclusions in literature reviews [23]. Future research can examine each theme group in greater detail and on a wider scale, thanks to bibliometric analysis. The increase of short films in e-commerce will be examined in this study by examining publications that were indexed in the Scopus database between 2014 and 2024. Identifying significant study clusters and important issues in this area, examining the connections between research topics, and influencing blockchain research in short-term commerce are the three main goals. This work attempts to contribute to the growth of this subject by offering a thorough and current review of the present research environment on blockchain in e-commerce through a mix of three methods: keyword co-occurrence, co-citation analysis, and bibliographic coupling.

This is how the rest of the study is organized: In Section II, the research gap is identified and the associated literature is reviewed. The suggested methodological architecture is shown in Section III. The experimental setup and evaluation findings are covered in Section IV. A discussion of the results and their implications is given in Section V. The work is finally concluded in Section VI, which also offers recommendations for further research.

II. Literature Review

A. E-Commerce

The term "e-commerce" describes online buying and selling. E-commerce, however, encompasses more than just monetary exchanges between customers and companies. It also includes non-monetary exchanges between the company and its customers [24]. The current literature on e-commerce has been categorized and arranged systematically by previous review studies. In one of the first review papers on e-commerce, the field into three areas: applications, technical issues, and implementation and support [25]. Themes like reference architectures, recommendation systems, online consumer behavior research, and e-commerce in specific geographic locations [26].

Previous scholarly studies have extensively examined the development of e-commerce. The industry has undergone a substantial digital transition, according to Kauffman et al. [27], who emphasize how information technology has changed e-commerce by creating value based on business networks. In a similar vein, Schulze et al. [28] present a framework that looks at the extent of e-business adoption and how it affects firm performance. According to this framework, organizational characteristics like competitor and customer orientation, organizational learning capacity, and top management support, as well as competitive conditions like normative pressures and customer power, serve as important antecedents of adoption and success. Their results also show that the degree of technological and market uncertainty affects the relationship between adoption intensity and performance.

B. Blockchain and E-Commerce

The Internet required several decades to evolve from a communication-oriented network serving mainly academic and military organizations into a technological infrastructure capable of supporting commercial activities [29]. Nevertheless, shortly after the emergence of the World Wide Web, the number of commercial websites increased dramatically, and e-commerce rapidly gained recognition as a global business model [25].

According to modern businesses, the internet has proven to be useful for improving marketing strategies. It approaches in a number of situations, such as conducting marketing research, offering customer service and experiences, distributing products, and resolving problems [30]. Modern firms are able to produce new products and services, boost market transparency, and operate more effectively and efficiently because of the inherent value of internet marketing [31]. Over the past decade, e-commerce has grown rapidly and emerged as a major industry [25]. Due to a number of recent technological advancements, online shopping has become one of the most popular consumer pastimes. Among these is blockchain technology [32]. A blockchain is a kind of peer-to-peer, decentralized database that is spread throughout every node in the network of trustless blockchains. A blockchain is a collection of blocks, as the name suggests. Each block contains specific features to maintain the integrity of the entire blockchain. To preserve this integrity, the blockchain uses robust cryptography [33].

"A fully distributed system designed to cryptographically record and preserve a consistent, immutable, and linear log of transactions among network participants", is a generic description of this technology [34]. This definition reflects the growing ubiquity of cloud-connected digital devices, growing cloud storage infrastructures, and sophisticated data analytics, all of which demonstrate how resilient blockchain is to technical advancements in the digital age [35]. Furthermore, a variety of cutting-edge financial instruments can be developed thanks to blockchain's highly flexible and programmable character, especially in the fields of payment and transaction systems [36].

E-commerce is the practice of purchasing and selling goods and services via the Internet [25], utilizing electronic communication and information processing technology in business dealings [37]. This digital environment enables consumers to interact, share opinions, and compare experiences online, thereby expanding their choices and facilitating rapid evaluations of products and services [38]. In this context, blockchain technology offers highly secure transaction services by eliminating intermediaries and protecting buyers' financial information, as all activities are cryptographically secured and transaction records among verified participants are permanently maintained [39].

Blockchain represents a set of technologies that influences e-commerce by addressing challenges related to organizational structure, quality assurance, customer trust, regulatory compliance, and technological efficiency. It relies on various consensus mechanisms for validation and creates unprecedented technological possibilities for digital commerce [40]. Based on these characteristics, blockchain systems can be categorized into three main types: permissionless blockchains, where all nodes are allowed to read, submit, and validate transactions; public permissioned blockchains, in which transactions are publicly visible but only authorized nodes may write or validate them; and private permissioned blockchains, where access to viewing, submitting, and processing transactions is restricted to approved participants [12].

III. Methodology

A. Bibliometric Analysis

According to [41], bibliometrics is a research methodology that has grown in popularity as a means of comprehending scholarly literature as electronic versions have become more widely available. The term "bibliometrics" refers to a broad category of methods that differ in their nature and purpose, including co-word analysis, citation analysis, bibliographic coupling analysis, and co-citation assessment [42, 43]. This method is widely used in information science and libraries and is thought to be a crucial instrument for analysis, planning, and assessment. Through content analysis or citation analysis, it frequently offers quantitative insights that are useful for evaluating the significance, applicability, and evolution of scholarly publications. The use of statistical analysis in the creation of bibliographies is the primary characteristic that distinguishes bibliometrics. In order to conduct a more effective literature review, this study employs the scientific mapping approach, which is a general procedure of analyzing and visualizing domains [44].

The literature search and analysis in this study are conducted using the bibliometric evaluation method that Donthu et al. [45] provided. There are four primary steps in it: Step 1: Outlining the bibliometric study's goals and parameters. Step 2: Choosing the assessment method. Step 3: Gathering information for bibliometric evaluation. Conducting the bibliometric analysis and summarizing the results is step four.

B. Data Collection

The study's data collection phase can be carried out using a variety of information sources or by gaining access to reliable academic databases like Web of Science, Scopus, and Google Scholar [46]. SCOPUS's output data information is used in this study due to its excellent coverage, thoroughness, and quick data updates. Similar documents can occasionally be found on Google Scholar or the Web of Science [41]. We have extracted a total of 1.132 (samples/documents) in the scope of "Article title, Abstract, Keywords" with the search keyword "Blockchain" AND in the scope of "All fields" with the search keyword "e-commerce" OR "electronic commerce" OR "online shopping" OR "digital marketplace". Articles from the last ten years, from 2014 to 2024, are included in the research time frame. This makes the essay more objective with current data and assesses the general overview of the blockchain topic, which helps to best direct the research. The real procedure for doing bibliographic analysis is shown in Fig. 1. In order to gather data for the final analysis, this method involves filtering processes.

C. Data Analysis Procedure

Graphs facilitate conclusion-making, decision-making, and prediction by making information easy to comprehend and assess. Using VOSviewer, a free tool for creating and displaying bibliometric analysis, we may create various networks based on keywords, citations, publishing sources, authors, and common citations [47]. In this study, bibliometric analysis is conducted using the software "VOSViewer", which contains facilities for graphical depiction of multidimensional data.

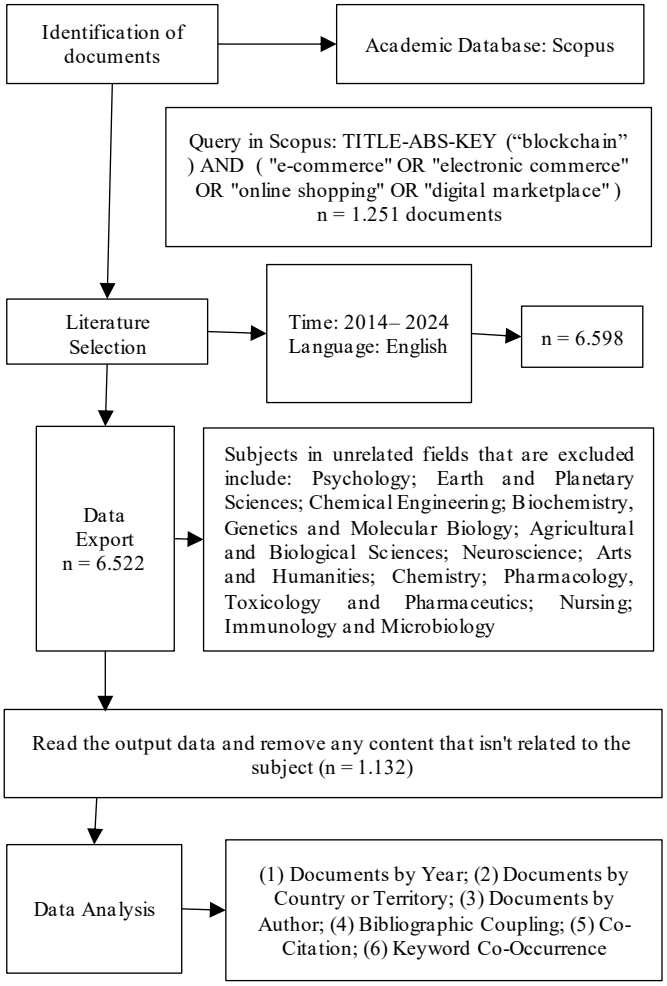


Fig. 1. The actual process of conducting bibliographic analysis.

IV. Results

A. Bibliometric Analysis

Blockchain technology began in 1991 when Haber and Stornetta came up with the concept of a cryptography-secured digital ledger system [48]. Their approach laid the groundwork for what would eventually be known as Blockchain by enabling transparent and unchangeable tracking of document modifications. Although preliminary research started in 2014, blockchain has gained popularity among scholars worldwide since the end of 2016, when e-commerce took off. Statistics on the quantity of publications by year are displayed in Fig. 2. The statistical findings allow for a three-stage analysis of the evolution of blockchain research:

Stage 1 (2014–2015): There was just one publication annually, and the number of investigations stayed low. This suggests that at the time, blockchain technology in e-commerce was still in its infancy.

Stage 2 (2016–2017): Blockchain research gained traction starting in 2016, as seen by a notable spike in publications, particularly in 2018. This expansion might be related to the fact that a lot of e-commerce companies started looking into how blockchain could improve supply chain management, transaction transparency, and efficiency, as well as product information verification. For blockchain technology to progressively infiltrate the e-commerce industry in the ensuing years, this was a critical first step.

Stage 3 (2018–2024): There were roughly 48 studies in 2018 compared to over 264 in 2024, and there are no indications that this number will be declining very soon. This suggests that the scientific community is paying more and more attention to blockchain as a "hot" study topic.

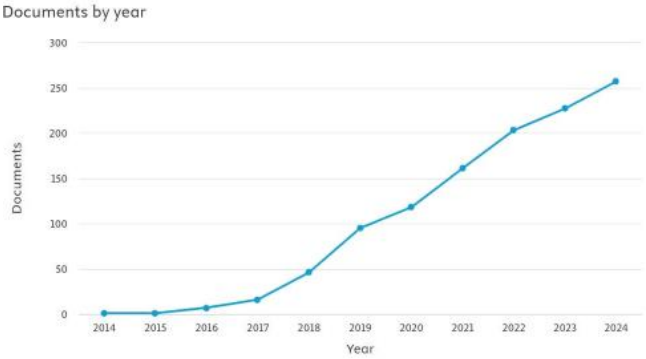


Fig. 2. Number of publications published by year from the Scopus database.

B. Analysis of Documents by Country or Territory

Based on statistical data from 2014 to 2024, Fig. 3 displays 1,168 research publications about blockchain technology that have been published globally. When compared to other nations, China dominates with 348 publications. This outcome is indicative of China's robust investment approach in blockchain research and implementation, specifically in the domains of digital payments, supply chains, and e-commerce [49]. With 216 articles, India comes in second, indicating the swift expansion of its innovation ecosystem and blockchain-based solutions catering to the local digital commerce industry [50].

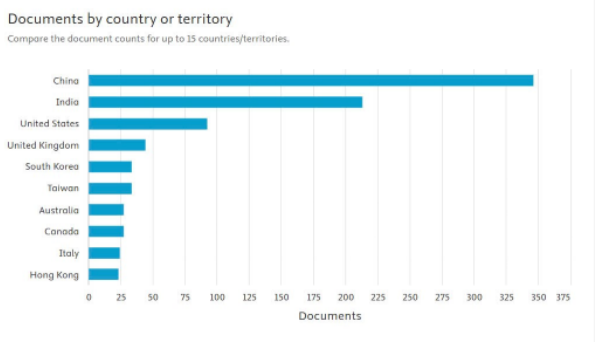


Fig. 3. Documents by country or territory. Source: From the Scopus database.

With 94 publications, the US comes in third. Despite being a global leader in the development of blockchain technology, there aren't many studies that are especially about e-commerce. This could be the result of a wider field of research or disciplinary fragmentation. With publishing numbers ranging from 27 to 45, other industrialized nations like the United Kingdom, South Korea, Taiwan, Australia, and Canada also have some interest in this subject. All things considered, Asia is becoming a center for blockchain research in the e-commerce space, which has enormous opportunities for the

creation of distributed technology-based digital business models.

C. Analysis of Documents by Author

A concentration of research within a small group of scientists is indicated by the fact that some writers have more publications than others. Close scientific collaboration and a quick expansion of the field's knowledge may result from this. Numerous people contribute to the study of blockchain and e-commerce, despite the presence of a few well-known authors. This demonstrates a wide range of interest in the subject and the possibility of many viewpoints and approaches. This study examines the author's publication count, highlighting the noteworthy contributions of a select few academics while also demonstrating the diversity of the blockchain and e-commerce research team. Finding top subject matter experts and research cooperation opportunities for upcoming publications can be facilitated by this information. Some authors with at least four publications, with notable research articles on blockchain and e-commerce are depicted in Fig. 4.

The development and improvement of blockchain systems in e-commerce is the main focus of the research of the five most prolific authors in this subject, as Table I demonstrates. To enhance supply chain management effectiveness, security, and dependability, these studies have helped to build and improve traceability models in blockchain-based e-commerce. Studies on blockchain systems in e-commerce were made possible by the work of Ferrer-Gomila and Hinarejos [51]. Other researchers might combine blockchain, IoT, and AI to improve real-time traceability systems, broaden applicability in different e-commerce domains, and assess usefulness using real-world deployment models.

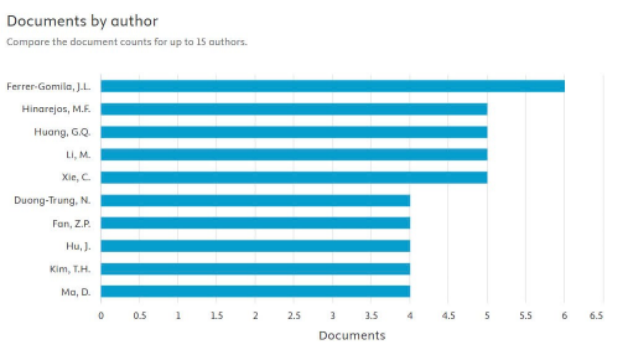


Fig. 4. Number of publications by author.

TABLE I. CORE RESEARCH AUTHORS ON BLOCKCHAIN

Authors		Title	General findings from the articles	No. of
Ferrer-Gomila, J.L.	Ferrer-Gomila and Hinarejos	"A Hard-Timeliness Blockchain-Based Contract Signing Protocol"	- Applying blockchain in electronic contract signing to replace trusted third parties (TTP), thereby enhancing fairness, timeliness, and non-repudiation in transactions. - Using the BC-Optimistic model, which activates blockchain only in cases of dishonest behavior, helps reduce costs and increase efficiency. - Applying blockchain in multi-party or multi-supplier contexts to meet the need for "all-or-nothing" contract agreements. - Proposing a blockchain-based reward points system shared among multiple merchants, ensuring security and transferability. - Addressing the limitations of traditional solutions while affirming the technological and economic feasibility of blockchain in practical e-commerce scenarios.	6
	Hinarejos et al.	"Enforcing Fairness With Blockchain Support: Proposals for Multi-Two-Party Contract Signing"		
	Hinarejos et al.	"A Secure Solution for a Blockchain-Based Consortium Promotional Scheme"		
	Ferrer-Gomila and Hinarejos	"A multi-party contract signing solution based on blockchain"		
	Ferrer-Gomila, and Hinarejos	"A 2020 perspective on "A fair contract signing protocol with blockchain support""		
	Ferrer-Gomila et al.	"A fair contract signing protocol with blockchain support"		
Hinarejos, M.F.	Ferrer-Gomila and Hinarejos	"A Hard-Timeliness Blockchain-Based Contract Signing Protocol"	- Applying blockchain in electronic contract signing to replace trusted third parties (TTP), thereby enhancing fairness, timeliness, and non-repudiation in transactions. - Using the BC-Optimistic model, which activates blockchain only in cases of dishonest behavior, helps reduce costs and increase efficiency. - Applying blockchain in multi-party or multi-supplier contexts to meet the need for "all-or-nothing" contract agreements. - Proposing a blockchain-based reward points system shared among multiple merchants, ensuring security and transferability. - Addressing the limitations of traditional solutions while affirming the technological and economic feasibility of blockchain in practical e-commerce scenarios.	5
	Hinarejos et al.	"Enforcing Fairness With Blockchain Support: Proposals for Multi-Two-Party Contract Signing"		
	Hinarejos et al.	"A Secure Solution for a Blockchain-Based Consortium Promotional Scheme"		
	Ferrer-Gomila and Hinarejos	"A multi-party contract signing solution based on blockchain"		
	Ferrer-Gomila and Hinarejos	"A 2020 perspective on "A fair contract signing protocol with blockchain support""		
Huang, G.Q.	Rachana et al.	"Blockchain-enabled digital assets tokenization for cyber-physical traceability in E-commerce logistics financing"	- Proposing a tokenization system to enable asset traceability and transparent data sharing within the supply chain. - Developing a platform integrating IoT and	5
	Rachana et al.	"Log-flock: A blockchain-enabled platform for digital		

		asset valuation and risk assessment in E-commerce logistics financing"	blockchain to support pricing and financial risk management in e-commerce logistics. - Designing a smart contract system to help small businesses gain easier access to financing through the supply chain. - Building a system that allows efficient sharing of logistics resources among parties via blockchain. - Introducing a lean resource-sharing model based on blockchain to enhance logistics efficiency.	
	Li et al.	"Blockchain-enabled logistics finance execution platform for capital-constrained E-commerce retail"		
	Li et al.	"Blockchain-enabled workflow operating system for logistics resources sharing in E-commerce logistics real estate service"		
	Li and Huang	"Blockchain-enabled workflow management system for fine-grained resource sharing in E-commerce logistics"		
Li, M.	Rachana et al.	"Blockchain-enabled digital assets tokenization for cyber-physical traceability in E-commerce logistics financing"	- Using blockchain to tokenize digital assets, enhancing traceability and transparency in financial logistics for e-commerce. - Applying blockchain and auction mechanisms to flexibly share cloud-based warehousing resources. - Developing a blockchain platform to provide financial support for underfunded e-commerce businesses in the logistics sector. - Creating a blockchain-based operating system for sharing real estate resources in logistics. - Implementing a detailed, real-time logistics resource-sharing system powered by blockchain.	5
	Li et al.	"Toward resilient cloud warehousing via a blockchain-enabled auction approach"		
	Li et al.	"Blockchain-enabled logistics finance execution platform for capital-constrained E-commerce retail"		
	Li et al.	"Blockchain-enabled workflow operating system for logistics resources sharing in E-commerce logistics real estate service"		
	Li and Huang	"Blockchain-enabled workflow management system for fine-grained resource sharing in E-commerce logistics"		
Xie, C.	Xie and Luo	"Solution Design of Traceability System for E-commerce Agricultural Product Quality and Safety Based on Blockchain"	- Applying blockchain technology to build traceability systems that ensure the quality and safety of agricultural products in e-commerce. - Enhancing transparency, reliability, and supply chain management efficiency in agriculture through digital systems capable of verifying product origins. - Emphasizing blockchain as a promising technology to improve quality, safety, and traceability in the electronic agricultural supply chain.	5
	Xie and Xiao	"Traceability of agricultural product quality and safety based on blockchain – taking fresh e-commerce as an example"		
	Luo and Xie	"Traceability System Construction of Agricultural Products Cross-Border E-commerce Logistics from the Perspective of Blockchain Technology"		
	Xie and Xiao	"Research on decision support system of E-commerce agricultural products based on blockchain"		
	Xie and He	"Design of traceability system for quality and safety of agricultural products in e-commerce based on blockchain technology."		

D. Bibliographic Coupling

The concept that two published studies with comparable references are most likely about the same topic is the foundation of a scientific mapping technique known as bibliographic coupling [52]. This study's data analysis based on common keywords used by authors in clusters did not include keywords that were also used as "search terms" (which will be looked at separately in the keyword co-occurrence analysis method below). This is because the purpose of these keywords is to serve as a helpful evaluation tool to uncover the content [53]. Fig. 5 shows the four main research clusters that were found, and they are as follows:

1) Data sharing, fraud detection, and security: This cluster focuses on using blockchain technology to improve security, identify fraud, and facilitate safe data exchange in digital systems. [54, 55] are important studies.

2) Supply chain and logistics management: The focus of this cluster is on using blockchain technology to increase supply chain and logistics management's efficiency, traceability, and transparency. The [56, 57] are notable studies.

3) Digital rights management and the sharing economy: This cluster investigates the use of blockchain technology in digital rights management, the sharing economy, and the creation of legal frameworks via smart contracts. The [58, 59] are important studies.

4) Management of business processes and manufacturing: This cluster focuses on using blockchain technology to manage manufacturing and business processes to improve industrial operations' dependability, efficiency, and transparency. The [60, 61] are significant studies.

The analysis's findings demonstrate the variety of blockchain-related e-commerce study areas. Numerous facets of blockchain technology have been examined in studies, such as supply chain and logistics management, digital rights management, fraud detection, data security, and safe data exchange, as well as applications in business process management and production. Each cluster highlights the growth and adaptability of blockchain technology across several e-commerce-related areas, reflecting a unique study strategy. With an emphasis on combining blockchain with other technologies like IoT, AI, and smart contracts, the research trend indicates a move away from theoretical studies and toward workable solutions. Furthermore, topics including operational efficiency, privacy, openness, and sustainability are increasingly taking center stage in current research. This suggests that blockchain is evolving into a fundamental platform for reimagining digital business models rather than just a technology that facilitates transactions.

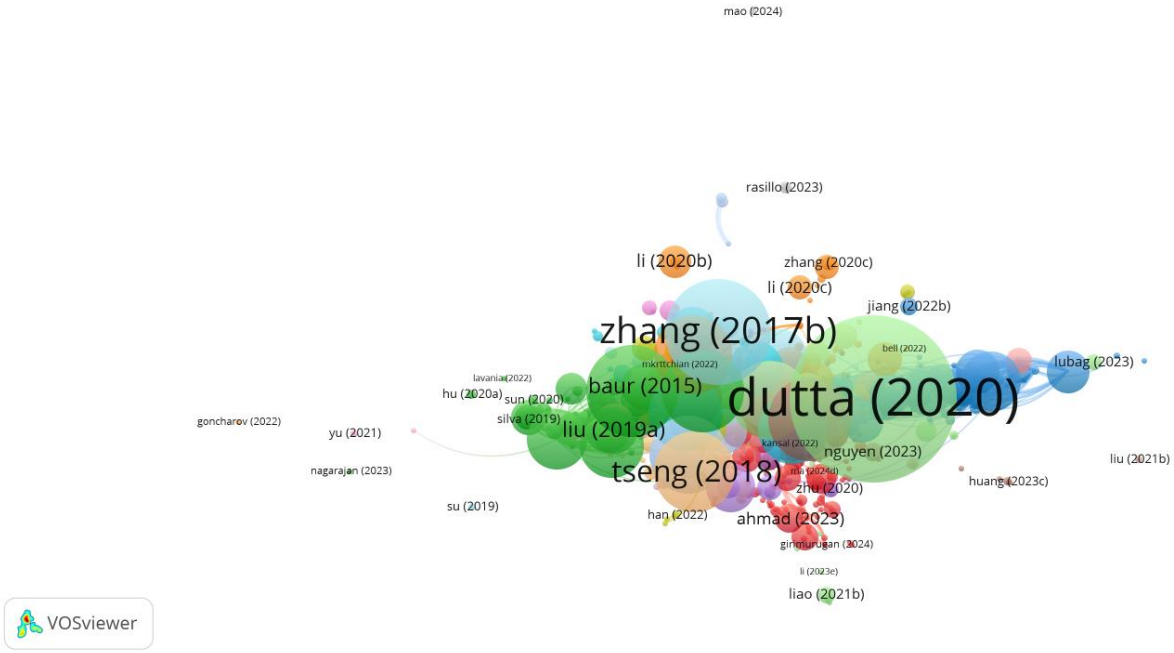


Fig. 5. Bibliographic coupling analysis results from VOSviewer.

E. Co-Citation

Co-citation analysis can be regarded as a technique to gauge the coherence between publications, since it concentrates on the frequency with which other documents quote two documents together [62, 63]. Co-citation analysis of author data is the main topic of this research. Finding out whose works are mentioned in the same article and the evolution of the research community may be done through author co-citation analysis [64]. As seen in Fig. 6, the co-citation analysis results reveal four unique clusters.

The green cluster reflects the growing interest in applying blockchain technology in fields such as e-commerce, digital markets, and energy trading. Studies in this cluster show that blockchain is not only a technology that supports financial transactions but also holds great potential for enhancing transparency, security, and efficiency across various sectors. The diversity of applications mentioned—from European research markets to peer-to-peer energy trading—demonstrates blockchain's scalability and flexibility in addressing both current and future challenges [65, 66].

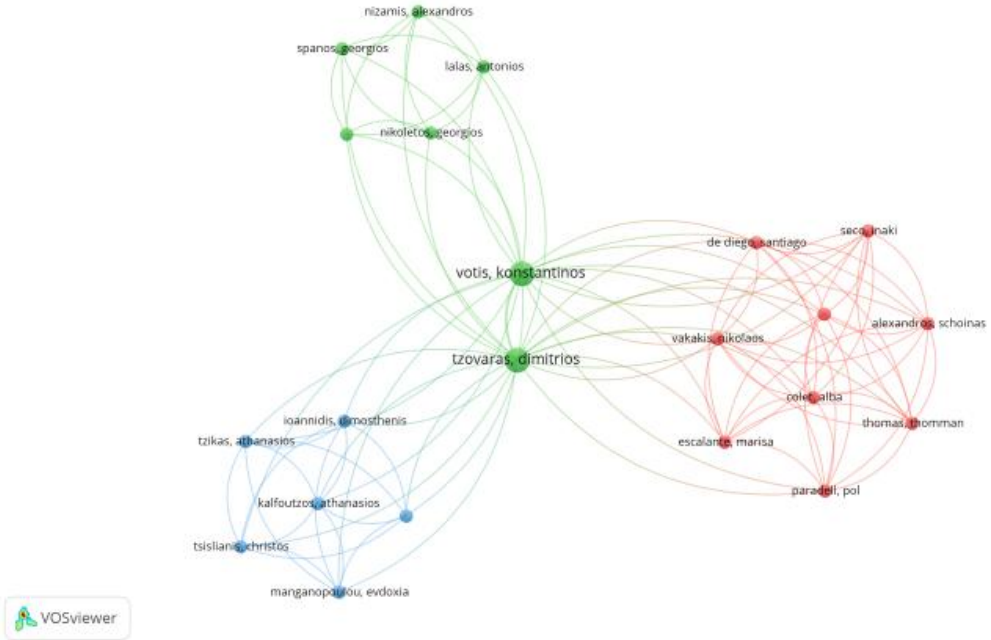


Fig. 6. Co-citation analysis results on VOSviewer.

The red cluster reflects the increasing interest in applying blockchain technology in areas such as supply chains, personal data management, and consumer behavior. Studies in this cluster indicate that blockchain is not merely a tool for financial transactions but also possesses significant potential in improving transparency, security, and efficiency across a range of industries. The variety of applications discussed, from coffee supply chains to consent management in IoT, illustrates the scalability and adaptability of blockchain in tackling present and future issues [67, 68].

The blue cluster reflects the interest in applying blockchain technology in distributed systems, e-commerce, and personal data management. Research in this cluster reveals that blockchain is more than just a financial transaction tool; it also has considerable potential to enhance transparency, security, and efficiency in numerous areas. The range of applications discussed—from distributed marketplaces to consent management in IoT—demonstrates blockchain's scalability and flexibility in solving current and future challenges [69, 70].

F. Keyword Co-Occurrence

Keyword co-occurrence analysis (i.e., two keywords appearing in a text) can better expose the structure of research subjects in a field, who also claimed that it helps explain research themes. In support of the aforementioned viewpoint, keywords are a distilled version of the crucial information that researchers include in an article. This approach reveals the structure and knowledge components of a scientific area by examining the connections between terms in a document. As a crucial literary component, keywords can offer a succinct synopsis of the main ideas and points of an article. To reaffirm the study topic's high level of focus, we increased the frequency of keyword recurrence in a publication to at least five times. The 331 research papers yielded 5.625 keywords in total. Following data processing, the analysis included 89 standardized keywords. The 15 keywords with the highest frequency of occurrence in the analysis of short movies in e-commerce are listed in Table II.

TABLE II. FREQUENCY OF CO-OCCURRENCE OF KEYWORDS

Rank	Keywords	Frequency
1	Blockchain	771
2	Electronic commerce	446
3	Block-chain	438
4	e- commerces	209
5	e-commerce	203
6	smart contract	146
7	Blockchain technology	120
8	Supply chains	115
9	sale	95
10	Supply chain management	75
11	Decentralised	70
12	Cryptography	67
13	smart contracts	66
14	Internet of Things	65
15	Digital storage	57

The keyword clusters are closely interconnected, illustrating the multi-dimensional nature of blockchain applications in e-commerce, as visualized in Fig. 7. The central node “blockchain” connects prominently with several major clusters such as “smart contract” (blue), “blockchain technology” (red), “e-commerce” (green), and “data privacy” (yellow-purple), highlighting the comprehensive integration of blockchain with digital commerce systems. For instance, the blue cluster centers on “smart contract” and “e-commerce”, indicating a strong focus on how blockchain automates and secures online transactions through decentralized mechanisms. It also includes terms like “decentralised”, “Ethereum”, and “cybersecurity”, reflecting technological infrastructure and security considerations. The red cluster, comprising “blockchain technology”, “supply chain management”, “trust”, and “fintech”, focuses on the technological adoption of blockchain in business processes. This cluster emphasizes the operational efficiency and trust-enhancing capabilities of blockchain, especially in logistics and finance. The green cluster is closely linked to commerce-specific contexts, with keywords such as “supply chains”, “commerce platforms”, “traceability”, and “agricultural products”. This cluster showcases practical applications of blockchain in improving transparency, efficiency, and traceability in cross-border and product-based e-commerce. The yellow-purple cluster, though smaller, includes emerging terms like “data privacy”, “authentication”, and “digital storage”, suggesting a new direction in research that deals with ethical and regulatory dimensions of blockchain. This reflects increasing scholarly attention on consumer protection and secure data handling—topics previously underexplored in blockchain-related e-commerce studies. Notably, this cluster may represent a future research avenue that intersects blockchain technology with digital rights, authentication mechanisms, and personalized privacy models. These insights help reinforce the technological and business-oriented clusters while laying the groundwork for ethical and user-centered innovations in blockchain adoption.

Cluster 1 (Red): “Technology Adoption and Trust in Blockchain”

Top keywords: blockchain technology, cryptocurrency, trust, decentralization, consensus algorithms, fintech, technology adoption, innovation. This cluster centers on the technological and institutional factors influencing the adoption of blockchain. It reflects a research focus on how trust, decentralization, and technological infrastructure affect the integration of blockchain into systems like fintech and e-commerce. The presence of keywords such as consensus algorithms and electronic money suggests technical considerations, while trust, innovation, and technology adoption point toward models evaluating user and organizational readiness. Research in this cluster aims to understand how blockchain can disrupt or enhance existing financial and technological ecosystems.

Cluster 2 (Green): “Blockchain Applications in E-Commerce and Supply Chains”

Top keywords: e-commerce, supply chains, commerce platforms, traceability, cross-border, agricultural products, competition, marketing. This cluster focuses on the practical

application of blockchain in commerce and logistics. The integration of e-commerce and supply chain terms indicates that researchers are investigating how blockchain enhances transparency, efficiency, and traceability in global and cross-border trade. Topics like agricultural products and traceability suggest their role in product origin tracking, while marketing and commerce platforms reflect business-side optimization. This cluster highlights blockchain's potential in improving trust and reducing friction in traditional supply chains and e-commerce transactions.

Cluster 3 (Blue): "Smart Contracts and Security Infrastructure"

Top keywords: smart contracts, e-commerce, decentralised, Ethereum, network security, cryptography, cybersecurity, data privacy. The blue cluster highlights the intersection of blockchain with security and automation technologies. It centers on how smart contracts and cryptographic protocols are leveraged in decentralized systems to secure e-commerce activities. Keywords such as network security, data privacy, and cybersecurity point to a strong focus on data protection and secure transaction environments. Ethereum and decentralised suggest research interest in public blockchain infrastructures. This cluster explores both the opportunities and challenges of using smart contracts in secure digital commerce ecosystems.

Cluster 4 (Yellow-Purple): "Privacy, Authentication, and Digital Infrastructure"

Top keywords: data privacy, authentication, privacy protection, digital storage, data sharing, smart city. This smaller but significant cluster highlights emerging concerns around ethical and legal aspects of blockchain deployment. The focus is on how to protect users' identities and personal information in digital transactions. Terms like authentication and privacy protection imply mechanisms to validate users securely, while smart city and data sharing suggest research into blockchain's role in broader digital infrastructure. This cluster represents a growing interest in governance, digital rights, and regulatory frameworks supporting responsible blockchain use.

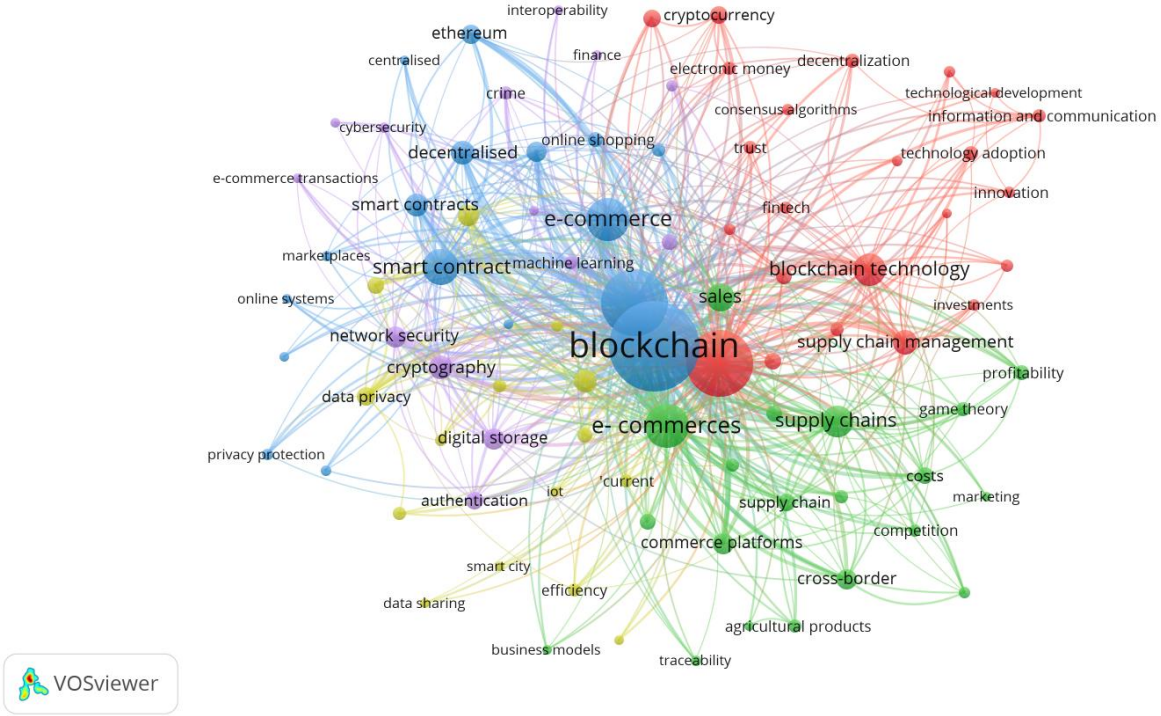


Fig. 7. Keyword co-occurrence analysis results from VOSviewer.

V. Discussion

A. Discussion of Research Results

The growth, thematic progression, and interrelationships of blockchain applications in e-commerce were examined in this study using bibliometric analysis. This discussion offers thorough answers to the three previously stated research questions based on the study's primary findings:

RQ1: What are the primary thematic clusters and research topics in the field?

Keyword co-occurrence analysis and bibliographic coupling revealed several prominent thematic clusters representing core research areas in blockchain-enabled e-commerce. The co-occurrence network showed strong connections among terms such as "blockchain", "e-commerce", "smart contracts", and "supply chain management", reflecting the close integration between blockchain technology and various business processes in digital commerce.

Four primary clusters were identified: Cluster 1: Technology Adoption and Trust. This cluster highlights the role of trust, decentralization, and technological infrastructure in blockchain adoption, especially in fintech and e-commerce. Keywords like "cryptocurrency", "consensus algorithms", and "innovation" suggest that researchers are focused on the factors

that enable or hinder blockchain integration. Cluster 2: Blockchain in E-Commerce and Supply Chains. This practical application cluster focuses on traceability, transparency, and efficiency in supply chains. Studies emphasize blockchain's role in improving logistics, especially for cross-border trade and product authenticity. Cluster 3: Smart Contracts and Security Infrastructure, this cluster centers on the application of smart contracts to automate e-commerce transactions. It includes concerns about data privacy, cybersecurity, and decentralization, particularly on platforms like Ethereum. Cluster 4: Privacy, Authentication, and Digital Infrastructure, though smaller, this emerging cluster reveals growing interest in ethical, legal, and data governance aspects. Keywords such as "data privacy", "authentication", and "smart city" indicate a shift towards secure identity verification and infrastructure planning. These clusters underscore that blockchain is no longer treated solely as a technical solution. Instead, it is now studied as an enabler of transparency, trust, and efficiency across the digital commerce ecosystem.

RQ2: What are the relationships between different research topics in this field?

Co-citation analysis was used to identify intellectual linkages across the field. The results revealed four distinct clusters of research thought: Cluster A: Blockchain for Digital Markets and Energy, which reflects blockchain's application beyond finance—e.g., in peer-to-peer energy trading and digital commerce platforms. Cluster B: Supply Chains and Personal Data Management focuses on product traceability and consumer data control, suggesting blockchain's utility in both logistics and consumer rights. Cluster C: Distributed Systems and Consent Management emphasizes the relevance of blockchain in managing decentralized systems and data permissions, notably in IoT and digital marketplaces.

These clusters are not isolated. For instance, blockchain solutions for secure transactions (Cluster C) often draw on the trust frameworks explored in Cluster A, and are operationalized through supply chain models in Cluster B. This interdependence shows that researchers are integrating knowledge across domains, forming a multi-dimensional understanding of blockchain's potential in e-commerce.

RQ3: How has research on blockchain in e-commerce evolved?

The analysis of publication trends from 2014 to 2024 indicates three distinct phases: Initial Phase (2014–2015): Very limited research activity, suggesting that blockchain was still an emerging concept in the context of e-commerce. Growth Phase (2016–2017): A surge in research occurred as interest in blockchain's applications—especially in logistics and data security—increased. This coincided with broader interest in fintech and the rise of platforms like Ethereum. Mature Phase (2018–2024): There was exponential growth in publications, particularly in 2023–2024. The increasing complexity and diversity of topics—ranging from supply chain finance to privacy regulations—reflect blockchain's transition from exploratory concept to implementation phase.

The continuous upward trend in publication volume suggests that blockchain remains a dynamic and strategic area of academic and industrial focus, with expanding applications in secure payment systems, contract automation e-commerce platforms.

B. Research Limitation and Future Research

This study has several limitations: First, the bibliometric approach was employed to analyze and explore the development trends of blockchain technology, specifically within the broader e-commerce field. While this quantitative analysis provides valuable insights based on existing published literature, qualitative methods such as interviews or case studies would further deepen the understanding of blockchain's practical applications and challenges in e-commerce.

Second, the data collection was limited to publications up to 2024, and more recent studies were not included, which may affect the comprehensiveness, given the fast-evolving nature of blockchain technology. Additionally, the study relied mainly on the SCOPUS database, excluding other academic databases and non-English publications, which could provide a more diverse and representative dataset.

Despite the promising potential of blockchain to address key issues in e-commerce—such as enhancing transaction security, ensuring data transparency, and improving payment processes—the technology's large-scale implementation remains limited. Many blockchain applications in e-commerce are still at the pilot or experimental stage. Technical challenges, such as high computational requirements due to blockchain's inherent transparency and immutability, hinder its wider adoption.

Blockchain has been extensively studied in finance and various industries, including agriculture and emerging technologies like the Internet of Things and big data. Future research should focus on increasing interdisciplinary collaboration to explore blockchain's integration into diverse e-commerce scenarios. Moreover, developing new technological advancements to overcome current blockchain limitations will be essential for its successful, large-scale deployment in e-commerce.

VI. Conclusion

By examining relevant literature on blockchain-supported e-commerce, this study seeks to examine the current state of blockchain technology implementation in e-commerce. First, the technological aspects of blockchain can successfully solve the issues that e-commerce platforms confront, according to the literature research and bibliometric analysis. Second, the Scopus database was used to gather pertinent literature, and bibliometric analysis was used to look at the trends in e-commerce and blockchain development. We note that there has been a recent surge in blockchain research, with major research hotspots in recent years mostly concentrating on the Internet of Things, supply chains, smart communities, cloud computing, aviation, the chemical industry, and other domains. We also concentrate on examining research patterns related to blockchain technology in e-commerce. It is also noted that blockchain technology plays a significant role in dividing up the e-commerce supply chain process in order to facilitate the growth of creative management practices. Additionally, we discover that blockchain can assist e-commerce in resolving

several of its current issues, including traceability, product information authenticity, logistics, goods distribution efficiency, and consumer information safety. In order to better explore possible innovation opportunities, the specialized functions of the blockchain-supported e-commerce industry have been examined and highlighted through the promotion of applications in production chains, distribution networks, and shopping processes. Additionally, this work offers a number of theoretical understandings and applications. Through creative management practices, blockchain technology can help e-commerce adopt flexible management and allocate resources effectively.

REFERENCES

[1] O. A. Ojubanire, H. Sebti, and S. Berbain, "Towards developing a national framework for industry 4.0 in African emerging economies," African Journal of Science Technology Innovation and Development, vol. 15, no. 4, pp. 496–513, 2022, doi: 10.1080/20421338.2022.2129347.

[2] G. Li, Z.-P. Fan, and X.-Y. Wu, "The choice strategy of authentication technology for luxury E-Commerce platforms in the blockchain era," IEEE Transactions on Engineering Management, vol. 70, no. 3, pp. 1239–1252, 2021, doi: 10.1109/tem.2021.3076606.

[3] Z. Zhou, M. Wang, C.-N. Yang, Z. Fu, X. Sun, and Q. M. J. Wu, "Blockchain-based decentralized reputation system in E-commerce environment," Future Generation Computer Systems, vol. 124, pp. 155–167, 2021, doi: 10.1016/j.future.2021.05.035.

[4] P. Jain, R. Kr. Singh, R. Mishra, and N. P. Rana, "Emerging dimensions of blockchain application in tourism and hospitality sector: a systematic literature review," Journal of Hospitality Marketing & Management, vol. 32, no. 4, pp. 454–476, 2023, doi: 10.1080/19368623.2023.2184440.

[5] M. Mkansi, "E-business adoption costs and strategies for retail micro businesses," Electronic Commerce Research, vol. 22, no. 4, pp. 1153–1193, 2021, doi: 10.1007/s10660-020-09448-7.

[6] X. Su, Y. Liu, and C. Choi, "A Blockchain-Based P2P transaction method and sensitive data encoding for E-Commerce transactions," IEEE Consumer Electronics Magazine, vol. 9, no. 4, pp. 56–66, 2020, doi: 10.1109/mce.2020.2969198.

[7] J. Singh et al., "A Systematic review of blockchain, AI, and cloud integration for secure digital ecosystems," ˜the œInternational Journal of Networked and Distributed Computing, vol. 13, no. 2, 2025, doi: 10.1007/s44227-025-00072-1.

[8] O. Ali, A. Jaradat, A. Kulakli, and A. Abuhalimeh, "A comparative study: Blockchain Technology Utilization Benefits, challenges and Functionalities," IEEE Access, vol. 9, pp. 12730–12749, 2021, doi: 10.1109/access.2021.3050241.

[9] S. Mazumdar, R. J. Kauffmann, T. Jensen, R. R. Mukkamala, and J. Damsgaard, "Developing blockchain-based transparent e-commerce solutions for Danish SMEs to promote sustainable design products," Blockchain Research and Applications, p. 100330, 2025, doi: 10.1016/j.bcra.2025.100330.

[10] M. D. Turjo, M. M. Khan, M. Kaur, and A. Zaguia, "Smart supply chain management using the blockchain and smart contract," Scientific Programming, vol. 2021, pp. 1–12, 2021, doi: 10.1155/2021/6092792.

[11] M. Hasnain, I. Ghani, D. Smith, A. Daud, and S. R. Jeong, "Cybersecurity challenges in blockchain-based social media networks: A comprehensive review," Blockchain Research and Applications, vol. 6, no. 3, p. 100290, 2025, doi: 10.1016/j.bcra.2025.100290.

[12] H. Treiblmaier and C. Sillaber, "The impact of blockchain on e-commerce: A framework for salient research topics," Electronic Commerce Research and Applications, vol. 48, p. 101054, 2021, doi: 10.1016/j.elerap.2021.101054.

[13] F. Almeida and E. Okon, "Impact of digitalization on SMEs performance: the mediating role of IoT," Digital Transformation and Society, vol. 4, no. 4, pp. 407–422, 2025, doi: 10.1108/dts-11-2024-0240.

[14] X. Shi, S. Yao, and S. Luo, "Innovative platform operations with the use of technologies in the blockchain era," International Journal of Production Research, vol. 61, no. 11, pp. 3651–3669, 2021, doi: 10.1080/00207543.2021.1953182.

[15] A. D. Kocabas, E. Calik, and B. Cetinguc, "Examining cryptocurrency usage by technology acceptance model in the Turkish context," African Journal of Science Technology Innovation and Development, vol. 16, no. 5, pp. 630–640, 2024, doi: 10.1080/20421338.2024.2364436.

[16] K. Govindan, P. Jain, R. Kr. Singh, and R. Mishra, "Blockchain technology as a strategic weapon to bring procurement 4.0 truly alive: Literature review and future research agenda," Transportation Research Part E Logistics and Transportation Review, vol. 181, p. 103352, 2023, doi: 10.1016/j.tre.2023.103352.

[17] M. Javaid, A. Haleem, R. P. Singh, S. Khan, and R. Suman, "Blockchain technology applications for Industry 4.0: A literature-based review," Blockchain Research and Applications, vol. 2, no. 4, p. 100027, 2021, doi: 10.1016/j.bcra.2021.100027.

[18] N. Kumar, K. Kumar, A. Aeron, and F. Verre, "Blockchain technology in supply chain management: Innovations, applications, and challenges," Telematics and Informatics Reports, vol. 18, p. 100204, 2025, doi: 10.1016/j.teler.2025.100204.

[19] M. Gholami, A. Ghaffari, N. Derakhshanfard, N. iBRAHIMOĞLU, and A. A. P. Kazem, "Blockchain integration in IoT: applications, opportunities, and challenges," Computers, Materials & Continua/Computers, Materials & Continua (Print), vol. 83, no. 2, pp. 1561–1605, 2025, doi: 10.32604/cmc.2025.063304.

[20] R. Mavilia and R. Pisani, "Blockchain and catching-up in developing countries: The case of financial inclusion in Africa," African Journal of Science Technology Innovation and Development, vol. 12, no. 2, pp. 151–163, 2019, doi: 10.1080/20421338.2019.1624009.

[21] S. Alam et al., "Blockchain-based Initiatives: Current state and challenges," Computer Networks, vol. 198, p. 108395, 2021, doi: 10.1016/j.comnet.2021.108395.

[22] Y. Yuan and Q. Wang, "Characteristics, hotspots, and prospects of short video research: A review of papers published in China from 2012 to 2022," Heliyon, vol. 10, no. 3, p. e24885, 2024, doi: 10.1016/j.heliyon.2024.e24885.

[23] T. Pölkki, O. Kanste, M. Kääriäinen, S. Elo, and H. Kyngäs, "The methodological quality of systematic reviews published in high-impact nursing journals: a review of the literature," Journal of Clinical Nursing, vol. 23, no. 3–4, pp. 315–332, Mar. 2013, doi: 10.1111/jocn.12132.

[24] M. Bao, S. Latif, D. Bao, Z. Latif, and J. Lu, "Overcoming e-commerce barriers in developing markets: A review of data-driven strategies for sustainable growth," Sustainable Futures, vol. 10, p. 101408, Oct. 2025, doi: 10.1016/j.sftr.2025.101408

[25] S. Gupta, Pooja. S. Kushwaha, U. Badhera, P. Chatterjee, and E. D. R. S. Gonzalez, "Identification of benefits, challenges, and pathways in E-commerce industries: An integrated two-phase decision-making model," Sustainable Operations and Computers, vol. 4, pp. 200–218, Jan. 2023, doi: 10.1016/j.susoc.2023.08.005.

[26] J. Yin, X. Qiu, and Y. Wang, "The Impact of AI-Personalized Recommendations on Clicking Intentions: Evidence from Chinese E-Commerce," Journal of Theoretical and Applied Electronic Commerce Research, vol. 20, no. 1, p. 21, Feb. 2025, doi: 10.3390/jtaer20010021.

[27] R. J. Kauffman, T. Li, and E. Van Heck, "Business Network-Based value creation in Electronic Commerce," International Journal of Electronic Commerce, vol. 15, no. 1, pp. 113–144, Oct. 2010, doi: 10.2753/jec1086-4415150105.

[28] A. Schulze, J. D. Townsend, and M. B. Talay, "Completing the market orientation matrix: The impact of proactive competitor orientation on innovation and firm performance," Industrial Marketing Management, vol. 103, pp. 198–214, Apr. 2022, doi: 10.1016/j.indmarman.2022.03.013.

[29] A. Razaque, S. Hariri, A. M. Alajlan, and J. Yoo, "A comprehensive review of cybersecurity vulnerabilities, threats, and solutions for the Internet of Things at the network-cum-application layer," Computer Science Review, vol. 58, p. 100789, Jul. 2025, doi: 10.1016/j.cosrev.2025.100789.

[30] B. Rizvanović, A. Zutshi, A. Grilo, and T. Nodehi, "Linking the potentials of extended digital marketing impact and start-up growth: Developing a macro-dynamic framework of start-up growth drivers supported by digital marketing," Technological Forecasting and Social Change, vol. 186, p. 122128, Nov. 2022, doi: 10.1016/j.techfore.2022.122128.

[31] C. Treichler, "Consulting Industry and Market Trends: A Two-Sided View," in Contributions to management science, 2018, pp. 253–272. doi: 10.1007/978-3-319-95999-3_12.

[32] H. Albayati, S. K. Kim, and J. J. Rho, "Accepting financial transactions using blockchain technology and cryptocurrency: A customer perspective approach," Technology in Society, vol. 62, p. 101320, Jul. 2020, doi: 10.1016/j.techsoc.2020.101320.

[33] K. Christidis and M. Devetsikiotis, "Blockchains and smart contracts for the internet of things," IEEE Access, vol. 4, pp. 2292–2303, Jan. 2016, doi: 10.1109/access.2016.2566339.

[34] M. Risius and K. Spohrer, "A blockchain research framework," Business & Information Systems Engineering, vol. 59, no. 6, pp. 385–409, Dec. 2017, doi: 10.1007/s12599-017-0506-0.

[35] T. Alladi, V. Chamola, R. M. Parizi, and K.-K. R. Choo, "Blockchain Applications for Industry 4.0 and Industrial IoT: A review," IEEE Access, vol. 7, pp. 176935–176951, Jan. 2019, doi: 10.1109/access.2019.2956748.

[36] H. Taherdoost, "Blockchain: a catalyst in fintech future revolution," Future Technology, vol. 2, no. 2, pp. 25–31, Nov. 2022, doi: 10.55670/fpll.futech.2.2.3.

[37] S. Shorman, M. Allaymoun, and O. Hamid, "DEVELOPING THE E-COMMERCE MODEL A CONSUMER TO CONSUMER USING BLOCKCHAIN NETWORK TECHNIQUE," International Journal of Managing Information Technology, vol. 11, no. 02, pp. 55–64, May 2019, doi: 10.5121/ijmit.2019.11204.

[38] H. S. Yoon and L. G. Occeña, "Influencing factors of trust in consumer-to-consumer electronic commerce with gender and age," International Journal of Information Management, vol. 35, no. 3, pp. 352–363, Mar. 2015, doi: 10.1016/j.ijinfomgt.2015.02.003.

[39] M. Javaid, A. Haleem, R. P. Singh, R. Suman, and S. Khan, "A review of Blockchain Technology applications for financial services," BenchCouncil Transactions on Benchmarks Standards and Evaluations, vol. 2, no. 3, p. 100073, Jul. 2022, doi: 10.1016/j.tbench.2022.100073.

[40] M. Smits and J. Hulstijn, "Blockchain applications and institutional trust," Frontiers in Blockchain, vol. 3, Mar. 2020, doi: 10.3389/fbloc.2020.00005.

[41] A. S. Krymskaya, "The Bibliometrics of Bibliometrics as a new area of research," Scientific and Technical Information Processing, vol. 50, no. 4, pp. 286–291, Dec. 2023, doi: 10.3103/s0147688223040147.

[42] X. Y. Leung, J. Sun, and B. Bai, "Bibliometrics of social media research: A co-citation and co-word analysis," International Journal of Hospitality Management, vol. 66, pp. 35–45, Jul. 2017, doi: 10.1016/j.ijhm.2017.06.012.

[43] A. Klarin, "How to conduct a bibliometric content analysis: Guidelines and contributions of content co-occurrence or co-word literature reviews," International Journal of Consumer Studies, vol. 48, no. 2, Mar. 2024, doi: 10.1111/ijcs.13031.

[44] C. Chen, "Science Mapping: A Systematic Review of the literature," Journal of Data and Information Science, vol. 2, no. 2, pp. 1–40, Mar. 2017, doi: 10.1515/jdis-2017-0006.

[45] N. Donthu, S. Kumar, D. Mukherjee, N. Pandey, and W. M. Lim, "How to conduct a bibliometric analysis: An overview and guidelines," Journal of Business Research, vol. 133, pp. 285–296, May 2021, doi: 10.1016/j.jbusres.2021.04.070.

[46] L. Legito and N. E. Andriani, "Emerging Technologies and Marketing Strategy: A Bibliometric review of Digital Marketing and innovation," The Eastasouth Journal of Information System and Computer Science, vol. 1, no. 01, pp. 13–24, Aug. 2023, doi: 10.58812/esiscs.v1i01.130.

[47] Q. Liu, N. L. Ali, and H. Y. Lee, "Applying VOSviewer in a bibliometric review on English language teacher education research: an analysis of narratives, networks and numbers," Cogent Education, vol. 12, no. 1, Jan. 2025, doi: 10.1080/2331186x.2025.2449728.

[48] S. Haber and W. S. Stornetta, "How to time-stamp a digital document," Journal of Cryptology, vol. 3, no. 2, pp. 99–111, Jan. 1991, doi: 10.1007/bf00196791.

[49] C. Le, R. Zheng, T. Lu, and Y. Chen, "User Real Comments Incentive Mechanism Based on Blockchain in E-Commerce Transactions—A Tripartite Evolutionary Game Analysis," Entropy, vol. 26, no. 12, p. 1005, Nov. 2024, doi: 10.3390/e26121005.

[50] A. Singh, K. Ramachandran, S. H. Krishna, C. Nayak, K. Anusha, P. B. Acharjee & S. Srivastava, "A novel and secured bitcoin method for identification of counterfeit goods in logistics supply management within online shopping," International Journal of Information Technology, vol. 16, no. 8, pp. 5371–5377, Aug. 2024, doi: 10.1007/s41870-024-02021-7.

[51] J.-L. Ferrer-Gomila and M. F. Hinarejos, "A Hard-Timeliness Blockchain-Based contract signing protocol," Computers, vol. 12, no. 12, p. 246, Nov. 2023, doi: 10.3390/computers12120246.

[52] R.-L. Liu and C.-K. Hsu, "Improving Bibliographic Coupling with Category-Based Cocitation," Applied Sciences, vol. 9, no. 23, p. 5176, Nov. 2019, doi: 10.3390/app9235176.

[53] A. Bengoa, A. Maseda, T. Iturralde, and G. Aparicio, "A bibliometric review of the technology transfer literature," The Journal of Technology Transfer, vol. 46, no. 5, pp. 1514–1550, Jan. 2020, doi: 10.1007/s10961-019-09774-5.

[54] H. Vranken, "Sustainability of bitcoin and blockchains," Current Opinion in Environmental Sustainability, vol. 28, pp. 1–9, May 2017, doi: 10.1016/j.cosust.2017.04.011.

[55] Y. Cai and D. Zhu, "Fraud detections for online businesses: a perspective from blockchain technology," Financial Innovation, vol. 2, no. 1, Dec. 2016, doi: 10.1186/s40854-016-0039-4.

[56] Y. Liu, D. Ma, J. Hu, and Z. Zhang, "Sales mode selection of fresh food supply chain based on blockchain technology under different channel competition," Computers & Industrial Engineering, vol. 162, p. 107730, Oct. 2021, doi: 10.1016/j.cie.2021.107730.

[57] B. Niu, Z. Mu, B. Cao, and J. Gao, "Should multinational firms implement blockchain to provide quality verification?," Transportation Research Part E Logistics and Transportation Review, vol. 145, p. 102121, Nov. 2020, doi: 10.1016/j.tre.2020.102121.

[58] S. Abramova and R. Böhme, "Perceived benefit and risk as multidimensional determinants of Bitcoin use: a Quantitative Exploratory study," International Conference on Information Systems, pp. 1–20, Jan. 2016, doi: 10.17705/4icis.00001.

[59] P. De Filippi, M. Mannan, and W. Reijers, "Blockchain as a confidence machine: The problem of trust & challenges of governance," Technology in Society, vol. 62, p. 101284, Jun. 2020, doi: 10.1016/j.techsoc.2020.101284.

[60] M. Li, S. Shao, Q. Ye, G. Xu, and G. Q. Huang, "Blockchain-enabled logistics finance execution platform for capital-constrained E-commerce retail," Robotics and Computer-Integrated Manufacturing, vol. 65, p. 101962, Apr. 2020, doi: 10.1016/j.rcim.2020.101962.

[61] X. Li, D. Wang, and M. Li, "Convenience analysis of sustainable E-agriculture based on blockchain technology," Journal of Cleaner Production, vol. 271, p. 122503, Jun. 2020, doi: 10.1016/j.jclepro.2020.122503.

[62] A. Gupta, S. Gupta, M. Bisht, P. Hooda, and M. Salik, "Document Co-citation Analysis using Concept Lattice," Engineering Technology & Applied Science Research, vol. 13, no. 5, pp. 11837–11842, Oct. 2023, doi: 10.48084/etasr.6201.

[63] N. Mustafee, K. Katsaliaki, and P. Fishwick, "Exploring the modelling and simulation knowledge base through journal co-citation analysis," Scientometrics, vol. 98, no. 3, pp. 2145–2159, Oct. 2013, doi: 10.1007/s11192-013-1136-z.

[64] X. Zhao, J. Zuo, G. Wu, and C. Huang, "A bibliometric review of green building research 2000–2016," Architectural Science Review, vol. 62, no. 1, pp. 74–88, Jun. 2018, doi: 10.1080/00038628.2018.1485548.

[65] G. Nikoletos et al., "Digital marketplaces in European research landscape: A systematic literature review," Open Research Europe, vol. 4, p. 223, Oct. 2024, doi: 10.12688/openreseurope.18657.1.

[66] D. P. Sakas, N. T. Giannakopoulos, D. P. Reklitis, and T. K. Dasaklis, "The effects of cryptocurrency trading websites on airlines'

advertisement campaigns," Journal of Theoretical and Applied Electronic Commerce Research, vol. 16, no. 7, pp. 3099–3119, Nov. 2021, doi: 10.3390/jtaer16070169.

[67] A. O. Tashtemirovich and M. E. Balbaa, "The Role of Blockchain in Supply Chain Transparency for E-Commerce," in Lecture notes in computer science, 2024, pp. 365–376. doi: 10.1007/978-3-031-60994-7_31.

[68] K. Rantos, G. Drosatos, K. Demertzis, C. Ilioudis, and A. Papanikolaou, "Blockchain-based consents management for personal data processing in the IoT ecosystem," Proceedings of the 15th International Joint Conference on e-Business and Telecommunications, pp. 572–577, Jan. 2018, doi: 10.5220/0006911005720577.

[69] A. Theodouli et al., "Towards a secure and transparent Blockchain-Based system for e-Commerce deliveries," in Lecture notes in computer science, 2024, pp. 113–125. doi: 10.1007/978-3-031-52947-4_9.

[70] E. Kapassa, M. Touloupos, D. Kyriazis, and M. Themistocleous, "A smart distributed marketplace," in Lecture notes in business information processing, 2020, pp. 458–468. doi: 10.1007/978-3-030-44322-1_34.

Related Multi-Task Allocation Scheme Based on Greedy Algorithm in Mobile Crowdsensing

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***Abstract*—With the popularity of mobile intelligent devices, the mobile crowdsensing (MCS) network based on wireless sensor networks and crowdsourcing technology came into being. There is more and more research on MCS, and it has been applied in many scenarios. Due to the increase in data volume of the MCS platform, the task shows exponential growth. Among them, there will be irreplaceable tasks that belong to the same category, that is, tasks with correlation. If the related tasks can be allocated to the same person for execution, the overhead will be greatly reduced, and the success probability of task allocation will be improved. Firstly, the spatio-temporal distribution of tasks and users is predicted by fuzzy logic to divide spatio-temporal scenarios in this study, and a more suitable multi-task allocation algorithm is selected. Then, when allocating multi-tasks, considering the correlation of tasks, the greedy algorithm is used to allocate multi-tasks according to different scenarios. The experimental results show that compared with the benchmark scheme, the proposed related multi-task allocation scheme based on the greedy algorithm improves the task allocation completion rate by 25.2%, and significantly improves the task allocation success rate in MCS.**

Keywords*—Mobile crowdsensing; task allocation; fuzzy logic; greedy algorithm

I. Introduction

With the emergence of intelligent mobile devices and the Internet of Things, mobile crowdsensing (MCS) using wireless sensor networks and crowdsourcing technology has gained a lot of attention. MCS uses mobile devices to collect and process all kinds of sensing data to complete a variety of complex sensing tasks. By using the intelligent mobile terminal as the basic sensing unit, MCS can build a large-scale sensing system that transcends time and space, and complete complicated sensing tasks compared with the traditional sensing technology that relies heavily on professionals and testing tools. As a result, MCS has become a popular new way of sensing. In recent years, MCS has been widely used in environmental monitoring [1],[2], intelligent transportation [3], public safety [4] and health services [5],[6].

The life cycle of MCS can be divided into three parts, namely task allocation, data collection and data aggregation. As the first step in the life cycle of MCS, task allocation is the basis for the successful completion of the whole sensing system. Due to the complexity and diversity of sensing tasks, the completion of a sensing task usually requires the participation of many participants. However, among many participants, each participant has different willingness and proficiency in different sensing tasks, so it is necessary to select the right participant to better complete the task. If the task allocation is unreasonable, it will lead to the poor quality of sensing data or users will refuse to perform sensing tasks, resulting in the wastage of sensing costs and the failure of task sensing. With the in-depth use of the sensing platform, the number of tasks published by the platform has increased rapidly. If the tasks cannot be allocated quickly and reasonably, it will lead to the accumulation of tasks on the platform, low processing efficiency and high task cost, but at the same time, it is difficult for users to obtain matching tasks to execute. Therefore, the quality of task allocation has a significant impact on the quality and cost of sensing task completion.

First, the two cores of task allocation are to consider the order of task allocation and how to choose the executor. The specific implementation of both is related to the temporal and spatial distribution of tasks and related participants. Therefore, the temporal and spatial distribution of tasks and participants is an important factor affecting task allocation. For example, in a time and space, if the distribution of tasks and participants is dense or sparse, it is less difficult to allocate tasks and the completion rate of task allocation is high; in a time and space, if tasks are sparsely distributed and participants are densely distributed, or tasks are densely distributed, and participants are sparsely distributed. In both cases, if the traditional task allocation method is followed, it will lead to unreasonable task allocation and prolong the task allocation period, which will make the allocated tasks unable to be completed within the time constraint and reduce the task completion rate of the whole platform. Therefore, it is very important to determine the temporal and spatial distribution of tasks and participants for the platform to successfully allocate tasks.

Existing research usually uses quantitative statistical methods to count the temporal and spatial distribution of tasks or participants (Citation). Specifically, the spatio-temporal distribution statistics of tasks can be analyzed according to the data collected by the platform most intuitively. However, because the task publishers are free to move, the number of tasks counted by the platform at a certain time point cannot represent the task distribution in a time period. At the same time, in view of the temporal and spatial distribution of participants, the traditional method can realize statistics by asking participants to provide their location information when collecting sensing data. However, this method will not only lead to the leakage of sensing data privacy but also increase the platform overhead. Therefore, how to reasonably determine the temporal and spatial distribution of tasks and participants in MCS is very important. Secondly, the correlation between multiple tasks is also crucial to the success rate of task allocation. We define correlation as that two tasks belong to the

same category, but they can't replace each other, so we think they are related. If two tasks belong to the same category or time and space are mutually exclusive, they are considered not relevant. For example, U is a user who cares about his own health. After we allocated task A (collecting exercise data) to user U, task B appeared to collect diet data. Because task B and task A belong to the personal health category, they are related. If task B is also allocated to user U, user U will probably execute task B while executing task A, which will improve the completion rate of task A and task B. Therefore, when allocating multiple tasks, if we can consider the correlation of tasks and allocate related tasks to the same user for execution, it will greatly improve the completion rate of tasks and reduce extra expenses.

At present, with the increase of tasks, multi-task allocation [10]-[16] has become the mainstream research trend of task allocation. However, when allocating multiple tasks, the existing work not only ignores the correlation between the above tasks but also fails to take into account the prediction of the temporal and spatial distribution of users and tasks, which makes it difficult to implement the optimal allocation method in various scenarios and leads to the failure of task allocation.

Aiming at the above problems, this study proposes a related multi-task allocation scheme based on a greedy algorithm. In multi-task allocation, the proposed scheme can determine the temporal and spatial distribution of tasks and users, and based on this, use the correlation between tasks to achieve as many task allocations as possible. The main contributions of this study are summarized as follows:

1) In this study, a task-participant spatio-temporal distribution prediction algorithm based on fuzzy logic is proposed. The uncertain input is processed by fuzzy logic, and the accurate spatio-temporal distribution of tasks and users is obtained, which provides reliable parameter support for subsequent allocation algorithms.

2) Based on the calculated time-space distribution values of tasks and users, combined with the task correlation, we design a related multi-task allocation scheme based on a greedy algorithm, and propose two allocation algorithms for different time-space distributions of tasks and participants in the scheme. Aiming at the situation that the distribution of tasks and participants is balanced or there are enough participants, Algorithm 1 is proposed, which uses correlation allocation to improve the task allocation rate as much as possible; Aiming at the shortage of participants' distribution, Algorithm 2 is proposed. In Algorithm 2, the completion rate of task allocation is improved as much as possible with the help of correlation allocation and the incentive provided by the cost saved by Algorithm 1.

3) Experimental results show that compared with the benchmark scheme, the proposed related multi-task allocation scheme based on a greedy algorithm improves the task allocation completion rate by 25.2%, which significantly improves the task allocation success rate in MCS.

The remainder of this study is organized as follows: Section II introduces the related work of multi-task allocation in MCS. Section III presents the proposed related multi-task allocation scheme based on greedy algorithm. Section IV reports and analyzes the experimental results. Section V concludes the study and discusses directions for future work.

II. Related Work

The core of task allocation is to allocate as many tasks as possible through certain strategies under the condition of satisfying relevant constraints, to obtain sensing data that meets quality requirements.

At present, researchers have put forward a series of task allocation schemes. Among them, the single task allocation is simple, and the key problem at this stage is to find a suitable executor for the task. For example, Zhang et al. [7] propose a blockchain-based hybrid reliable user selection and task allocation scheme for MCS, which achieves decentralized task management through blockchain and smart contracts to enhance system performance. From the user's point of view, An et al. [8] proposed a privacy-preserving scheme for high-quality user recruitment in mobile crowdsensing, which evaluates sensing quality based on data deviation and variance under differential privacy and employs a combinatorial multi-armed bandit to achieve budget-constrained user selection. Wang et al. [9] propose a user recruitment method for sparse mobile crowdsensing that leverages deep nonnegative matrix factorization based on social relationships to identify communities and combines community collaboration with task matching to achieve high-quality sensing data collection and accurate sensing map reconstruction using a small number of users under budget constraints.

With the in-depth study of MCS, it has been applied to more and more fields, which leads to the further expansion of the MCS platform and carries more and more tasks. Therefore, single task allocation can no longer meet the growing sensing needs, and then multi-task allocation appears.

In the task allocation scenario, there are two scenarios: offline task allocation and online task allocation. Different from offline task allocation, online task allocation can't determine the number of participants, so it will affect the distribution quality. Therefore, Yang et al. [10] first predicted the number of participants, and then distributed the platform tasks by using the online task allocation method based on the improved genetic algorithm, to maximize the platform utility and minimize the moving cost of participants. In task allocation, the study of individual task allocation will ignore the characteristics between tasks, such as task distance, task similarity, and task priority level, resulting in poor quality of task allocation. Yin et al. [11] studied a new task allocation and path planning problem in MCS. By considering the routing distance, task similarity, and task priority, a group of task locations is allocated to suitable workers, and the location access order of individual workers is determined to realize the overall rationality of the maximum location sequence. Previous studies paid more attention to the completion rate of task allocation or the minimum cost of task allocation, while ignoring the individual situation of platform staff. Because each participant's sensing willingness, knowledge level, and credibility are different, Rahman et al. [12] put forward a new

quality-aware personalized task matching framework, which can better match tasks with participants.

For multi-task allocation, the sensing will of the participant is also very important. Because of the difference in users' sensing ability, the sensing result will be inaccurate. To overcome these problems, Ji et al. [13] proposed a comprehensive multi-task allocation model. Based on the three constraints of the total task budget, perceiving the quality and workload of a single task, the proposed large-scale evolutionary algorithm, a specific problem-solving strategy, and a new genetic operator, multi-task allocation can get as many feasible tasks as possible. In order to recruit suitable users for heterogeneous tasks, Ma et al. [14] proposed three user recruitment algorithms based on greed to solve the problem of heterogeneous user recruitment for multi-heterogeneous tasks, thus minimizing the total platform payment and maximizing the task coverage. In task allocation, users will also be unwilling, or objective conditions will not allow them to move to the task area. Gao et al. [15] proposed a UAV-assisted multi-task allocation method. This method uses drones to verify the data collected by users and uses drones to collect data in data areas not covered by human participants to optimize the sensing coverage and data quality of multi-task allocation. When MCS is applied in an energy transportation system, there are some challenges, such as a single point of failure, low efficiency of independent task allocation, and inability to deal with safety emergency tasks in time. In order to solve these problems, Li et al. [16] defined a decentralized ITS architecture based on blockchain and proposed a concurrent task and safety emergency task allocation method based on reinforcement learning, which can maximize the utility of concurrent tasks on the basis of meeting the requirements of safety emergency tasks.

At present, the focus of multi-task allocation is on multi-task allocation under time constraints [17]-[21]. Li & Zhang [17] studied the multi-task allocation under time constraints, mainly considering the leisure time owned by users and the due time of each task. Huang et al. [18] focus on the execution time of tasks, which solves the problem that mobile users with a limited time budget undertake multiple sensing tasks. Under the limited time limit, the optimal solution can be obtained through the multi-task framework by selecting the participants who have completed the tasks the most times and the shortest total travel distance. In time-limited multi-task allocation, existing research tends to assign most tasks to users with high reputation, which is unfair to new users and leads to low efficiency of task execution. To overcome these problems, Shen et al. [19] proposed a constrained multi-objective optimization model for variable-speed multi-task allocation. Through the three-stage multi-objective mixed shuffling frog leading algorithm, the user returns to the maximum extent and the task completion time is minimized.

In addition, with the complexity of sensing scenes and the diversification of time constraints, taking time constraints as a single auxiliary constraint can no longer achieve a good task allocation scheme. Wei et al. [20] proposed a semi-conditional moving sensation (SO-MTTA) scheme to solve the task allocation problem with multiple time constraints, to maximize the sensing value obtained by the platform. Meitei & Marchang [21] proposed a greedy task allocation method based on interval partition to maximize the profit of the platform in a time-dependent sensing environment.

With the deepening of research, spatial constraints have also become an important research point. Most scholars consider the overall distribution effect when considering the meaning of multitasking. Although the constraints of overall execution time or overall sharing are minimized or met, respectively, according to the distribution results, it is possible that the tasks published are not effectively executed for each task publisher. Wang et al. [22] conducted extensive research on this issue and suggested using the task framework to define the threshold for measuring effective task execution. Only tasks that exceed the threshold are considered as valid tasks. Specifically, the system uses space-time coverage to measure tasks. The task is regarded as a low-quality execution, and if the coverage of time and space is below the threshold, it will not improve the overall task execution quality. The framework can effectively identify tasks suitable for workers and ensure the best performance of each task through the above methods. Liu et al. [23] proposed a privacy-preserving task allocation method for mobile crowdsensing that protects users' temporal and spatial information while maximizing worker income. Ye et al. [24] studied a new task allocation problem in a multi-center supply chain environment with multiple distribution centers. In order to solve this problem, a task allocation framework based on geographical division is proposed. The first stage is the geographical division stage, and the second stage is the task allocation stage. This method can effectively maximize the total number of allocated tasks and minimize the difference in the average number of allocated tasks. To solve the problem of interruption in the task allocation process, wang et al. [25] proposed a method based on the allocation graph to solve the problem of RoBust task allocation (RBTA), which can reduce the cost of workers' detour and minimize the robustness of the allocation scheme.

Fuzzy logic has been applied to the field of mathematics in theory. With the development of computer science and artificial intelligence, it needs to be applied to industrial control systems. Such progress requires computers to perform based on human cognition. Fuzzy logic has been widely incorporated into the computer field.

For example, by extending the standard Mamdani fuzzy logic controller, an expert system based on fuzzy logic to diagnose patients with possible heart disease was established [26]. With regard to bringing fuzzy logic into the proofreading system, some dough was made under the supervision of a fuzzy control system. According to different initial temperatures, different amounts of yeast were added to the dough. The controller will make judgments and adjustments in the whole process to control the volume of dough. In this case, the fuzzy logic controller provides optimal control and improved interference suppression characteristics without a mathematical model [27]. Wang et al. [28] put forward a spatio-temporal model based on a transformer, which uses spatio-temporal relationships to infer and predict sparse sensing data. By using short-term perceived data to predict long-term data, not only is the data cost reduced, but also the data trend can be identified, which effectively improves the working effect of the model.

Yang et al. [29] used fuzzy logic to predict the distribution of users and solved the multi-task allocation problem under time and space constraints through a hybrid greedy algorithm. Zhang et al. [30] put forward a multi-task allocation method based on liquidity prediction, which uses fuzzy logic to analyze historical data to predict the movement of workers, so that workers can better match tasks and complete tasks as much as possible.

Although the above technologies show superior performance in some aspects, they only consider some temporal or spatial characteristics of tasks and participants, and also lack comprehensive analysis and modeling of participant density in time and space. Moreover, the above research did not consider the correlation between multiple tasks. If two related tasks are allocated to the same participant, it will greatly save time of task execution. On the contrary, if the related tasks are allocated to different executors, it will lead to a waste of time and resources. The existing research on multi-task allocation does not consider the correlation between tasks, which may lead to the failure of task allocation or the difficulty of matching tasks with the most suitable participants, resulting in waste of resources and low task completion rate.

Therefore, this study fully considers and analyzes the influence of task distribution and participant distribution on task allocation through the fuzzy logic control method and studies the task correlation in multi-task allocation under time and space constraints in order to achieve the maximum task completion rate.

III. METHODS

A. System Model

The realization of MCS is based on the sensing platform, on which task publishers and task participants complete the corresponding cooperation according to their own wishes and the task allocation strategy of the platform, as shown in Fig. 1. Specifically, there are the following steps:

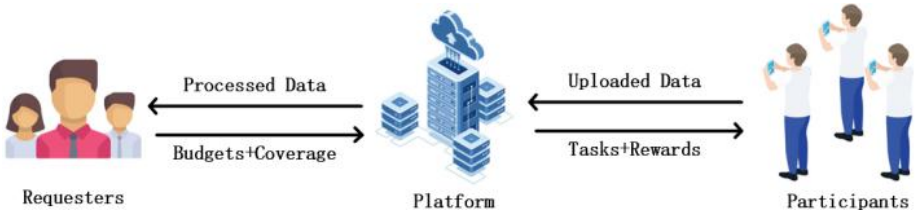


Fig. 1. The illustration of task allocation.

First, the task publisher will publish the task according to its own needs and hand it over to the platform. The submitted data contains the specific information on the task and the rewards that the participants are willing to pay after completing it. Secondly, after receiving the task information, the platform will sort it out and publish it for the participants to check; subsequently, the participants will release their willingness to execute to the platform. The platform will select the appropriate participants to perform the task according to the execution time, implementation place and user's willingness to perform the task. The selected participants will choose whether to perform the task according to their own situation and the task reward. Finally, participants who perform tasks are selected to collect sensing data and upload them to the sensing platform. Thus, a complete sensing task is completed.

The scheme of this study mainly includes two parts. The first part is to determine the temporal and spatial distribution of tasks and participants. The second part is to allocate tasks according to the temporal and spatial distribution of tasks and participants, combined with the correlation between multiple tasks.

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, MKS, CGS, sc, dc, and rms do not have to be defined. Do not use abbreviations in the title or headings unless they are unavoidable.

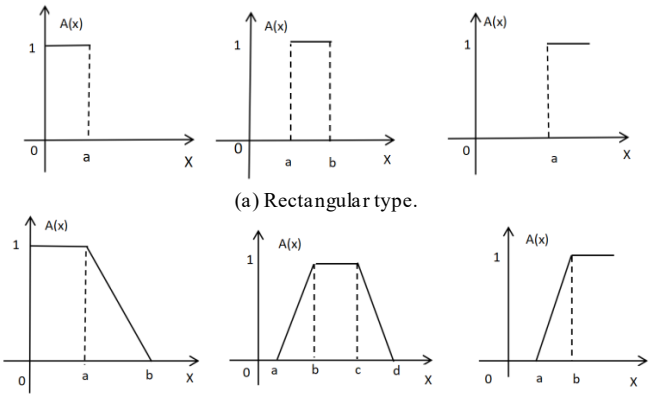
B. Fuzzy Logic

In the traditional description of temporal and spatial distribution, some non-quantitative words are usually used to describe the distribution of tasks or participants, such as "more", "a little less" and "sparse". In daily communication, because it is only necessary to express the meaning correctly, such a description can make the two sides understand each other's meaning. But in the computer world, machines can't understand these non-quantitative words, and what computers can understand must be a specific and accurate numerical value. Therefore, we need to introduce fuzzy logic to solve the problem of semantic uncertainty.

Fuzzy logic mainly includes the following three steps, namely fuzzification, fuzzy reasoning and defuzzification. The so-called fuzzification is to process our specific inputs and get a fuzzy set of inputs. Secondly, according to the fuzzy set output in the first step, combined with fuzzy rules, an output fuzzy set can be obtained, which is fuzzy reasoning. The third step is defuzzification, and the fuzzy conclusions are transformed into concrete and clear output values.

1) Fuzzy set: The definition of a fuzzy set can decompose an input into the membership degree of each part in the set. For example, we define the fuzzy set of rain sizes as "heavy rain, moderate rain and light rain". Then, for 20 ml of rainfall, the membership degree of light rain is 0.3, the membership degree of moderate rain is 0.5, and the membership degree of heavy rain is 0.2.

2) Membership function: The most used membership functions are rectangular and (semi) trapezoidal functions, which are divided into small, large and intermediate types. The specific membership function expressions are shown in Fig. 2.



(a) Rectangular type.

(b) Trapezoidal type.

Fig. 2. Common membership function diagram.

3) Fuzzy rules: After fuzzy input, we need to construct rules and use the operation of fuzzy logic to combine the obtained membership degrees as the basis for decision-making. The decision rules of fuzzy logic are sets containing a series of logical statements, which have the following structure:

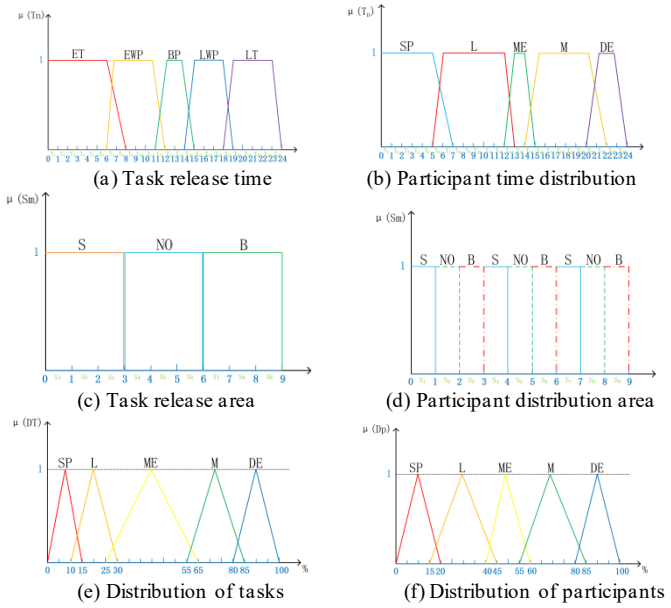
IF <antecedents> THEN <consequent>

4) Defuzzification: In fuzzy logic, we convert input values into membership degrees of each set through fuzzification and then get some effective output values through fuzzy rules. However, having only a few output values is not helpful for problem analysis, so we need to transform some fuzzy output values. Therefore, the process of converting some fuzzy output values into accurate values is called defuzzification.

C. Temporal and Spatial Distribution of Tasks and Participants

For the definition of the temporal and spatial distribution of tasks and participants, the two core influencing factors are time and space. For example, during working hours and in densely populated areas, the amount of task release is relatively large. However, in the rest time and sparsely populated areas, the amount of task publishing is relatively rare. Therefore, with the help of fuzzy logic, we define the input as time and space. In view of time, this scheme divides 24 hours a day into l parts, which are recorded as $T_L = \{T_1, \ldots, T_n, \ldots, T_l\}$. For space, this scheme divides a region into p sub-regions, which are denoted as $S_P = \{S_1, \ldots, S_m, \ldots, S_p\}$. Therefore, we can use time and space as the input of fuzzy logic to calculate the temporal and spatial distribution of tasks and participants. As the output of fuzzy logic, we define the spatio-temporal distribution parameters of tasks as D_T and the spatio-temporal distribution parameters of participants as D_P.

First, we need to determine the fuzzy set of the spatio-temporal distribution of tasks and the spatio-temporal distribution of participants. We define the fuzzy set of task release and participants' participation time periods as early trough (ET), early wave peak (EWP), balance period (BP), late wave peak (LWP) and late trough (LT). Then, the fuzzy sets of the sub-regions where the tasks and participants are located are defined as small (S), normal (NO) and big (B). As for the output variables, the fuzzy set of the spatio-temporal distribution of tasks and participants is defined as sparse (SP), less (L), medium (ME), more (M) and dense (DE).



(a) Task release time

(b) Participant time distribution

(c) Task release area

(d) Participant distribution area

(e) Distribution of tasks

(f) Distribution of participants

Fig. 3. Membership function diagram.

Referring to common models, we divide a day into 24 equal parts, so l=24, $T_L = \{T_1, \ldots, T_n, \ldots, T_{24}\}$. Divide an area into 12 sub-areas, p=12, $S_P = \{S_1, \ldots, S_m, \ldots, S_{12}\}$. According to experience, we can get the membership function curve in Fig. 3.

Because the input conditions of this scheme are time and space, and the output is a time-space distribution, the rules can be defined by fuzzy reasoning. Specifically, the rules defined in this scheme are shown in the following table:

TABLE I. FUZZY LOGIC RULE TABLE

S_m \ T_n / D_t / D_p	ET	EWP	BP	LWP	LT
S	SP	ME	L	ME	SP
NO	L	M	ME	M	L
B	ME	DE	M	DE	ME

According to the rules in Table I, if the task release period is in the early trough and its area is a partition with few tasks, it can be obtained that the temporal and spatial distribution of tasks is sparse. Through the IF-THEN rule, we can express this rule as: IF (T_n = ET) and (S_m = S), THEN (D_T = SP). Similarly, if the movement period of participants is at the late wave peak, and the area where they are located is a partition with many tasks, it can be obtained that the spatial and temporal distribution of participants is dense. The above rules can be expressed as: IF (T_n=LWP) and (S_m= B), THEN (D_P = DE). For the calculation rule "and" in the above fuzzy logic, this study adopts the principle of minimum membership.

Based on the above work, this study uses the weighted average method to achieve defuzzification, and the specific formula is as follows:

$$OT=\frac{\sum_1^i u(D_i) * OW_i}{\sum_1^i u(D_i)} \quad (1)$$

Among them, $u(D_i)$ represents the value of the membership function D and the weight OW_i, usually taking the middle value of each set. Through Formula (1), we can convert some fuzzy outputs into a usable, accurate output value.

We will illustrate it with examples. Assume that the two input values of the task fuzzy logic method are time point 7.5 and sub-area 4. Firstly, we can get IF (T_n= ET) and (S_m= S), THEN (D_T= SP), IF (T_n= EWP) and (S_m= S), THEN (D_T = ME) by consulting the rule diagram. Then the fuzzy set is calculated by using the membership function of these two inputs. It can be obtained that the value of the early trough T_n(ET [7.5])= 0.25, the value of the early wave peak T_n(EWP [7.5])=0.75, and the value of the member function of the small amount S_m(S [4])= 1. Because the conditional parts of two fuzzy logic rules are connected by the AND method, the value of the membership function will be calculated by the minimum value of the corresponding membership functions. For the rules IF(T_n= ET)and(S_m= S), THEN(D_T= SP), the value ofD_T= SP can be calculated as min(0.25, 1)= 0.25 by the minimum membership rule, and for the same rules IF(T_n= EWP)and(S_m= S), THEN(D_T= ME), the value of D_T= ME can be calculated as min(0.75, 1)=0.75 by the minimum membership rule. Then the clear value is 35.625 by defuzzification with the weighted average method.

Similarly, we assume that the two input values of the participant's fuzzy logic method are time point 5.5 and sub-region 2. Firstly, we can get IF (T_n= ET) and (S_m= NO), THEN (D_P= L), IF (T_n= EWP) and (S_m= NO), THEN (D_P = M) by consulting the rule diagram. Then the fuzzy set is calculated by using the membership function of these two inputs. It can be obtained that the value of early trough T_n(ET [5.5]) = 0.75, the value of early wave peak T_n(EWP [5.5]) = 0.25, and the value of normal (NO) member function S_m(NO [2]) =1. Because the conditional parts of two fuzzy logic rules are connected by the AND method, the value of the membership function will be calculated by the minimum value of the corresponding membership functions. For the rules IF (T_n= ET) and (S_m= NO), THEN (D_P= L), the value of the membership function D_P= L can be calculated as min (0.75, 1) = 0.75 through the minimum membership rule. Similarly, for IF (T_n= EWP) and (S_m=NO), THEN (D_P= M), the value of membership function D_P=M can be calculated as min (0.25, 1) = 0.25 through the minimum membership degree rule. Then the clear value is 40 by defuzzification with the weighted average method.

D. Multi-Task Allocation Scheme

To facilitate the following description, we first explain the parameters used:

In time T_n and space S_m, this scheme defines task sets as Task={t_1, t_2, ..., t_i}, participant sets as Part ={p_1, p_2, ... , p_j}, and the compensation that the task publisher is willing to pay for task sets is B_i={b_1, b_2, ..., b_i} respectively, and the cost of participant for each task is $c_{i,j}$ [see Formula (2)]:

$$C_{i,j}=\begin{bmatrix} c_{1,1} & \cdots & c_{1,j} \\ \cdots & & \cdots \\ c_{i,1} & \cdots & c_{i,j} \end{bmatrix} \quad (2)$$

To describe the participants' willingness to perform tasks, this scheme defines $PW_{i,j}$ as the sensing willingness of participant p_j to perform task t_i, and the parameter $PW_{i,j}$ is binary. When $PW_{i,j}$=1, the participant is willing to perform the sensing task; otherwise, $PW_{i,j}$=0, the participant is unwilling to perform the task.

In addition, we define the parameter TC(t_i,t_j) to describe the correlation between tasks. In detail, if task $t_i$and task t_j belong to the same category and time-space, and the participants can perform task t_j while performing task t_i, it is considered that they are related, and TC (t_i, t_j) = 1; on the other hand, it is considered that tasks t_i and t_j are irrelevant, and the correlation coefficient TC (t_i, t_j) = 0. For example, task 1 is to collect automobile acceleration data, and task 2 is to collect automobile driving recorder data. Task 1 and task 2 belong to automobile data and can be executed in the same time and space, but they are irreplaceable, so task 1 and task 2 are related.

When performing sensing tasks, because the participants have moved to a certain time-space area when performing task t_i, if task t_j is related to task t_i, at this time, for users, performing task t_j does not need additional space movement, so compared with simply performing task t_j, it can save a certain time-space cost. At the same time, because task t_j and task t_i belong to the same kind of tasks, participants can perform them at the same time without secondary learning, so the execution cost of participants will be further reduced and the willingness to perform will be enhanced. We define the coefficient as a way to calculate the cost saved by users in performing related tasks. If a user has already allocated a task t_i and then allocated a related task t_j, the user's execution cost will be reduced from c_j to a*c_j(0<a<1). At this time, because of the correlation allocation, we define the funds saved by the correlation allocation as the balance expenditure, which is expressed by R.

In addition, in the process of allocating tasks, some tasks are urgent, and some tasks are not so urgent. To distinguish the urgency of the task, we define the parameter ε to describe the urgency of the task. The greater the parameter ε, the more urgent the task is, and it needs to be allocated to the participants as soon as possible. On the contrary, it means that the urgency of the task is average and can be allocated later.

1) Multi-task allocation algorithm: Based on the fuzzy logic calculation before, we can get the time and space distribution of tasks and participants in a certain time and space interval. In a time T_n and space S_m, if the spatio-temporal distribution $D_T$of tasks is greater than or equal to the threshold β_P, and the spatio-temporal distribution D_P of participants is greater than or equal to the threshold β_T, or the

spatio-temporal distribution D_T of tasks is less than the threshold β_T, then we think that the resources of tasks and participants can match in this area, which is defined as case 1. If the spatio-temporal distribution D_T of tasks is greater than or equal to the threshold β_T, and the spatio-temporal distribution D_P of participants is less than the threshold β_T, it means that there are more tasks and fewer participants in this spatio-temporal area, and it is necessary to provide some incentives for participants to encourage them to complete tasks as much as possible, which is defined as case 2. However, if the temporal and spatial distribution D_T of tasks is less than the threshold β_T, and the temporal and spatial distribution D_P of participants is greater than or equal to the threshold β_P, it means that there are few tasks and many participants in this area, and there is no need to provide additional incentives for participants, which is defined as case 3.

It can be observed that for the above cases 1 and 3, either the number of participants and the number of tasks are balanced, or the number of tasks is large and the number of participants is small. In both cases, we can adopt a general distribution strategy and do not need additional incentives to motivate users to perform tasks. Therefore, we classify cases 1 and 3 into the first situation. In case 2, there are more tasks and fewer participants. To enable users to complete tasks as much as possible, extra incentives should be given to users. Therefore, we regard case 2 as the second kind of situation. The task allocation strategy in each case is as follows:

We divide the Task set into the first kind of case, task set $Task_1$ and the second kind of situation, task set $Task_2$. The allocated task set is defined as TA, and the initial value is ta = $\emptyset$.

For the first kind of situation: firstly, we sort the tasks $Task_1$ according to the urgency from high to low and find out the task t_{i1} with the highest urgency. Among all users, we screen out the users who are willing to sense the task t_{i1}, and among these willing users, we find out the user p_{j1} who has the lowest sensing cost of t_{i1}. If the cost of executing task t_{i1} by user p_{j1} is less than or equal to the offer that task t_{i1} is willing to pay, task t_{i1} is allocated to user p_{j1} for execution. Then, firstly, the tasks that user $p_{j1}$is willing to perform are screened out from the task list, and among these tasks, the related task t_{i2} of task t_{i1} is found according to the urgency from high to low. At this time, if the cost $a*c_{i2,j1}$ of allocating the task t_{i2} to the user p_{j1} is less than or equal to the minimum cost $Minc_{i2}=\min(c_{i2,1},...,c_{i2,j})$ of the task t_{i2} being executed by all users, and $a*c_{i2,j1}$ is less than or equal to the cost that the corresponding publisher is willing to pay for the task t_{i2}, then the related task is allocated and the task t_{i2} is allocated to the user p_{j1} to be executed together.

In the process of allocation, we define R as the saving cost of task allocation in the first case, then $R=\sum_1^n (1-a) * c_{i,j}$, where n is the number of times to complete the related task allocation.

Algorithm 1 gives the task allocation process in the first situation.

Algorithm 1: Related multi-task allocation algorithm in the first situation based on the greedy algorithm.

Input: Task, Part, B_i, $C_{i,j}$, $PW_{i,j}$, TC（t_i，t_j）,ε,a
Output: TA, R

1. //In the first case, assigning $Task_1$ to participants.
2. R=0
3. Rank tasks in $Task_1$ by ε
4. Repeat
5. for $t_i \in Task_1$, i from 1 to i , do
6. the max(ε) task t_i from $Task_1$ call t_{i1}
7. select all p_j when $PW_{i1,j}$=1 call P
8. find min($C_{i1,j}$) p_j from P call p_{j1}
9. if min($C_{i1,j1}$) ≤ B_{i1} then
10. task t_{i1} is allocated to participant p_{j1}
11. $Task_1$=$Task_1$-t_{i1}, TA=TA+t_{i1}
12. select all task t_i from $Task_1$ when $PW_{i,j1}$=1 call T
13. find the max(ε)task t_i from T when TC（t_{i1}，t_i）=1 call t_{i2}
14. If $a*C_{i2,j1} \le \min(C_{i2,j})$ & $a*C_{i2,j1} \le B_{i2}$ then
15. task t_{i2} is allocated to participant p_{j1}
16. $Task_1$=$Task_1$-t_{i2}, TA=TA+t_{i2}
17. R=R+(1-a)*$C_{i2,j1}$
18. else
19. continue
20. else
21. Continue
22. return TA, R

For the second kind of situation: firstly, find out the task t_{i3} with the highest urgency in the task set $Task_2$, screen out the users who are willing to sense the task t_{i3}, and find out the user p_{j2} who has the lowest sensing cost for the task t_{i3} among these willing sensing users, and if the cost for the user p_{j2} to execute the task t_{i3} is less than or equal to the reward paid for the task t_{i3}, allocate the task t_{i3} to the user p_{j2} for execution; If the cost $C_{i3,j2}$ of user p_{j2} executing task t_{i3} is greater than the offer b_{i3} that task t_{i3} is willing to pay, and it still needs R_{i3}=$C_{i3,j2}$-b_{i3} funds to distribute the task, then the remaining balance cost R′=R-R_{i3} at this time, if $R' \ge 0$, incentive R_{i3} is carried out to distribute task t_{i3} to user p_{j2} for execution.

When the task t_{i3} is allocated to the user p_{j2} for execution, the tasks that the user p_{j2} is willing to execute are first screened out in the task list, and then the related task t_{i4} of the task t_{i3} is found in the order of urgency. At this time, if the cost $a*c_{i4,j2}$ of allocating task t_{i4} to user p_{j2} is less than or equal to the minimum cost of task t_{j4} being executed by all users $Minc_{i4}=\min(c_{i4,1},...,c_{i4,j})$, and $a*c_{i4,j2}$ is less than or equal to the cost paid by the task publisher to task t_{i4}, relevant tasks are

allocated, and task t_{i4} is allocated to user p_{j2} to be executed together. At this time, the remaining cost is $R'=R'+(1-a)*c_{i4,j2}$; if the cost $a*c_{i4,j2}$ of allocating task t_{i4} to user p_{j2} at this time is less than the minimum cost of task t_{i4} being executed by all users $Minc_{i4}=\min(c_{i4,1},...,c_{i4,j})$, and $a*c_{i4,j2}$ is greater than the cost b_{i4} that task publisher is willing to pay for executing task t_{i4}, the extra incentive required at this time is $R_{i4}=a*c_{i4,j2}-b_{i4}$, and the saving cost is $R''=R'-R_{i4}$. If $R'' \geq 0$, the incentive is carried out and task t_{i4} is allocated to user p_{j2} for execution.

Repeat the above process until all tasks are allocated or the number of users is exhausted.

Algorithm 2 gives the task allocation process in the second situation.

Algorithm2: Related multi-task allocation algorithm in the second situation based on the greedy algorithm.

Input: Task, Part, B_i, $C_{i,j}$, $PW_{i,j}$, TC（t_i，t_j）,ε,a,R

Output: TA

```
1. //In the second case, assigning Task_2 to participants.
2. Rank tasks in Task_2 by ε
3. Repeat
4. for t_i ∈ Task_2, i from 1 to i , do
5.    the max(ε) task t_i from Task_2 call t_i3
6.    select all p_j when PW_i3,j=1 call P′
7.    find min(C_i3,j) p_j from P′ call p_j2
8.    if min(C_i3,j2) ≤ B_i3 then
9.      task t_i3 is allocated to participant p_j2
10.        Task_2=Task_2-t_i3, TA=TA+t_i3
11.    else
12. R_i3=C_i3,j2-b_i3
13. R′=R-R_i3
14.   if R′ ≥0 then
15.        provide incentive R_i3 for task t_i3
16.        task t_i3 is allocated to participant p_j2
17.        Task_2=Task_2-t_i3, TA=TA+t_i3
18.        R=R-R_i3
19.       else
20.         continue
21. if task t_i3 is allocated to participant p_j2 then
22. select all task t_i from Task_2 when PW_i,j2=1 call T′
23.       find the max(ε)task t_i from T′ when TC（t_i3，t_i）=1 call
t_i4
24.        If a*C_i4,j2 ≤ min(C_i4,j) & a*C_i4,j2 ≤ B_i4 then
25.        task t_i4 is allocated to participant p_j2
26.        Task_2=Task_2-t_i4, TA=TA+t_i4
27. R′=R′+（1−a）*c_i4,j2
28.        else
29.          R_i4=a*c_i4,j2-b_i4
30.          R′=R′-R_i4
31.   if R′ ≥0 then
32. provide incentive R_i4 for task t_i4
33.          task t_i4 is allocated to participant p_j2
34.          Task_2=Task_2-t_i4, TA=TA+t_i4
35.          R′=R′-R_i4
36.         else
37.           continue
38.        else
39.          Continue
40.   return TA
```

IV. RESULTS

To illustrate the performance of the proposal, this section compares the proposed algorithms with the baseline algorithm derived from the existing work [29]. Note that the core idea of [29] is allocating sensing tasks by means of a greedy algorithm. Therefore, the classical greedy algorithm is adopted as the baseline for comparison.

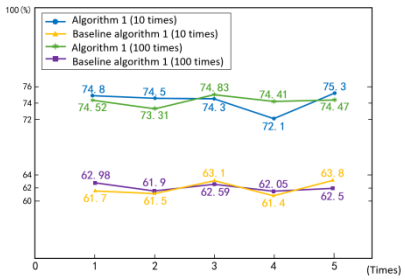
A. Task Allocation Rate

We set the discount coefficient a=0.5, the urgency ε is randomly generated between 1 and 10, the participants' wishes $PW_{i,j}$ and the correlation coefficient TC（t_i，t_j） are randomly assigned between 0 and 1, the compensation B_i that the task publisher is willing to pay for the task is randomly generated between 1 and 15, and the cost $C_{i,j}$ that the user i needs to perform the task j is randomly generated between 5 and 20.

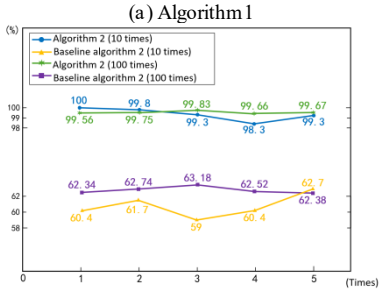
Task set of algorithm 1 contains 100 randomly generated Tasks, set Part contains 50 randomly generated participants, task set of algorithm 2 contains 100 randomly generated tasks, and set Part contains 20 randomly generated participants. In the process of testing, we tested two groups of data respectively. The first group of data was tested 10 times, each time, with five times. The second set of data is tested 100 times at a time, with five times.

As can be seen from Fig. 4, in the first set of data, the average task allocation rate of Algorithm 1 is 74.24%, that of Algorithm 2 is 99.34%, and that of Algorithm 1 and 2 is 86.77%. At the same time, the average algorithm allocation rates of baseline Algorithm 1 and baseline Algorithm 2 are 62.3% and 60.84%, respectively, so the total average task allocation rate of the baseline algorithm is 61.57%. Compared with the baseline algorithm, Algorithm 1 improves the task allocation rate by 11.9% because of the use of related task allocation. Compared with the baseline algorithm, the average task allocation rate of Algorithm 2 is 99.34%, which is 38.5% higher than that of the baseline algorithm, which proves the superiority of the algorithm.

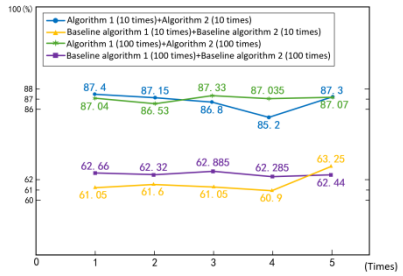
By comparing the first group of data (10 times in each group) with the second group of data (100 times in each group), the fluctuation of the task allocation rate of the algorithm will decrease and the allocation completion rate will tend to be stable with the increase of task execution times.



(a) Algorithm1



(b) Algorithm2



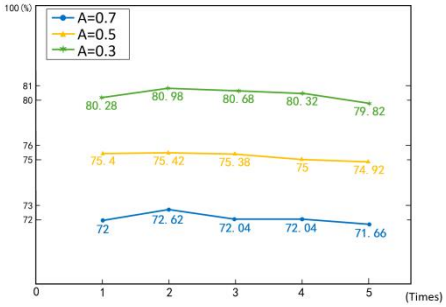
(c) Algorithm1+Algorithm2

Fig. 4. Algorithm task allocation rate result.

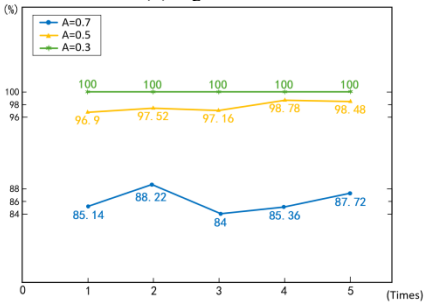
B. Discount Coefficient

We tested three sets of data, and set the discount coefficients a=0.3, a=0.5 and a=0.7, respectively. The urgency ε is randomly generated between 1 and 10, the participants' willingness $PW_{i,j}$ and the correlation coefficient TC（t_i，t_j）are randomly assigned between 0 and 1, the compensation B_i that the task publisher is willing to pay for the task is randomly generated between 1 and 15, and the cost $C_{i,j}$ that the user i needs to perform the task j is randomly generated between 6 and 20. Task set of Algorithm 1 contains 500 randomly generated Tasks, set Part contains 100 randomly generated participants, task set of Algorithm 2 contains 500 randomly generated tasks, and set Part contains 50 randomly generated participants. In the process of testing, each group of data is tested 10 times, and there are five groups. The test results are summarized in Fig. 5.

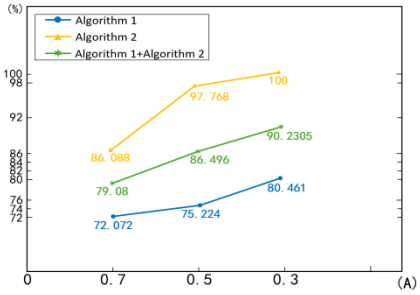
When a=0.7, the average task allocation rate of Algorithm 1 is 72.072%, the average task allocation rate of Algorithm 2 is 86.088%, and the overall average task allocation rate of algorithm is 79.08%. When a=0.5, the average task allocation rate of algorithm 1 is 75.224%, the average task allocation rate of algorithm 2 is 97.768%, and the overall average task allocation rate of algorithm is 86.496%. When a=0.3, the average task allocation rate of Algorithm 1 is 80.416%, the average task allocation rate of Algorithm 2 is 100%, and the total average task allocation rate of algorithm is 90.208%. From the comparison of three data, the smaller the coefficient a is, the greater the cost saved by related allocation, and the greater the incentive provided for the second allocation, the higher the average task allocation rate.



(a) Algorithm 1



(b) Algorithm 2



(c) Algorithm1+Algorithm2

Fig. 5. Under different A values, the task allocation rate.

V. Conclusion

In this study, a related multi-task allocation scheme based on a greedy algorithm is proposed. By quantifying the temporal and spatial distribution characteristics of tasks and participants, different application scenarios are distinguished, and two allocation algorithms suitable for scenarios with sufficient participants and limited resources are designed respectively. Experimental results show that, compared with the benchmark method, the proposed scheme can effectively improve the success rate of task allocation in the mobile crowd sensing (MCS) system in various temporal and spatial distribution scenarios. Especially in scenes with strong task correlation or limited participants' resources, this method shows more stable and consistent performance advantages through joint allocation of related tasks and optimization of incentive costs. Overall, the experimental results verify the effectiveness of the proposed algorithm in improving task allocation efficiency and completion rate from different scene levels.

Although the method in this study has achieved remarkable performance improvement in the experiment, there are still some research limitations. First of all, the task correlation modeling is coarse-grained, which is mainly measured from the perspective of overall correlation, and has not fully described the fine-grained correlation characteristics between users and tasks in terms of historical behavior and ability differences, which limits the applicability of the algorithm in complex practical scenarios to some extent. Secondly, the uncertainties of participants' behaviors, dynamic changes of tasks, communication and calculation overhead in real MCS system have not been fully considered, and the generalization ability of the results needs further evaluation. In addition, although the proposed greedy strategy has advantages in computational efficiency, it still has potential for improvement in global optimality.

Future research will focus on the above limitations. On the one hand, the modeling of task correction and user correction will be further refined, and the multidimensional features and learning mechanism will be introduced to improve the accuracy of the allocation decision. On the other hand, the algorithm will be verified in more complex and real application scenarios, and the multi-task allocation strategy combined with intelligent optimization or learning method will be explored to achieve more efficient and robust MCS multi-task allocation.

REFERENCES

[1] L. Islam et al., "A blockchain-based crowdsourced task assessment framework using smart contract," International Journal of Advanced Computer Science and Applications, vol. 12, no. 1, pp. 590-600, 2021.

[2] A. S. Alashaikh and F. M. Alhazemi, "Efficient mobile crowdsourcing for environmental noise monitoring," IEEE Access, vol. 10, pp. 77251-77262, 2022.

[3] W. Alasmary, "An innovative smartphone-based solution for traffic rule violation detection," International Journal of Advanced Computer Science and Applications, vol. 11, no. 1, 2020.

[4] Y. Liu, Z. Yu, H. Cui, S. Helal, and B. Guo, "SafeCity: A heterogeneous mobile crowd sensing system for urban public safety," IEEE Internet of Things Journal, vol. 10, no. 20, pp. 18330-18345, 2023.

[5] J. M. Cecilia, J. C. Cano, E. Hernández-Orallo, C. T. Calafate, and P. Manzoni, "Mobile crowdsensing approaches to address the COVID-19 pandemic in Spain," IET Smart Cities, vol. 2, no. 2, pp. 58-63, 2020.

[6] M. Alghasham, M. Alzakan, and M. Al-Hagery, "A review of trending crowdsourcing topics in software engineering highlighting mobile crowdsourcing and AI utilization," International Journal of Advanced Computer Science and Applications, vol. 14, no. 4, 2023.

[7] S. Zhang, Z. Li, W. Liang, K.-C. Li, and Z. A. Bhuiyan, "Blockchain-based hybrid reliable user selection scheme for task allocation in mobile crowd sensing," IEEE Transactions on Network Science and Engineering, 2024.

[8] J. An et al., "Privacy-preserving user recruitment with sensing quality evaluation in mobile crowdsensing," IEEE Transactions on Dependable and Secure Computing, vol. 22, no. 1, pp. 787-803, 2024.

[9] J. Wang, X. Zhan, Y. Yan, and G. Zhao, "A method of user recruitment and adaptation degree improvement via community collaboration in sparse mobile crowdsensing systems," Engineering Applications of Artificial Intelligence, vol. 128, p. 107464, 2024.

[10] G. Yang, D. Guo, B. Wang, X. He, J. Wang, and G. Wang, "Participant-Quantity-Aware Online Task Allocation in Mobile Crowd Sensing," IEEE Internet of Things Journal, 2023.

[11] B. Yin, J. Li, and X. Wei, "Rational task assignment and path planning based on location and task characteristics in mobile crowdsensing," IEEE Transactions on Computational Social Systems, vol. 9, no. 3, pp. 781-793, 2021.

[12] M. M. Rahman et al., "A Framework of Quality-Aware Personalized Task Matching For Mobile Crowdsensing," in 2023 IEEE 13th Symposium on Computer Applications & Industrial Electronics (ISCAIE), 2023: IEEE, pp. 309-314.

[13] J. Ji, Y. Guo, D. Gong, and X. Shen, "Evolutionary multi-task allocation for mobile crowdsensing with limited resource," Swarm and Evolutionary Computation, vol. 63, p. 100872, 2021.

[14] G. Ma, H. Chen, Y. Huang, W. Wei, X. Liu, and Z. Wang, "Utility-based heterogeneous user recruitment of multitask in mobile crowdsensing," IEEE Internet of Things Journal, vol. 10, no. 11, pp. 9796-9808, 2023.

[15] H. Gao, J. Feng, Y. Xiao, B. Zhang, and W. Wang, "A UAV-assisted multi-task allocation method for mobile crowd sensing," IEEE Transactions on Mobile Computing, vol. 22, no. 7, pp. 3790-3804, 2022.

[16] M. Li, M. Ma, L. Wang, B. Yang, T. Wang, and J. Sun, "Multitask-Oriented Collaborative Crowdsensing Based on Reinforcement Learning and Blockchain for Intelligent Transportation System," IEEE Transactions on Industrial Informatics, vol. 19, no. 9, pp. 9503-9514, 2022.

[17] X. Li and X. Zhang, "Multi-task allocation under time constraints in mobile crowdsensing," IEEE Transactions on Mobile Computing, vol. 20, no. 4, pp. 1494-1510, 2019.

[18] Y. Huang et al., "OPAT: Optimized allocation of time-dependent tasks for mobile crowdsensing," IEEE Transactions on Industrial Informatics, vol. 18, no. 4, pp. 2476-2485, 2021.

[19] X. Shen, Q. Chen, H. Pan, L. Song, and Y. Guo, "Variable speed multi-task allocation for mobile crowdsensing based on a multi-objective shuffled frog leaping algorithm," Applied Soft Computing, vol. 127, p. 109330, 2022.

[20] W. Wei, H. Chen, X. Liu, G. Ma, Y. Liu, and X. Liu, "Towards time-constrained task allocation in semi-opportunistic mobile crowdsensing," Ad Hoc Networks, vol. 150, p. 103282, 2023.

[21] M. G. Meitei and N. Marchang, "A Greedy Task Allocation Mechanism for Time-Dependent Mobile Crowdsensing Systems," in 2022 IEEE International Conference on Service Operations and Logistics, and Informatics (SOLI), 2022: IEEE, pp. 1-6.

[22] J. Wang et al., "Multi-task allocation in mobile crowd sensing with individual task quality assurance," IEEE Transactions on Mobile Computing, vol. 17, no. 9, pp. 2101-2113, 2018.

[23] Y. Liu et al., "Optimizing task allocation with temporal-spatial privacy protection in mobile crowdsensing," Expert Systems, vol. 42, no. 2, p. e13717, 2025.

[24] G. Ye, Y. Zhao, X. Chen, and K. Zheng, "Task allocation with geographic partition in spatial crowdsourcing," in Proceedings of the 30th ACM International Conference on Information & Knowledge Management, 2021, pp. 2404-2413.

[25] L. Wang et al., "Towards robust task assignment in mobile crowdsensing systems," IEEE Transactions on Mobile Computing, vol. 22, no. 7, pp. 4297-4313, 2022.

[26] I. Iancu, "Heart disease diagnosis based on mediative fuzzy logic," Artificial intelligence in medicine, vol. 89, pp. 51-60, 2018.

[27] A. Yousefi-Darani, O. Paquet-Durand, and B. Hitzmann, "Application of fuzzy logic control for the dough proofing process," Food and bioproducts processing, vol. 115, pp. 36-46, 2019.

[28] E. Wang, W. Liu, W. Liu, C. Xiang, B. Yang, and Y. Yang, "Spatiotemporal Transformer for Data Inference and Long Prediction in Sparse Mobile CrowdSensing," in IEEE INFOCOM 2023-IEEE Conference on Computer Communications, 2023: IEEE, pp. 1-10.

[29] G. Yang, Y. Zhang, B. Wang, X. He, J. Wang, and M. Liu, "Task allocation through fuzzy logic based participant density analysis in mobile crowd sensing," Peer-to-Peer Networking and Applications, vol. 14, pp. 763-780, 2021.

[30] J. Zhang and X. Zhang, "Multi-task allocation in mobile crowd sensing with mobility prediction," IEEE Transactions on Mobile Computing, vol. 22, no. 2, pp. 1081-1094, 2021.

A Lightweight Rule-Based Detection Approach for ARP Flooding Malware in Office Networks

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***Abstract*—Address Resolution Protocol (ARP) is a standard protocol used to map an IP address to its MAC address so the network can send packets to its destination. Office networks, which typically have limited network resources, are vulnerable to ARP flooding attacks launched by malware. ARP flooding can be used by malware to create network disruption and jam the networks. This study presents a rule-based detection method, Time Density ARP Thresholding with Binding Consistency Monitoring (TDCM), to identify ARP flooding using a simple mechanism, making it suitable for use in networks with limited hardware. To detect flooding anomalies, the TDCM algorithm monitors the flow of ARP packets and the consistency between MAC IP bindings in ARP packets. In this study, a series of experiments was conducted and repeated multiple times. On average, the experiment shows that the system performs well under high-volume ARP attack conditions. This proposed method offers an alternative to machine learning techniques, making it more suitable for deployment in resource-constrained office networks. Future work will focus on improving detection in low-volume attack scenarios, validating performance in real-world environments, and implementing on devices with limited computing resources.**

***Keywords*—ARP flooding; cybersecurity detection; rule-based detection; lightweight intrusion detection**

I. Introduction

Today, office networks play a crucial role in our daily activities. High usage of office networks and internet connectivity introduces cybersecurity threats, particularly from malware. Malware can exploit vulnerabilities in protocols to disrupt network operations [1]. For example, the Address Resolution Protocol (ARP) flooding technique can be used by malware to cause network and device congestion. ARP flooding is a network-based attack that exploits the mechanism in the ARP protocol. It has a function that maps IP addresses to MAC addresses at the data link layer [2]. In an ARP flooding attack, an attacker sends a large number of malicious ARP packets into the network, causing ARP Table overflow on network devices. This results in incorrect or missing address resolutions and disruption of network services [2].

A high volume of ARP flooding attacks can cause network denial-of-service (DoS) attacks, data loss, and potential breaches of sensitive information [3]. ARP flooding attacks generate a high volume of ARP request/reply packets from malicious sources within a short time frame [4]. These traffic spikes sometimes exceed the number of ARP activities observed in typical LAN environments, which typically maintain stable ARP caches and low ARP exchange rates. Attackers often used spoofed or randomized MAC and IP addresses, generating inconsistent ARP Table updates that lead to Table exhaustion or overflow [5]. Sometimes, forged ARP packets are broadcast across the subnet to maximize the effect [6]. Those characteristics can be used as a foundation for constructing rule-based detection mechanisms [7].

Some approaches have been developed to detect and mitigate ARP flooding attacks, from traditional fingerprint-based techniques to machine learning and deep learning methods. Conventional methods rely on static rules, such as port security, static ARP entries, dynamic ARP inspection, and a whitelist based on IP MAC binding validation [2]. Other methods, such as monitoring ARP request rates, tracking consistency between MAC and IP addresses, and identifying bulk packet broadcasts from non-gateway devices, could help administrators quickly detect ARP flooding attempts. However, such approaches may lack adaptability to evolving threats.

Currently, ARP attack detection is shifting toward more intelligent and adaptive mechanisms. Using machine learning and deep learning models, such as Random Forest, Convolutional Neural Networks, and Bi-directional Long Short-Term Memory (Bi-LSTM) architectures, achieves high accuracy and low false-positive rates in identifying malicious ARP traffic [5], [7], [8]. In industrial contexts, especially in the Internet of Things environments, hybrid CNN and Bi-LSTM models can detect large-scale ARP-based attacks [7]. The adoption of Software-Defined Networking (SDN) can also enhance ARP security by enabling centralized binding verification and automated mitigation strategies [6]. Another solution employs blockchain-based immutable address-resolution records and cloud-based ARP monitoring systems, thereby enhancing scalability and resilience for ARP detection in distributed environments [5].

Although machine learning and deep learning show promising results, they have limitations. They require large datasets for training, which are challenging to obtain in real-world ARP flooding scenarios. Machine learning and deep learning also make detection more complex for administrators to interpret [9]. These models consume substantial computing resources during training and inference, making deployment less practical [6]. Modified packets may also bypass those models by exploiting a threshold in the machine-learning algorithm. In contrast, fingerprint-based mechanisms can offer deterministic, explainable, and lightweight detection that can be used with minimal resources [4].

This study proposes an algorithm, Time Density ARP Thresholding with Binding Consistency Monitoring (TDCM), for detecting ARP flooding attacks using a rule-based detection

approach. With low computational requirements, TDCM can be deployed on resource-constrained devices. The algorithm detects common ARP flooding characteristics, such as bulk ARP packet broadcasts within short intervals and spoofing signs, in which a single IP address is associated with multiple MAC addresses. This mechanism is evaluated through simulations involving both regular network traffic and ARP attack scenarios.

II. Theoretical Foundation and Related Works

An office network designed to connect multiple devices within a work environment, enabling communication, data sharing, and resource sharing among employees and departments. The network infrastructure typically comprises both wired and wireless local area networks. Wired connections often rely on Ethernet cables connected to switches and routers, providing stable, high-speed connectivity for desktop computers, servers, and network printers. Wireless networks, by contrast, offer flexibility and mobility, enabling laptops, tablets, and mobile devices to connect without physical cabling. A central switch or a set of interconnected switches serves as a backbone that manages traffic flows between devices. These switches are often connected to one or more routers that provide internet access and enable communication with wide-area networks. Depending on the organization's size and structure, the network may be divided into segments or virtual LANs to separate traffic for security and performance reasons [10].

Another important aspect of office networking is sharing resources. File servers are commonly used to store organizational data and to enable employees to share files and documents. Network printers and scanners are connected through print servers, enabling centralized management and reducing the need for individual device setups. In larger organizations, directory services are often implemented to manage users, devices, and policies in a unified manner. This centralized approach simplifies administration while maintaining a consistent security framework.

Network administrators must ensure that bandwidth is allocated appropriately to prevent congestion, especially during peak hours when many users are online simultaneously. Quality-of-service configurations may be applied to prioritize critical traffic, such as voice over IP calls or video conferencing, over less time-sensitive data transfers. Regular network assessments help identify bottlenecks and potential failures before they affect productivity. Finally, office networks are designed for scalability. As businesses grow, additional devices, users, and services need to be integrated without causing significant disruptions.

The Address Resolution Protocol (ARP) is a fundamental component of computer networks. It operates at the data link layer and plays an essential role in maintaining network connectivity. Its primary function is to map IP addresses to corresponding MAC addresses. Each device on the network maintains an ARP Table, which contains a list of IP-to-MAC address mappings for other devices. When a computer application wants to send data, it uses a system call in the operating system. The operating system first checks its ARP Table to see whether the destination IP address already has a corresponding MAC address. If it does not, the operating system broadcasts an ARP request on the network, asking which MAC address corresponds to that IP address. Upon receiving the ARP request, the corresponding device responds with its MAC address. However, if the IP address is in a different subnet, the router responds instead, using its own MAC address. Upon receipt of the reply, the ARP Table is updated with the new information. Over time, if an entry is no longer valid or the time to live expires, the IP-to-MAC pair is removed from the Table [10].

The ARP packet flows through the network without any encryption or authentication mechanism [11]. Any device on the network can generate a bogus or fake ARP packet, which can lead to network errors and disruption. This lack of protection means that any device connected to the network can generate a fake or bogus ARP packet. When this happens, it can result in serious problems such as network errors or even the complete disruption of communication between devices [3]. This weakness has long been recognized as a major security vulnerability, and attackers often take advantage of it to intentionally cause malfunctions and interruptions in computer networks. However, because ARP is a widely used protocol and an integral part of the network layer, the vulnerability still exists. Hong et al. [11] and other researchers have already proposed ideas to enhance security in the ARP protocol, but changing the current ARP protocol requires significant effort, especially changing the code embedded in millions of network devices worldwide.

ARP flooding is a type of network attack that exploits a vulnerability in the ARP protocol. In this attack, the attacker generates a large number of ARP packets and sends them across the network [12]. The continuous flow of these fake packets can overwhelm the ARP tables in the targeted devices, filling them with unnecessary or false ARP entries. When the ARP table becomes overloaded, the device may no longer function properly, leading to errors in communication between hosts on the network. Another major effect of ARP flooding is the excessive traffic it creates on the network. Because so many packets are being transmitted at once, the network bandwidth becomes congested. As a result, legitimate traffic, such as actual data transmissions between users, may be delayed or even completely blocked. This may lead to denial of service or upper-layer service disruption [5]. ARP flooding is not only a direct attack on specific devices but also a threat to the stability and availability of the entire network.

Certain types of malware exploit weaknesses in the ARP protocol by using ARP flooding to launch denial-of-service (DoS) attacks or to position themselves for man-in-the-middle (MITM) attacks [3]. One common method involves sending a large number of ARP request packets into the network, which forces devices with the corresponding IP addresses to repeatedly respond. In some cases, the malware may also send a large volume of ARP reply packets, which can overwhelm the targeted devices. This continuous flooding puts heavy pressure on the ARP cache and consumes a significant amount of CPU resources, eventually disrupting normal network operations and causing a denial of service. If the attack is directed at critical infrastructure such as routers or switches, the impact can be even more severe. It could shut down the entire network and interrupt communication for all connected devices.

ARP flooding attacks typically exhibit distinct traffic patterns that can be detected using rule-based mechanisms. One primary characteristic is a high volume of ARP request or reply packets, often originating from a single host or multiple forged sources within a short time frame [12]. This abnormal packet volume is usually much higher than the expected ARP traffic in a typical local area network, which typically maintains stable ARP caches and exhibits low ARP exchange rates [4]. Additionally, ARP flooding often involves spoofed or randomized source MAC and IP addresses, resulting in continuous updates to the ARP tables of switches or hosts, eventually leading to table exhaustion [5]. Another notable feature is the broadcast nature of forged ARP packets, as they are typically sent to the entire subnet to maximize network disruption [6]. These traits, such as packet rate threshold violations, inconsistent or unknown MAC and IP bindings, and repetitive broadcast ARP replies, form the basis for rule-based detection mechanisms. By implementing static thresholds, whitelist-based validation of IP and MAC pairs, and monitoring for excessive ARP broadcasts from non-gateway devices, network administrators can define deterministic rules to promptly identify and block ARP flooding attempts without relying on complex models or machine learning [7].

Alongside intelligent detection models, recent research also underscores the importance of integrating detection with prevention frameworks. For instance, deploying Dynamic ARP Inspection in SDN-controlled environments has enabled rapid identification and isolation of malicious nodes [4]. Furthermore, cloud-based ARP monitoring systems that use real-time data analysis have shown scalability and effectiveness in large, distributed networks [5]. Integrating IP and MAC static binding in industrial SDN settings and using blockchain for immutable address resolution records represent emerging frontiers in ARP security [6]. These developments reflect a broader trend toward building resilient, autonomous systems that not only detect but also actively adapt to evolving ARP-based threats across enterprise, cloud, and IoT networks.

Despite the growing adoption of machine learning and deep learning for ARP flooding detection, these approaches have notable limitations compared with traditional fingerprint-based mechanisms [9]. A major drawback is reliance on large, well-labeled datasets for effective training. In practice, collecting real-world ARP flooding data can be challenging, leading to models that may generalize poorly across different network environments [5]. Additionally, machine learning and deep learning models often act as black boxes, making it difficult for network administrators to interpret or justify detection outcomes. By contrast, fingerprint-based systems are rule-driven and inherently explainable. Furthermore, these techniques tend to consume significant computational resources, especially during training and real-time inference, which can hinder deployment in resource-constrained environments. Another concern is their vulnerability to adversarial inputs; carefully crafted packets can potentially bypass detection by manipulating model behavior. In contrast, fingerprint-based mechanisms, while limited to known attack signatures, offer fast, deterministic, and lightweight detection that is easier to implement and maintain [4]. These tradeoffs highlight the need for a balanced approach, where intelligent systems are supported by traditional methods to ensure comprehensive and resilient ARP flooding defense.

In parallel with network-level attacks, recent studies have highlighted the growing threat of side-channel attacks, in which attackers exploit indirect information leakage, such as timing behavior, power consumption, cache access patterns, or electromagnetic emissions, to infer sensitive data [13]. Side-channel attacks have been demonstrated against both classical cryptographic implementations and lightweight cryptography, which is increasingly adopted in resource-constrained environments such as IoT and embedded systems [14],[15]. While lightweight cryptographic primitives reduce computational overhead, several works report that simplifications in control flow and reduced noise may unintentionally amplify side-channel leakage. Similarly, emerging post-quantum cryptography (PQC) algorithms, although designed to resist quantum adversaries, are vulnerable to timing and cache-based side-channel attacks due to complex polynomial operations and memory-intensive structures [16][17]. Prior research emphasizes that security mechanisms designed for constrained environments must consider not only algorithmic robustness but also implementation-level leakage. These findings reinforce the relevance of lightweight, deterministic, and transparent security mechanisms—such as rule-based detection approaches—that minimize attack surfaces and reduce exploitable side-channel behaviors in real-world deployments.

III. Research Method

This research starts with a literature study, the development of a simulation, an experiment, and the creation of conclusions. First, a literature review was conducted by analyzing existing ARP flooding detection techniques, both traditional and machine learning based, comparing the pros and cons of both mechanisms. This provided the theoretical foundation for the proposed rule-based detection framework. Second, a Python-based simulation environment was developed to model ARP traffic in a controlled office network scenario. The simulator was designed to generate both normal and attack traffic. The detection module was implemented to monitor ARP packet density and MAC IP binding anomalies. The burst packets are identified with a short timestamp among packets. The traffic simulation algorithm can be seen in Algorithm 1. Third, experiments were performed by executing multiple simulations with varying attack intensities. Each scenario was repeated five times, and detection performance was measured using metrics such as the number of undetected attack packets, true positives, and false positives. Results were averaged and visualized to reveal detection trends.

Algorithm 1: Traffic Simulation

```
SimulateTraffic():
now ← current time
attack_count = 100, 150, 200, …, 1000
normal_count = attack_count/2
For each in 1 to normal_count:
Create packet with:
src_ip = fixed unique IP
```

```
src_mac = fixed unique MAC
timestamp = now + randomFloatTime(0,5)
is_attack = False
Add to packets

For each in 1 to attack_count:
Create packet with:
src_ip = fixed IP
src_mac = unique or duplicate MAC
timestamp = now + randomFloatTime(0,5)
is_attack = True
Add to packets
```

The proposed mechanism is called Time Density ARP Thresholding with Binding Consistency Monitoring (TDCM). It combines analysis of ARP packet density with tracking of IP and MAC binding behavior, without using statistical learning models or training data. The core of the TDCM system comprises two parallel components, as shown in Fig. 1.

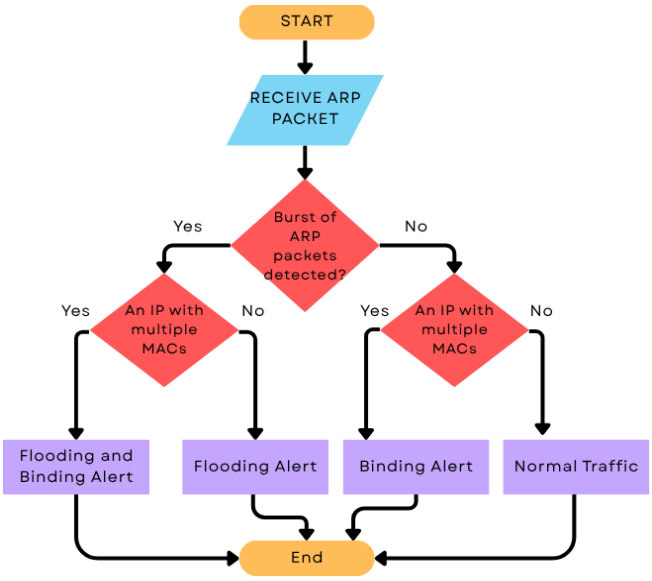


Fig. 1. Flow of the TDCM method.

The first component focuses on time-density monitoring, measuring the arrival rate of ARP packets within a predefined time window. A burst of ARP packets is detected when the number of ARP packets from a single host or targeting a particular IP address exceeds a set threshold within a short period. In this case, the system raises a potential flooding alert or a combination of flooding and binding alerts. If incoming packets contain an IP address with multiple MAC addresses, the attack is categorized as an ARP flooding and spoofing attack. Otherwise, the attack is categorized as ARP flooding only, without spoofing. This approach is based on the insight that ARP flooding attacks generate unusually high volumes of ARP traffic over a short period, which deviates significantly from typical network behavior. By calibrating this threshold based on historical network baselines, false positives can be reduced without the need for adaptive learning. Malware sometimes combines ARP flooding with a spoofed MAC address to initiate a man-in-the-middle attack.

The flooding alert component tracks the number of ARP requests and replies received per source MAC address over fixed intervals. If a particular source exceeds a predefined packet-per-interval threshold, the system flags it as a flooding candidate. Unlike static rate limiting, this approach uses sliding windows to account for short bursts while avoiding false positives from legitimate activity.

The second component, binding consistency monitoring, monitors the consistency of IP-MAC pairings over time. In a normal network, a specific IP address is usually bound to a fixed MAC address within a session or subnet. During ARP spoofing or flooding scenarios, MAC-IP bindings in ARP packets change rapidly. Multiple MAC addresses may be associated with the same IP address, or vice versa. TDCM tracks these inconsistencies and flags them as malicious packets.

Each incoming ARP packet is checked against a list of verified IP and MAC pairs. If a device continuously uses different MAC addresses with the same IP address in a short time frame, it is marked as suspicious. This check is also performed after packets are detected as burst ARP packets.

This approach offers a reliable and efficient method to detect ARP-based attacks. By using deterministic rule-based logic, it enhances interpretability and operational transparency, two aspects that often lack in machine learning approaches. Network administrators can trace each alert back to a specific condition or packet pattern, facilitating faster incident response and better threat understanding.

An optional quarantine queue can be activated when both modules flag a source: traffic from the suspicious node is rate-limited or redirected to an isolated VLAN for further inspection or logging. This multi-aspect detection, based on time density and binding logic, enables fast, deterministic identification of ARP flooding attacks using simple thresholds and lookups.

IV. Results and Discussion

To evaluate the detection effectiveness of the proposed TDCM algorithm, we conducted a series of simulations emulating ARP flooding attacks of varying intensities. The simulations generated two distinct traffic patterns. The first was legitimate ARP traffic from a single device with a fixed IP-to-MAC pairing, and the second was malicious flooding traffic that imitated a spoofing attack by sending a large volume of ARP packets from a single IP address with randomly generated MAC.

The legitimate traffic simulated a normal device transmitting ARP requests or responses at a moderate rate. Conversely, the flooding traffic was designed to trigger TDCM alerts by exceeding the time density threshold and violating binding consistency. The number of malicious ARP packets injected into the network increased from 100 to 1000 in steps of 50. This allowed testing both low-volume and high-volume attack scenarios, representative of stealthy and aggressive attack profiles.

Each configuration was executed five times with randomized MAC address generation and minor timing fluctuations during packet injection. The detection engine recorded the number of undetected packets for each run, and the results were averaged. The key metric analyzed was the

percentage of undetected malicious packets relative to the total number injected. The results in Table I represent the average number of undetected attack packets across these five runs.

TABLE I. SIMULATION RESULTS

Total packet	Flooding alert	Binding alert	False Positive (%)	False Negative (%)
150	0	91	0.00	9.00
225	0	140	0.00	6.67
300	0	191	0.00	4.50
375	0	241	0.00	3.60
450	0	291	0.00	3.00
525	0	341	0.00	2.57
600	10	391	0.00	2.25
675	34	439	5.56	2.00
750	55	491	10.00	1.80
825	80	541	13.64	1.64
900	108	591	16.67	1.50
975	136	641	19.23	1.38
1050	157	691	21.43	1.29
1125	186	741	23.33	1.20
1200	215	791	25.00	1.13
1275	234	841	26.47	1.06
1350	259	891	27.78	1.00
1425	289	941	28.95	0.95
1500	312	990	30.00	0.90

The number of packets in this simulation ranged from 150 to 1500 total packets. The total packet count consisted of one- third normal packets and two- thirds attack packets. The goal was to observe the system's ability to trigger flooding and binding alerts and measure its accuracy through false- positive and false-negative rates. At lower traffic volumes (below 600 packets), the system issued no flooding alerts, and only binding alerts were triggered. This indicates that low- volume attacks can be handled by the binding consistency module alone. However, as the total packet count increased beyond 600, the system began generating flooding alerts, starting with 34 alerts at 675 packets and increasing progressively to 312 alerts at 1500 packets.

The detection system maintained a zero false- positive rate up to 600 packets. As the packet volume increased, however, the false- positive rate gradually rose, reaching 30% at 1500 packets. This tradeoff reflects the system's sensitivity under stress, as aggressive ARP flooding patterns resemble high-volume traffic spikes that may sometimes be misclassified. On the other hand, the false- negative rate consistently decreased as the total packet count increased, from 9% at 150 packets to 0. 0.9% at 1500 packets, indicating that the system becomes more accurate at detecting attacks as flooding intensity rises.

The simulation results show the effectiveness of TDCM in detecting ARP flooding attacks. The method, which combines flooding threshold monitoring and MAC IP binding, can detect malicious ARP packet activity while maintaining a reasonable false- positive rate. These results also show that balancing packet data with traffic activity can maintain accuracy in flooding detection.

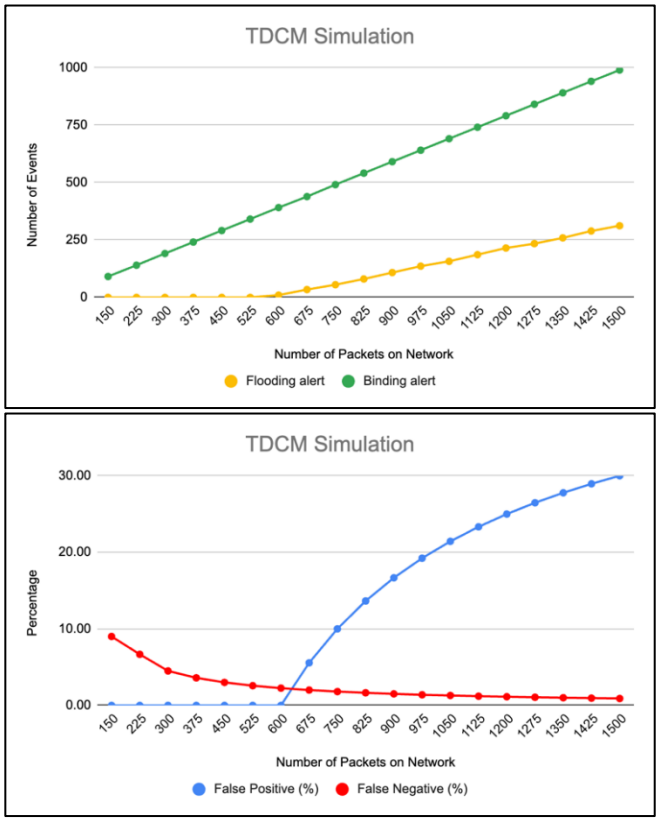


Fig. 2. Graph of simulation result.

Fig. 2 shows a trend with larger attack volume. This trend indicates that the TDCM algorithm will be more effective at recognizing ARP flooding as the number of packet attacks increases. The reduction in undetected packets suggests that the system's time density and MAC IP consistency thresholds will likely be triggered more often in high- packet- attack scenarios. This shows that TDCM may have poor performance in low-volume attacks, but it will increase its performance on large-scale ARP flooding attacks.

Compared to machine learning-based approaches, the TDCM mechanism offers a comparable alternative in high-volume ARP flooding attack scenarios. As demonstrated in the latest simulation, TDCM achieved a detection rate of up to 99% with a false-negative rate as low as 0.9% at 1500 total packets, without relying on model training or feature engineering. This indicates that TDCM can match the effectiveness of ML models in identifying large-scale flooding attacks while maintaining low computational complexity. Furthermore, while recent studies [4] acknowledge the scalability and adaptability of machine learning and deep learning techniques, they also highlight concerns about their black-box nature and limited interpretability during real-time deployment.

In contrast, TDCM's rule-based approach offers transparent detection logic, making it easier for administrators to trace and understand alerts during live network monitoring. TDCM's

approach, based on defined rules and simple logic, offers transparency and low overhead. It doesn't need a powerful computer or a GPU-powered device, making it ideal for resource-limited hardware. Because of its simplicity, TDCM can be implemented using the C programming language and deployed on low-cost IoT hardware. Technically, TDCM can also be implemented using a shell script running common networking tools on a tiny Linux system, making it feasible to deploy in resource-limited office network environments.

V. Conclusion

This study introduced a simple rule-based mechanism, Time Density ARP Thresholding with Binding Consistency Monitoring (TDCM), to detect ARP flooding malware in office networks. The proposed method combines two strategies: monitoring the number of ARP packets in the network and checking the consistency of IP-MAC bindings. TDCM does not require model training, large datasets, or high computational resources to implement.

Simulation and experiments show that the TDCM algorithm performs well under high-volume ARP flooding. MAC and IP binding detection plays a significant role in detecting most attacks. Combined with its monitoring strategies, TDCM can maintain a reasonable false-negative rate. The number of detected attack packets increased as the volume of malicious traffic increased. At a low injection level of 100 packets, the system missed an average of 10 packets. However, as the attack volume reached 1000 packets, the undetected rate dropped to less than 1%. This shows that TDCM is effective in identifying flooding attempts, making it suitable for practical deployment in infrastructure-limited office environments.

TDCM's transparency and deterministic rule structure provide an advantage in interpretability, so network administrators can readily understand, audit, and tune detection logic. This makes the system ideal for environments with limited staffing. Furthermore, its low overhead ensures compatibility with legacy systems, unmanaged switches, and embedded devices, where machine learning-based solutions are often impractical. Despite its strengths, TDCM showed reduced sensitivity to low-rate ARP flooding scenarios.

VI. Future Work

Future work will focus on enhancing detection granularity during such attacks. One promising direction is to integrate adaptive thresholding techniques that adjust detection parameters based on observed traffic baselines. Additionally, field testing in production networks is essential to assess performance under real-world conditions, including traffic noise, heterogeneous devices, and mixed protocol loads. Another possible direction for future research is to apply the algorithm in wireless environments with limited computing resources, such as IoT networks. IoT systems are an excellent setting for testing and applying TDCM because they typically comprise numerous small devices with limited processing power and memory. Experimenting with TDCM in this type of environment could yield valuable insights into how well the algorithm performs under real-world limitations. Over time, studies across different device types and network conditions could further refine the algorithm and enable more efficient, practical implementations of TDCM.

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Declaration on Generative AI

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References

[1] T. Alsmadi and N. Alqudah, "A Survey on malware detection techniques," 2021 International Conference on Information Technology, ICIT 2021 - Proceedings, pp. 371–376, Jul. 2021, doi: 10.1109/ICIT52682.2021.9491765.

[2] D. R. Raviya, D. Satasiya, H. Kumar, and A. Agrawal, "Detection and prevention of ARP poisoning in dynamic IP configuration," 2016 IEEE International Conference on Recent Trends in Electronics, Information and Communication Technology, RTEICT 2016 - Proceedings, pp. 1240–1244, Jan. 2017, doi: 10.1109/RTEICT.2016.7808030.

[3] S. Oei, Y. Suyanto, and R. Pulungan, "A Comprehensive Approach for Detecting and Handling MitM-ARP Spoofing Attacks," IEEE Access, vol. 13, pp. 115503–115519, 2025, doi: 10.1109/ACCESS.2025.3585463.

[4] Y. Lu, C. Zheng, and C. Tang, "Design of ARP Attack Defense System Based on SDN Architecture in Industrial Internet," 2024. [Online]. Available: https://h-tsp.com/://creativecommons.org/licenses/by/4.0/

[5] M. Kumar and C. S. Dash, "Detecting and Preventing ARP Spoofing Attacks Using Real-Time Data Analysis and Machine Learning," International Journal of Innovative Research in Engineering & Management, vol. 12, no. 5, pp. 47–55, Sep. 2024, doi: 10.55524/IJIRCST.2024.12.5.7.

[6] Q. Li and Y. Dong, "Advanced approaches to prevent ARP attacks," Applied and Computational Engineering, vol. 44, no. 1, pp. 124–137, Mar. 2024, doi: 10.54254/2755-2721/44/20230410.

[7] J. Wang, "Industrial Internet of Things ARP Virus Attack Detection Method Based on Improved CNN BiLSTM," Journal of Cyber Security and Mobility, vol. 13, no. 5, pp. 1173–1206, Sep. 2024, doi: 10.13052/JCSM2245-1439.13516.

[8] A. Tran, X. P. L. Ngô, Q. C. Nguyễn, N. Bui Trung, and T. M. T. Dinh, "Using different machine learning models for address resolution protocol spoofing attack detection in software-defined network architecture," International Journal of Pervasive Computing and Communications, 2025, doi: 10.1108/IJPCC-03-2024-0081/1250800/USING-DIFFERENT-MACHINE-LEARNING-MODELS-FOR.

[9] M. Ahmed, A. Naser Mahmood, and J. Hu, "A survey of network anomaly detection techniques," Journal of Network and Computer Applications, vol. 60, pp. 19–31, Jan. 2016, doi: 10.1016/J.JNCA.2015.11.016.

[10] J. F. Kurose et al., "Computer Networking A Top-Down Approach Seventh Edition," 2017, Accessed: Oct. 03, 2025. [Online]. Available: www.pearsoned.com/permissions/.

[11] S. Hong, M. Oh, and S. Lee, "Design and implementation of an efficient defense mechanism against ARP spoofing attacks using AES and RSA," Math Comput Model, vol. 58, no. 1–2, pp. 254–260, Jul. 2013, doi: 10.1016/J.MCM.2012.08.008.

[12] H. Prajapati and Z. Noorani, "A Survey on ARP Poisoning and Techniques for Detection and Prevention," International Journal of Advance Research and Innovative Ideas in Education, 2017.

[13] Y. Yarom and K. Falkner, "FLUSH+RELOAD: A high resolution, low noise, L3 cache side-channel attack," in USENIX Security Symp., 2014.

[14] M. M. Kermani, R. Azarderakhsh and Jiafeng Xie, "Error detection reliable architectures of Camellia block cipher applicable to different

variants of its substitution boxes," 2016 IEEE Asian Hardware-Oriented Security and Trust (AsianHOST), Yilan, Taiwan, 2016

[15] M. M. Kermani, R. Azarderakhsh, "Efficient Fault Diagnosis Schemes for Reliable Lightweight Cryptographic ISO/IEC Standard CLEFIA Benchmarked on ASIC and FPGA," in IEEE Transactions on Industrial Electronics, vol. 60, no. 12, pp. 5925-5932, Dec. 2013

[16] A. Jalali, R. Azarderakhsh, M. M. Kermani, D. Jao. "Towards Optimized and Constant-Time CSIDH on Embedded Devices". 2019.

[17] D. J. Bernstein et al., "Post-quantum cryptography," Nature, vol. 549, no. 7671, pp. 188–194, 2017

EfficientNet-Based Melanoma Classification with CBAM Attention and Monte Carlo Dropout for Robust Uncertainty Estimation

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***Abstract*—Recent developments in deep learning have demonstrated tremendous potential for enhancing medical picture classification tasks, particularly for the detection of skin malignancies like melanoma. However, it is still a huge challenge to guarantee high accuracy, reliability, and interpretability in real clinical settings. This study attempted to resolve these issues by proposing a novel approach to melanoma detection, by employing diverse techniques such as the Convolutional Block Attention Module (CBAM), binary focal loss, and Monte Carlo Dropout (MC Dropout) for uncertainty estimation. The CBAM attention module was inserted to help the network focus on important features of images, and focal loss was applied to solve class imbalance and encourage learning from hard samples. MC Dropout was used to achieve an uncertainty estimate in the test set, and thus, more reliable and interpretable predictions. The approach was implemented with a pre-trained deep CNN called EfficientNetB4 as the backbone and trained on a large melanoma dataset, which is separated into training sets, test sets, and validation sets in order to test the performance. Model evaluation was performed using accuracy, precision, recall, F1-score, and AUC, resulting in 0.95 for accuracy, whereas the AUC value is 0.98. Furthermore, the uncertainty estimate made a clearer decision-making, and the interpretability was crucial when used as a clinical task model. These results highlight the necessity to combine attention mechanisms, task-specific loss terms, and uncertainty quantification for building accurate and interpretable AI in medical domains. The study prototype has the potential for improving the detection of early-stage melanoma and provides useful guidance to future AI-based healthcare services.**

***Keywords*—Deep learning; CNN; accuracy; CBAM; EfficientNetB4**

I. Introduction

Melanoma is an aggressive skin cancer and has continued to be a leading cause of death from cancer worldwide [1]. Melanoma – which originates in the pigment-producing cells of the skin called melanocytes – can spread rapidly to other organs unless it is caught and treated early. Early detection of melanoma contributes significantly to the survival rates of patients and is, therefore, a critical area of research in medical imaging and diagnostics [2]. Diagnosis of melanoma is usually through clinical examination and histopathology, which are associated with human error and variability. Due to the visual aspect of the disease, automatic systems and methods, which make use of image analysis, are a central part of new scientific progress on accurate melanoma detection.

Recent advances in machine learning, particularly deep learning, have demonstrated significant potential for automated melanoma classification based on skin lesion images [3]. Convolution neural network (CNN) has been known as a successful technique for image classification, where it can learn and abstract features automatically from visual data. Melanoma classification has been tackled using different methods, with the use of diverse CNN architectures to enhance accuracy. However, there are still many issues, such as the limited labeled datasets in diverse domains, the differences between the quality levels of images and patterns of skin lesions complexity [4]. Hence, emerging models capable in their ways to go beyond these limitations and make more appealing predictions (in terms of reliability, interpretability and robustness) are always needed.

The problem of handling the uncertainty relating to the medical image analysis is one of the primary concerns for melanoma classification [5]. Despite their great power, deep learning models are typically unable to make predictions while also estimating the uncertainty of these predictions. Failure to estimate such uncertainty can lead to bad decisions in a clinical setting when missclassification is expensive [6]. Also, deep learning based algorithms are prone to overfitting when there is limited The study proposed a new deep learning framework for melanoma recognition, where the CBAM attention mechanism, focal loss and Monte Carlo Dropout (MC Dropout) were integrated to obtain uncertainty estimation. The incorporation produced a remarkable improvement in the performance and reliability. With the help of these sophisticated methods, our model could focus on important attributes and handle the issue of class imbalance to generate reliable predictions with uncertainty. With an accuracy of 95 and an AUC of 0.98, the model also has great potential in future real clinical applications. The novelty of our method lies in the usage of attention mechanism, focal loss and uncertainty estimation, optimizing them all simultaneously. This means to bring interpretability and robustness at the same time so that our model can generalize well for difficult tasks such as melanoma detection, training data or unbalanced data. All of these are reminiscent of the need to come up with methods that improve model accuracy and also provide uncertainty estimates' which is a necessary condition for well-calibrate decision support

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systems able to offer robustness and generalizability in clinical usage.

Another is to determine what are the most relevant parts in an image, particularly when diagnosing melanomas [7]. Even if the CNNs are good feature extractors, this learning does not exploit spatial relationships and contextual information among the entities in an image. It can result in a mistake with grouping, particularly if the melanoma lesion is not readily visible or partly covered. The Convolutional Block Attention Module (CBAM): This has proved beneficial to enhance the performance of CNNs, so they attend more on a most important part of an image. By utilizing an attention mechanism, CBAM makes networks pay more attention on informed regions to increase the classification accuracy and interpretability.

To tackle the above difficulties, a cost-effective and dynamic solution powered by an EfficientNet with CBAM attention-based model, incorporated with Monte Carlo Dropout (MCD) for uncertainty estimation. Derivation of network: EfficientNet has been chosen as it has strong and robust accuracy and computation efficiency according to retrospective training, testing using images regarding melanoma [8]. MCD can naturally give an approximate measure of prediction uncertainty, while the integration of CBAM may assist the network in attending to saliency parts on input images. This synergistic relationship leads to a stronger identification of melanoma, which in turn is good-performing (in terms of accuracy) and provides uncertainty, thereby allowing its application in the clinic where decisions are crucial.

II. Literature Survey

S. Nazari et al. [9] stressed the relevance of diagnostic models for real-world usage, which include smartphone based dermoscopyin order to enhance the diagnosis in rural regions. As per the ISIC2020 challenge, their approach demonstrated comparable outcomes to the first-place model while outperforming second and third places. These models established an appropriate compromise between accuracy and computational efficiency by using 98 % fewer parameters, thereby making them well suited for real-time deployment in resource constrained environment and increasing the reach of accessible healthcare.

A hybrid framework was proposed by P. K. Veni et al. [10] that integrates feature extraction from VGG16 with CBAM and classification with Caps Net. The proposed model was tested using augmented and non-augmented datasets, thereby displaying high performance results up to 100 % precision, 99 % accuracy, and an F1-score.

Skin-GAB, a deep learning based scheme, is proposed by J. Chen et al. [11] for classifying pigmented skin diseases. This approach makes use of augmentation, segmentation, network fusion, and the GAB mechanism for enhancing classification by highlighting essential characteristics. Skin GAB has enhanced the accuracy 2.89 % as compared to the previous model, projected to continue contributing to future diagnosis and managing pigmented skin illness.

A most dangerous type of skin cancer, focusing melanoma, was proposed by G. Dogan et al. [12]. If diagnosed early, it can be treated effectively.

Convolutional neural networks (CNNs), a popular deep learning tool, have shown great promise in accurately detecting melanoma. By integrating attention mechanisms with CNNs, their accuracy can be further enhanced. However, previous models for melanoma detection have not utilized attention mechanisms effectively. In order to help researchers use attention mechanisms effectively, this study investigates how they affect CNN performance. The authors investigated seven distinct attention mechanisms using a base CNN model and compared the outcomes.

The C3BAM-XAI model of CNN was proposed by M. J. Abbas et al. [13], integrating CBAM and explainable AI. It addresses data imbalance through augmentation and uses CBAM's attention modules for better feature extraction. Hyperparameters are optimized with Nadam for smoother training. The model, tested on the PD Kaggle dataset, achieved 93.33% accuracy by B. Mittal [14]. Ablation trials demonstrate that CBAM will enhance the interpretability and accuracy of the model, making it dependable for clinical usage, particularly for Parkinson's disease detection. This study highlights the expanding significance of deep learning approaches in improving medical diagnosis.

CACBL-Net, a lightweight deep CNN, was proposed by R. Agrawal et al. [15], tailoring portable diagnostic devices like smartphones, thereby addressing limitations of data imbalance and computational capacity. The study made use of focal loss for handling imbalance in the dataset and the Monte Carlo dropout method for uncertainty estimation to improve the robustness of diagnostic networks.

The network incorporates channel attention to enhance feature extraction and employs an adaptive class-balanced focal loss to prioritize complex cases while reducing the influence of simpler ones, B. Mittal [16]. On the HAM-10000, PAD-UFES-20 and MED-NODE datasets, CACBL-Net reached sensitivities of 90.60%, 91.88% and 91.31% with prediction times ranging from 0.006 to 0.011 s per case, respectively. These performances are superior to other models that prove the potential and CACBL-Net for skin lesion diagnosis using a mobile device with low computational cost.

Z. Ji et al. [17] introduced EFAM-Net as a new architecture for the classification of skin lesions. The low-level information of color and texture is learned by inserting an Attention Residual Learning ConvNeXt (ARLC) block in the shallow part, and as the depth increases, it is removed to employ a deeper layer with the Parallel ConvNeXt (PCNXt) block by M.K. Amber [18]. To enhance the feature fusion in multiple scales, a Multi-scale Efficient Attention Feature Fusion (MEAFF) block is proposed. We tested our method on ISIC 2019, HAM10000 and a private dataset and the experiment results showed it performed satisfactorily with classification accuracies of 92.30%, 93.95%, and 94.31%.

Y. Jia et al. [19] proposed a medical image classification approach, which adopted a contour processing attention mechanism to increase its accuracy through focusing on key

regions. The process comprises a step of photo converting and linearizing images, as well as contour generation.

The original gray-scale picture is convolved with these contours, creating a row-column feature map that can be further sharpened by means of point-wise multiplication by A. Siddiqui [20]. The resulting image is input to a residual network for classification. Experiments on three medical image datasets indicate noticeable enhancements are achieved with respect to accuracy, F1 score, and Kappa score. This technique also demonstrates value in other areas such as remote sensing and vehicle image recognition.

III. Proposed Model

A. Input Layer

The model receives data through the input layer. In this instance, the input layer is set up to accept photos of shape (224, 224, and 3), which means the images have three color channels (RGB) and a dimension of 224 by 224 pixels. In order to ensure the model correctly processes the data, this layer specifies the form of the input data that will be fed into the neural network.

$$Input = \mathbb{R}^{H \times W \times C} \quad (1)$$

where,

H stands for height, W for width, and C for the number of channels (3 for RGB) in the picture. This layer does not do any calculation; it only takes in the input.

B. EfficientNetB4

The foundation of the model for feature extraction is a pre-trained deep CNN called EfficientNetB. It belongs to an efficient net family, which is renowned for its excellent computational cost and parameter size efficiency. The top classification layers are eliminated by setting include top=False, allowing the model to focus on extracting relevant features from the image data. The model learns superior initial feature representations thanks to the pre-trained weights from ImageNet, which lessens the need for intensive training from the beginning. Similar to other convolutional neural networks, theEfficientNetB4 model processes the input image in several ways:

Convolution Operation:

$$Output = Conv(X, W, b) = (X * W) + b \quad (2)$$

where,

X is the input tensor.

Wis the filter (kernel).

b is the bias.

∗represents the convolution operation.

Activation: Following the convolution, an activation function such as ReLU is applied:

$$Output = ReLU\big(Conv(X, W, b)\big) \quad (3)$$

EfficientNetB4 uses advanced blocks like MBConv, Squeeze-and-Excitation (SE) blocks, and depth-wise separable convolutions, but the basic operation is a convolution followed by activation.

C. Dense Layers (Channel Attention)

The feature maps are transformed by the channel attention module dense layers following pooling operations. By using the ReLU activation function, the first dense layer reduces the number of channels by a factor of the ratio (usually set to 8). The feature map is compressed throughout this process, thereby allowing the network to learn more succinct representations. By returning the channel size to its initial value, the second dense layer produces an improved feature map that may be integrated with the attention mechanism.

First Dense Layer:

$$Output_1 = ReLU\left(\frac{X}{Ratio}\right) \quad (4)$$

where,

- X is the input feature map from the previous layer.
- Ratio is a hyperparameter (often set to 8).

Second Dense Layer:

$$\mathrm{Output}_2 = \mathrm{W}.\mathrm{Output}_1 + \mathrm{b}_1 \quad (5)$$

where,

- Wis the weight matrix.
- b is the bias vector.
- The dense layer performs a matrix multiplication followed by the addition of bias

D. GlobalAveragePooling2D

GlobalAveragePooling2D calculates the average of every feature map throughout the full spatial dimension (including height and width). It makes the output size uniform across various input images by reducing the spatial dimension to a single value per feature map. By ensuring that each feature map is summed up by its average value, this pooling procedure enables the model to incorporate global context and exclude spatial details that are less crucial for the job. The average of each feature map of all spatial locations is calculated via global average pooling:

$$Output_{avg}[c] = \frac{1}{H \times W} \sum_{h=1}^{H} \sum_{w=1}^{W} X[h, w, c] \quad (6)$$

where,

- Hand W are the height and width of the feature map.
- c is the index for the channels.
- The output is the average value of all the pixels in each channel of the feature map.

E. Reshape Layer

The reshape layer is used to transform the output of the global average pooling operation into a shape that corresponds to the layers it follows. In this instance, it ensures that the tensor has a single spatial dimension while retaining the channel information by reshaping the pooled tensor to a shape

of (1,1, channel). As a result, the feature map can be processed by the thick layers that follow, which are built to deal with a specific dimensionality.

$$\text{Reshaped Output} = \text{Reshape}\big(\text{Input}, (1,1,\text{Channels})\big) \quad (7)$$

The reshape operation doesn't modify the underlying data but changes the dimensions of the tensor to ensure compatibility with subsequent layers. The result is a tensor of shape (1,1,Channels), where each channel contains one averaged value.

F. GlobalMaxPooling2D

Similar to Global Average Pooling, Global Max Pooling calculates the maximum value for each feature map rather than averaging the values. The notable feature of each feature map is highlighted using this technique. For tasks that depend on identifying strong patterns, such as object recognition, it captures the most prominent spatial characteristic.

Global Max Pooling computes the maximum value for each feature map:

$$\text{Output}_{\max}[c] = \max_{h,w} X[h,w,c] \quad (8)$$

where,

- [h,w,c] is the value at spatial location h,w, and channel c.
- This outputs the maximum value for each feature map, providing a more extreme form of feature aggregation compared to averaging.

G. Dense (After MaxPooling)

After max pooling, the features are processed by the same dense layers that were used for average pooling. These layers help refine the pooled features by applying the same transformations (reduction in channels and restoration) as seen with average pooling. This dual processing allows the model to consider both the maximum and average features extracted from the input image.

$$\text{Output} = W \cdot X + b \quad (9)$$

where,

- W is the weight matrix,
- X is the input feature map from the pooling operation.
- b is the bias term.

This is a standard dense layer that performs matrix multiplication and bias addition.

H. Add Layer

The results from both average and max pooling are then aggregated (Add layer). This kind of addition has more rich feature representation by using complementary information involved in the two pooling types. With a Concatentity set, the model perhaps can more easily focus on both the prototype categories and the salient cues in the image.

$$\text{Output} = \text{avg_pool} + \text{max_pool} \quad (10)$$

This layer performs the addition of the output from average pooling and max pooling. Each result element is the sum of its two feature map elements.

I. Activation (Sigmoid)

The Activation layer, applying the sigmoid activation function, is used in order to squash attributes of two branches into [0, 1] value softening. This yields a tensor which can be employed as the attention weights. The attention map generated by this activation enables the network to focus on or ignore some feature channels according to their relevance to the task.

$$\text{Output} = \frac{1}{1+e^{-X}} \quad (11)$$

The sigmoid function normalizes values between 0 and 1, making it ideal for binary classification tasks, where the output is interpreted as a probability.

J. Multiply (Channel Attention)

The attention mechanism for the input features is added via the multiply layer. The input feature map is reweighted with the attention map of previous layers through element-wise multiplication. This operation enhances some objects while reducing others over the input. This attention mechanism successfully allows our network to pay more attention to the most essential parts of the input image.

$$\text{Output} = X \times A \quad (12)$$

The attention map A, produced by applying sigmoid activation to the attention mechanism, is element-wise multiplied with input feature map X. The operation highlights the most salient features while suppressing irrelevant ones.

K. Lambda Layer (Spatial Attention)

The Lambda layer average-pools the input feature map over its spatial dimensions. By means of spatial dimension reduction, it yields a tensor that characterizes the distribution of global features in the image. This enables the model to obtain context throughout the entire image, where contextual information may be important for feature relationships (e.g., object detection and segmentation).

$$\text{Output}_{\text{avg}} = \frac{1}{H \times W} \sum_{h=1}^{H} \sum_{w=1}^{W} X[h,w,:] \quad (13)$$

$$\text{Output}_{\max} = \max_{h,w} X[h,w,:] \quad (14)$$

In the Lambda layer, we calculate the mean and max pixel values for each feature map over spatial dimensions. This permits the spatial information to be 'out-of-context', thus facilitating attention-guiding.

L. Concatenate Layer

The results of average and max pooling are concatenated by the concatenate layer in the channels dimension. This concatenation results in a more enriched feature map, including the average and most discriminative spatial features, which could be utilized by the model for both average-based and peak-based aspects at some layers ahead. It facilitates the network to construct a better representation for images by modeling different types of feature information.

$$Output = Concatenate(avg_pool, max_pool) \quad (15)$$

The average and max pooled features are concatenated at channel level. This operation doubles the number of channels as both types of pooling information is merged into one tensor.

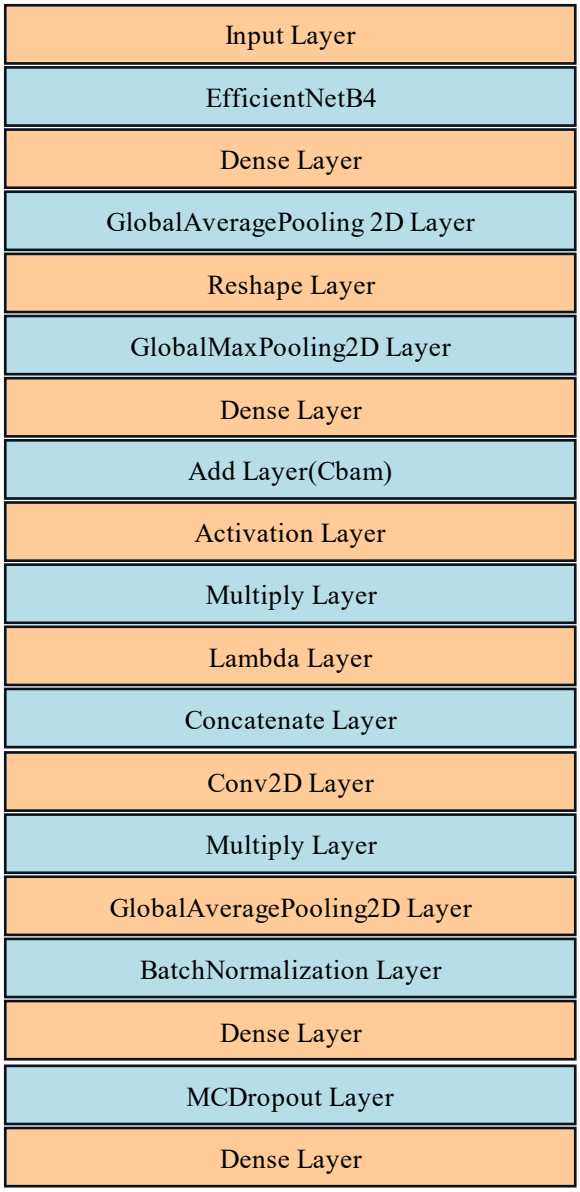


Fig. 1. Proposed model architecture.

Fig. 1 demonstrates the architecture of the proposed hybrid CNN model by combining EfficientNetB4 with CBAM for enhanced feature extraction. The layered structure in the figure illustrates components like convolution, pooling and attention mechanisms.

M. Conv2D (Spatial Attention)

A convolutional filter is then used by the Conv2D layer on the concatenated feature map to generate a spatial attention map. The layer is trained to pay attention to parts of the image, through learning of spatial features, so as to highlight the most relevant parts. Kernels size and strides are determined to maintain the spatial relationship in the image as well as computational efficiency. The sigmoid activation makes the attention values range within 0 and 1, controlling how much each spatial location needs to be weighted.

$$Output = Sigmoid\big(Conv2D(Concat, Filters, Kernel\ Size)\big) \quad (16)$$

A convolution operation is performed over the concatenated feature maps and fed into a sigmoid function for obtaining the spatial attention map, which emphasize the region at a spatial level that model should pay attentions to.

N. Multiply (Spatial Attention)

Similar to the channel attention mechanism, the multiply layer applies the spatial attention map to the input features. The input feature map is multiplied by the spatial attention map, allowing the model to focus on the important spatial regions while ignoring less relevant ones. This helps the network learn which regions in the image are critical for the task at hand.

$$\text{Output} = X \times A_{\text{spatial}} \quad (17)$$

The input feature map X is element-wise multiplied by the spatial attention map $A_{_spatial}$, highlighting the most important spatial regions. Which focuses on the most relevant spatial regions.

O. Global Average Pooling2D (Post Attention)

To summarize all feature maps, GlobalAverage Pooling 2D is applied after the application of CBAM attention mechanism. In order to prepare the output for thick layers, this pooling step reduces the spatial dimensions of each feature map to a single value. After using the attention mechanism, this step guarantees that network is taking into account global features in feature map.

$$\text{Output}_{\text{avg}} = \frac{1}{H \times W} \sum_{h=1}^{H} \sum_{w=1}^{W} X[h, w, :] \quad (18)$$

Global average pooling is applied again after the attention mechanism to summarize the entire feature map into a single value per feature map.

P. Batch Normalization

Batch Normalization helps to stabilize and speed up training by normalizing activation of neurons throughout the mini-batch. It guarantees the consistency of activation distribution by minimizing internal covariate shift. Furthermore, batch normalization improves the generalization of model and training process efficiently by acting as a regularization strategy.

$$\text{Output} = \gamma\left(\frac{X - \mu}{\sqrt{\sigma^2 + \epsilon}}\right) + \beta \quad (19)$$

Batch normalization normalizes the activations by subtracting the batch mean μ and dividing by the batch standard deviation σ. During training, the parameters γ(scale) and β(shift) are learned to adjust the normalized values.

Q. Dense (Fully Connected Layer)

The Dense layer of size 256 propagates the feature map through a fully connected transformation. It learns the high abstractions of stance properties (e.g., training structures) and is called “ReLU” which introduces non-linearity into the

model. This layer is important so that the model can learn complex patterns in between before outputting something simple. L2 regularization is introduced to avoid overfitting by punishing excessive weights.

$$\text{Output} = \text{ReLU}(W.X + b) \quad (20)$$

This dense layer performs a matrix multiplication between the input and weight matrix W, adds the bias term b, and applies the ReLU activation function.

R. MCDropout

The Dropout layer is a dropout layer with a custom forward pass that remains active during test. This is in contrast to traditional dropout, which is employed only at training time and thus cannot measure the uncertainty during test. This is especially valuable for uncertainty estimation tasks, where the interpretability of the model's confidence in prediction is key. Through the activation of dropout during inference, the model is able to produce a wider diversity of predictions, leading to a more reliable measure for uncertainty.

$$\text{Output} = \text{Dropout}(X, p = 0.5) \quad (21)$$

The MCDropout layer ensures that dropout is active during both training and inference, which allows the model to generate multiple stochastic forward passes and estimate uncertainty in predictions.

S. Dense (Output Layer)

The final Dense layer is the output with a single unit for binary classification and sigmoid activation to make it suitable for your prediction task. Finally, the output of the sigmoid gives a value between 0 and 1, which one might interpret as being the probability that your input is in the positive class. This layer is the final decision point of the network, and observations fit to the model are transformed into a modeled prediction.

$$\text{Output} = \text{Sigmoid}(W \cdot X + b) \quad (22)$$

The final output layer calculates the probability of the positive class (binary problem) with a sigmoid activation. The output is a score in the range of [0, 1], which indicates the probability that the input sample falls into the positive class.

The novel changes in the model could improve both performance and interpretability on a melanoma deep learning classifier. The contribution lies in integrating the CBAM (Convolutional Block Attention Module) that works with channel-wise and spatial attention. As a result, this allows the model to pay attention on most informative regions of the input image to improve feature extraction, which will automatically emphasize useful parts. Additionally, the model has a binary focused loss, which addresses class imbalance by emphasizing hard negatives more. The Monte Carlo dropout introduces uncertainty estimation during interference, which can be used to measure the degree of prediction confidence and reveal information about the dependability of the model. These enhancements are intended to maintain a reliable and understandable method of melanoma classification, which also improves the generalization of model performance and reduces overfitting.

Advanced data augmentation and specially designed callbacks like ReduceLROnPlateau and EarlyStopping, which aid in learning optimization and prevent overfitting, are some further contributions of the suggested model. The model uses EfficientNetB4 as a backbone to extract features, making it possible for the model to achieve high accuracy with computational cost under control. We train the model in multiple stages with heavy data augmentation like rotation, zoom and flip to be able to generalize well to unseen data. In the evaluations, besides these standard measures (accuracy, precision, recall and F1-score), we measure uncertainty using Monte Carlo sampling. This perspective offers a broader interpretation of model behavior that can guide confidence in clinical decisions.

IV. Experimental Results

The results produced by the method developed in this work during the current simulation studies are reviewed in this section of the study.

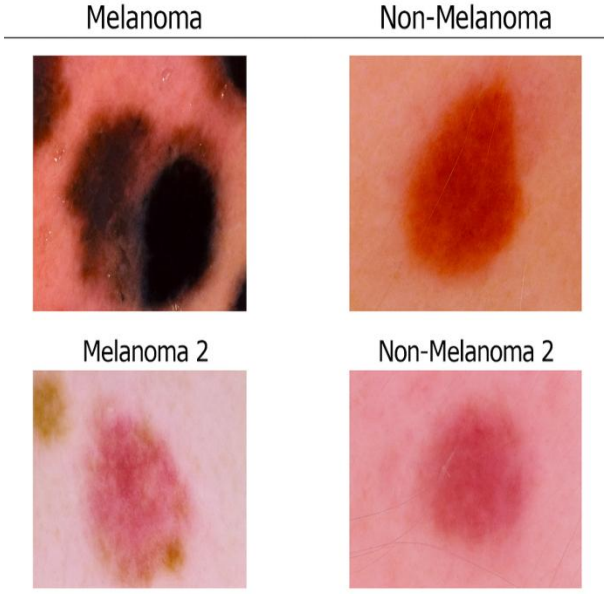


Fig. 2. Sample images for melanoma and not melanoma classification.

Fig. 2 shows the sample images taken for classifying Melanoma and Not Melanoma. The melanoma dataset was used for these experiments [17]. The data preprocessing techniques described earlier were also applied to this dataset in our work. The proposed work made use of ISIC 2019 [21], [22] and HAM10000 [23] public datasets available freely online on the International Skin Imaging Collaboration Challenge.

The plot in Fig. 3 shows the training and validation accuracy across 50 epochs. The training accuracy curve, indicated by the blue line, gets very jagged with vivid spikes and ascents. This might reflect a tendency to overfit, implying that the model is making its predictions too closely follow the training set (as opposed to other data). On the other hand, the validation accuracy (green) moves more steadily on small steps of improvement, which means better generalization to unseen data. The saturation of the generalization g between the two accuracy curves suggests that the depth-3DIHNN fails to

generalize well, and this problem would be alleviated by techniques such as model fine-tuning or regularization.

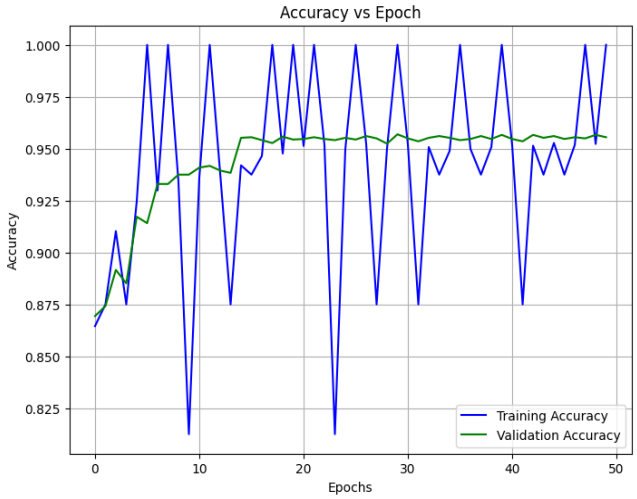


Fig. 3. Training and validation accuracy over epochs.

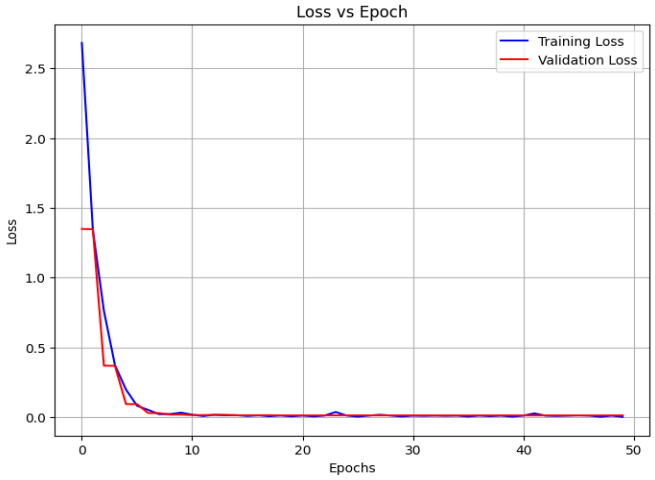


Fig. 4. Training and validation loss over epochs.

The above plot in Fig. 4 visualizes how loss changes over time with epochs as the independent variable. Training loss is the purple line, validation loss is the red line. Both the losses start large but decrease rapidly, indicating that the model makes good progress early in training. After this drop, there is some breakage, and the losses rapidly go lower in later epochs. Training and Validation loss have nearly no split, it means the model is not overfitting or underfitting. As the model is able to achieve low loss values, it suggests that the model can learn well.

The Receiver Operating Characteristic (ROC) curve, shown in Fig. 5, is a popular measure of the performance of a binary classifier is depicted in the above figure. The relationship of the true positive rate (TPR) versus the false positive rate (FPR) is also plotted with different threshold values. The blue line is shooting up towards high TPR values as FPR rises – this means that the model can differentiate between positive and negative classes well. The curve is shifted towards the upper left corner (optimal performance) with high sensitivity and specificity. The dashed diagonal line is a random classifier which have same TPR as it has FPR for any threshold. The ROC curve is also well above this diagonal, so it shows that the model beats random guessing. Area Under the Curve (AUC) is probably close to 1, indicating strong classification.

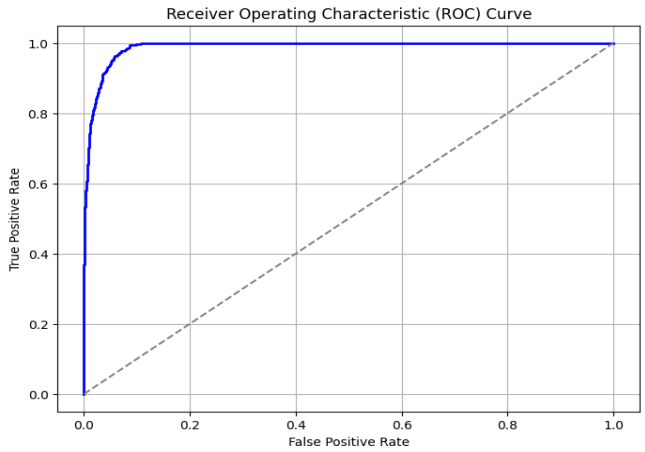


Fig. 5. Receiver Operating Characteristic (ROC) curve.

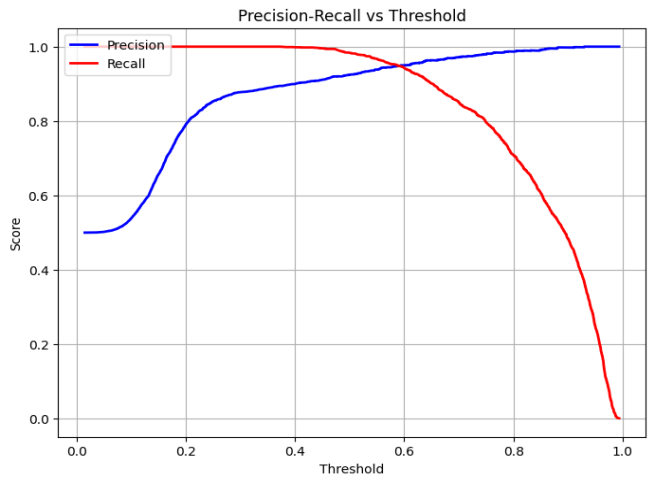


Fig. 6. Precision and recall vs. Threshold.

The above Fig. 6 shows the Precision-Recall curve against the classification threshold. The blue curve corresponds to precision, while the red one indicates recall. As we set the '+' threshold higher and higher, our precision improves drastically, approaching 1, which means that the model becomes increasingly confident in its positive predictions to yield high overall accuracy. But recall (the red curve) is decreasing as precision increases. This is a simple case of trade-off when we tune the threshold - recall increases (hits more true positives) and precision decreases (hits false positives). The feature space gives a geometrical picture of this trade-off, and allows to choose the best threshold with respect to the precision-recall trade-off according to the particular characteristics of the problem (e.g., more emphasis on precision or recall).

The Cumulative Gain Curve shown in Fig. 7 is something that will help you when it comes to evaluating the performance of a classifier for ranking problems. The curve displays the cumulative gain against the percentile of the samples. With the

number of samples, the cumulative gain increases as well and tends to 1. This indicates that if 80% of samples are retained by taking those after the 20th row, a larger percentage of the positive class is covered. The steep rise at the start of the curve shows that the model can quickly identify many relevant samples, which could be advantageous for systems such as targeted marketing or fraud detection. A perfect curve would indicate a sharp steep at the beginning, followed by a plateau, indicating that most positive samples are correctly included in top ranked portion of the test.

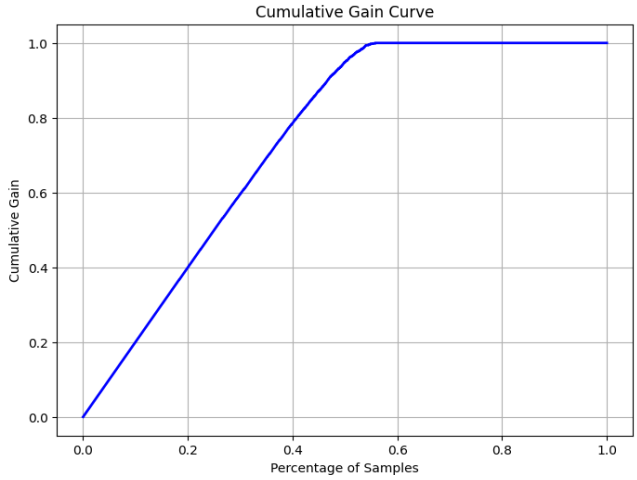


Fig. 7. Cumulative gain curve.

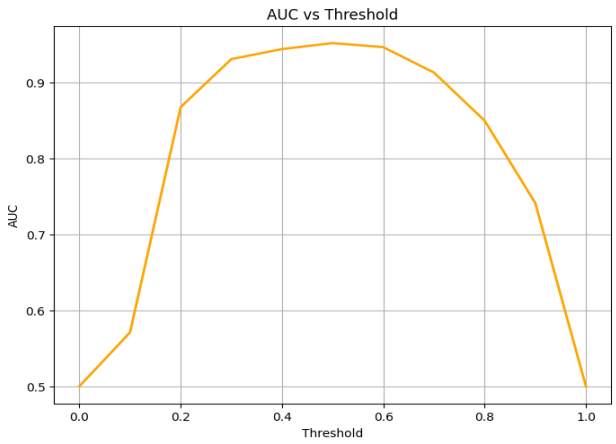


Fig. 8. AUC vs. Threshold.

Fig. 8 shows how the Area Under the Curve (AUC) and classification level relate. Plot of AUC as a function of the threshold defining positive and negative samples. At first, as the threshold increases substantially from 0 to about 0.3, AUC rapidly grows and it is close to the maximum value of almost 1.0, showing that the model has great classification performance at this threshold grain highly balanced class separation. More importantly, the AUC starts to decline when this threshold becomes larger, implying that with higher threshold values, the model down-weights positive samples and accordingly its capability of distinguishing positives from negatives weakens. Such behavior suggests that an optimal threshold can be found where AUC is the largest for indicating the threshold that results in the best classification performance.

This decline following the peak is expected due to the well-known trade-off between precision and recall with threshold.

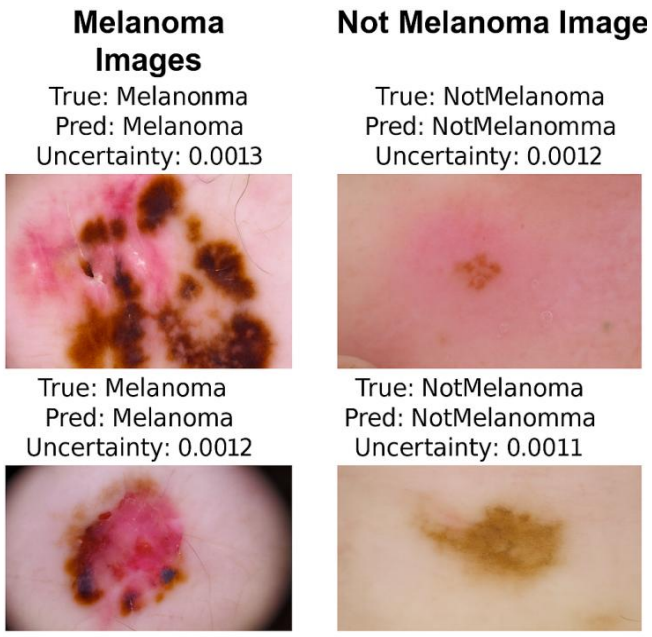


Fig. 9. Classification of melanoma and not melanoma images with prediction confidence.

The picture in Fig. 9 represents the classification between Melanoma and Not Melanoma images and model predictions with respective uncertainty values. The left column shows Melanoma cases that are correctly predicted as Melanoma, with uncertainty of 0.0013 and 0.0012, so the model is more certain in these predictions. The right column shows Not Melanoma images classified as such with even lower uncertainty values (U = 0.0011 and U = 0.0012). These very low levels of uncertainty indicate that the model is doing an excellent job accurately placing examples into one of two categories, and therefore can be thought to have high certainty in its predictions.

TABLE I. CLASSIFICATION REPORT

	Precision	Recall	F1-Score
Melanoma	0.98	0.91	0.95
Not Melanoma	0.92	0.98	0.95
Total Accuracy	0.95		

The above Table I is the classification report for a model that classifies between two labels, Melanoma and Not Melanoma. In the case of Melanoma, the model has high precision (0.98), which means that 98% are the predicted positive cases are comparable. Its recall (0.91) is a bit lower, which means that 91% of the actual positive cases have been recognized. Melanoma achieves F1-Score 0.95, balancing precision and recall. For Not Melanoma, it is 0.92 precision and a high recall of 0.98 indicates that the model accurately detects true positives at a high rate. The Not Melanoma F1-Score: 0.95 as well. The suggested model, making use of Efficient Net using CBAM Attention and Monte Carlo Dropout

for uncertainty estimation and the model's general accuracy of 0.95 indicates a strong performance for the two classes. The balanced F1-Scores and high accuracy demonstrate that the model performs well in detecting both conditions without significant bias.

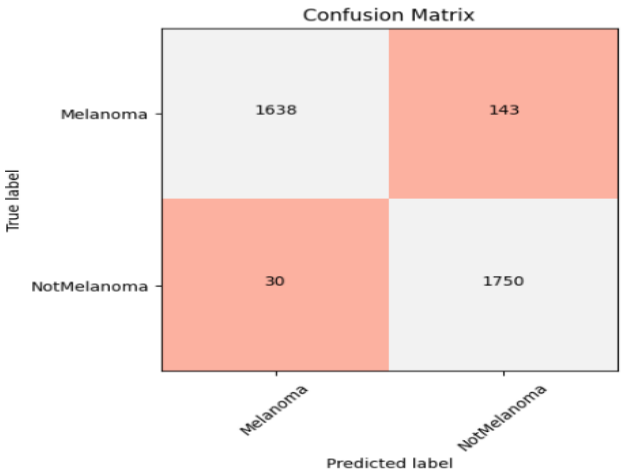


Fig. 10. Confusion matrix for melanoma classification.

Fig. 10 above shows the confusion matrix for a binary classification model distinguishing between Melanoma and Not Melanoma. Out of 2816 instances, the model correctly identified 1638 cases of Melanoma (True Positives) and 1750 cases of Not Melanoma (True Negatives). However, it made errors by incorrectly predicting 143 cases of Not Melanoma as Melanoma (False Positives) and 30 cases of Melanoma as Not Melanoma (False Negatives). While the matrix reflects the model's strong performance in accurately classifying Not Melanoma (with high True Negatives), it also reveals areas for improvement, particularly in reducing the False Positive and False Negative predictions.

TABLE II. COMPARATIVE ANALYSIS

Model Name	Accuracy (%)
ResNet50 [18]	0.88
Sequential [19]	0.92
CNN [20]	0.93
DenseNet121 [21]	0.93
InceptionV3 [22]	0.94
Proposed Model(EfficientNetB4)	0.95

A comparison of different deep learning models based on their accuracy for a particular task is shown in Table II. ResNet50, Sequential CNN, Dense Net 121, Inception V3, and the suggested EfficientNetModel are all included in the comparison. Among these, Inception V3 attains maximum accuracy at 0.94 while the ResNet50 model has the lowest accuracy at 0.88. With an accuracy of 0.95, the suggested model making use of EfficientNet using CBAM Attention and Monte Carlo Dropout for uncertainty estimation beats all the other models, demonstrating its superior performance on the task at hand.

V. RESULTS AND DISCUSSION

The proposed Efficient NetB4 model demonstrates an accuracy of 95 % and strong melanoma classification performance. The precision and recall are (0.98, 0.91) for melanoma and (0.92, 0.98) for not melanoma classes. From the confusion matrix, it is clear that the misclassification rate is low thereby confirming reliable discrimination between classes. The comparative study shows that proposed approach outperforms CNN based methods, showing correct classification with low uncertainty thereby validating its effectiveness for melanoma detection.

VI. CONCLUSION

A new deep learning framework for melanoma recognition is proposed in this study that includes the CBAM attention mechanism, focal loss and Monte Carlo Dropout (MC Dropout) in order to prove uncertainty estimation. The integration has significantly improved the performance and dependability. These advanced techniques allowed our model to concentrate on key characteristics and address the problem of class imbalance in order to produce accurate forests with uncertainty. The proposed model made use of CBAM attention and the Monte Carlo dropout method for uncertainty estimation and the accuracy of the model is 95, and AUC is 0.98, which indicates it has a lot of potential for actual clinical use in the future. Our approach is novel in that it simultaneously optimizes the attention mechanism, focus loss and uncertainty estimation. Admittedly, in the presence of predictions and impossibilities, perhaps it is indeed that the model offers some kind of practical way to aid early diagnosis of skin cancer. The study is clinically relevant to image classification-based clinical applications, and it highlights the advantage of applying cutting-edge AI techniques for improved decision diagnosis and support accuracy. Future work can incorporate multi-class lesion classification to further improve robustness.

REFERENCES

[1] Shukla, Man Mohan, B. K. Tripathi, Tanay Dwivedi, Ashish Tripathi, M. M. Shukla, B. K. Tripathi, T. Dwivedi, A. Tripathi, and B. K. Chaurasia, "A hybrid CNN with transfer learning for skin cancer disease detection," *Med. Biol. Eng. Comput.*, vol. 62, no. 10, pp. 3057–3071, 2024.

[2] H. Naseri and A. A. Safaei, "Diagnosis and prognosis of melanoma from dermoscopy images using machine learning and deep learning: a systematic literature review," *BMC Cancer*, vol. 25, no. 1, p. 75, 2025.

[3] G. Yang, S. Luo, and P. Greer, "Advancements in skin cancer classification: a review of machine learning techniques in clinical image analysis," *Multimedia Tools Appl.*, vol. 84, no. 11, pp. 9837–9864, 2025.

[4] A. Patil, A. Mehto, and S. Nalband, "Enhancing skin lesion diagnosis with data augmentation techniques: a review of the state-of-the-art," *Multimedia Tools Appl.*, pp. 1–40, 2024.

[5] B. Lambert, F. Forbes, S. Doyle, H. Dehaene, and M. Dojat, "Trustworthy clinical AI solutions: A unified review of uncertainty quantification in deep learning models for medical image analysis," *Artif. Intell. Med.*, vol. 150, p. 102830, 2024.

[6] S. Agius, C. Magri, and V. Cassar, "A cognitive task analysis for developing a clinical decision support system for emergency triage," *J. Emerg. Nurs.*, 2025.

[7] V. Singh, K. A. Sultanpure, and H. Patil, "Frontier machine learning techniques for melanoma skin cancer identification and categorization: an in-depth review," *Oral Oncol. Rep.*, vol. 9, p. 100217, 2024.

[8] P. Zhang and D. Chaudhary, "Hybrid deep learning framework for enhanced melanoma detection," *IEEE Trans. Comput. Biol. Bioinf.*, 2025.

[9] S. Nazari and R. Garcia, "Going smaller: Attention-based models for automated melanoma diagnosis," *Comput. Biol. Med.*, vol. 185, p. 109492, 2025.

[10] P. K. Veni and A. Gupta, "Revolutionizing acne diagnosis with hybrid deep learning model integrating CBAM and capsule network," *IEEE Access*, vol. 12, pp. 82867–82879, 2024.

[11] J. Chen *et al.*, "Pigmented skin disease classification via deep learning with an attention mechanism," *Appl. Soft Comput.*, vol. 170, p. 112571, 2025.

[12] G. Doğan, "Performance analysis of attention mechanisms for melanoma cancer detection," in *Proc. 8th Int. Artif. Intell. Data Process. Symp. (IDAP)*, 2024, pp. 1–6.

[13] M. J. Abbas *et al.*, "C3BAM-XAI: Convolutional block attention module enhanced explainable artificial intelligence-based Parkinson's disease stage classification," *Cogn. Comput.*, vol. 17, no. 3, p. 111, 2025.

[14] B. Mittal, "Melanoma cancer image dataset," Kaggle, 2023. [Online]. Available: https://www.kaggle.com/datasets/bhaveshmittal/melanoma-cancer-dataset. [Accessed: Aug. 23, 2025].

[15] R. Agrawal, N. Gupta, and A. S. Jalal, "CACBL-Net: A lightweight skin cancer detection system for portable diagnostic devices using deep learning–based channel attention and adaptive class balanced focal loss function," *Multimedia Tools Appl.*, pp. 1–24, 2024.

[16] B. Mittal, "Melanoma cancer image dataset," *Kaggle*, 2023. [Online]. Available: https://www.kaggle.com/datasets/bhaveshmittal/melanoma-cancer-dataset. [Accessed: Aug. 23, 2025].

[17] Z. Ji *et al.*, "Efam-net: A multi-class skin lesion classification model utilizing enhanced feature fusion and attention mechanisms," *IEEE Access*, 2024.

[18] M. K. Ambar, H. Oztoprak, and K. Yurtkan, "Optimizing ResNet-50 for multiclass classification: A multi-stage learning approach," *IEEE Access*, 2025.

[19] Y. Jia, L. Dong, and Y. Jiao, "Medical image classification based on contour processing attention mechanism," *Comput. Biol. Med.*, vol. 191, p. 110102, 2025.

[20] A. Siddique, K. Shaukat, and T. Jan, "An intelligent mechanism to detect multi-factor skin cancer," *Diagnostics*, vol. 14, no. 13, p. 1359, 2024.

[21] M. Combalia, N. C. F. Codella, V. Rotemberg, B. Helba, V. Vilaplana, O. Reiter, C. Carrera, A. Barreiro, A. C. Halpern, S. Puig, and J. Malvehy, "BCN20000: Dermoscopic lesions in the wild," *arXiv preprint* arXiv:1908.02288, 2019.

[22] N. C. F. Codella, D. Gutman, M. E. Celebi, B. Helba, M. A. Marchetti, S. W. Dusza, A. Kalloo, K. Liopyris, N. Mishra, H. Kittler, and A. Halpern, "Skin lesion analysis toward melanoma detection: A challenge at the 2017 International Symposium on Biomedical Imaging (ISBI), hosted by the International Skin Imaging Collaboration (ISIC)," in *Proc. IEEE 15th Int. Symp. Biomed. Imag. (ISBI)*, Apr. 2018, pp. 168–172, doi: 10.1109/ISBI.2018.8363547.

[23] P. Tschandl, C. Rosendahl, and H. Kittler, "The HAM10000 dataset: A large collection of multi-source dermatoscopic images of common pigmented skin lesions," *Sci. Data*, vol. 5, no. 1, Art. no. 180161, Aug. 2018, doi: 10.1038/sdata.2018.161.

Multi-Objective Design Optimization of Ventilation Duct Systems: A Graph-Informed Hybrid Evolutionary Approach

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***Abstract*—Optimizing silencer placement in Heating, Ventilation, and Air Conditioning (HVAC) systems is a complex multi-objective problem due to conflicting objectives (noise, energy, cost) and intricate topological constraints. Conventional Multi-Objective Evolutionary Algorithms (MOEAs) often exhibit inefficient convergence on such problems due to their reliance on random search strategies. Addressing this challenging HVAC design problem requires a more informed approach. This paper proposes the G-HNSGA-III (Graph-Informed Hybrid NSGA-III), a novel framework that enhances the NSGA-III algorithm by embedding domain-specific knowledge from the system's Directed Acyclic Graph (DAG) topology. This is achieved through two core components that leverage heuristic search: a Graph-Informed Initialization (GINI) strategy to provide a high-quality starting population and a Graph-Informed Local Search (GILS) module for post-processing refinement. The performance of G-HNSGA-III was comprehensively benchmarked against the baseline NSGA-III and six other established MOEAs on a complex data center test instance. The results demonstrate a marked superiority, with G-HNSGA-III achieving a 38.4% higher mean Hypervolume (HV) than the baseline NSGA-III and a 99.3% Set Coverage (SC) dominance over MOEA/D. The framework consistently converged to the best-known Pareto front, achieving a final mean Inverted Generational Distance (IGD) of 0.0030. These findings validate that the proposed graph-informed strategies effectively accelerate convergence and enable the discovery of a higher-quality Pareto front, providing superior and practically applicable solutions for complex engineering design problems.**

Keywords*—Multi-objective optimization; NSGA-III; graph-informed optimization; HVAC design; heuristic search; domain knowledge

I. Introduction

Modern facilities with strict climate control requirements—spanning from commercial complexes to critical infrastructure like hospitals—rely heavily on HVAC systems for operational stability [1-2]. While essential, these systems create a fundamental operational conflict. On one hand, the mechanical noise from fans degrades the acoustic environment; on the other, the fan power required to drive airflow constitutes a major operational cost, directly opposing sustainability targets [3-4]. The trade-off is physical and unforgiving: installing silencers to attenuate noise inherently increases airflow resistance (pressure drop), which forces fans to consume more energy to maintain the same flow rate. Therefore, optimizing the placement of these components is not merely a design preference but a central challenge in balancing energy efficiency with environmental quality.

This optimization task is compounded by the topological complexity of HVAC ductworks. Unlike simple linear systems, duct networks function as Directed Acyclic Graphs (DAGs), where the airflow dynamics are highly interdependent [5-6]. A design decision at a single upstream node propagates through the entire network, affecting pressure and noise levels at all downstream branches. Consequently, conventional design methodologies reliant on heuristics or trial-and-error fail to capture these global dependencies. They lack the mathematical rigor to navigate a search space characterized by discrete variables (e.g., specific silencer models) and strict physical constraints.

To address such high-dimensional engineering problems, Multi-Objective Evolutionary Algorithms (MOEAs) have become the established methodological standard [7-8]. However, their application to network-based systems faces a critical bottleneck: the quality of the initial population. Standard algorithms like NSGA-III typically rely on random initialization. In the strictly constrained solution space of an HVAC network, this stochastic approach often results in an inefficient search process, leading to slow convergence or stagnation in local optima—a limitation well-known in the field but rarely addressed with domain-specific logic.

We propose that embedding domain-specific topological knowledge into the evolutionary search can overcome these limitations. To this end, we introduce the Graph-Informed Hybrid NSGA-III (G-HNSGA-III) framework. This approach enhances NSGA-III by integrating DAG topology through two mechanisms: a Graph-Informed Initialization (GINI) strategy and a Graph-Informed Local Search (GILS) module.

The principal contributions of this paper are as follows:

- The proposal of a novel hybrid framework, G-HNSGA-III, that effectively embeds the topological knowledge from a DAG model into the evolutionary search process for HVAC optimization.
- The design and implementation of two specific algorithmic components: a GINI strategy to accelerate initial convergence and a GILS module to enhance the final solution set quality.

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- A comprehensive validation of the framework on a complex, real-world data center case study, demonstrating its significant performance superiority over the baseline NSGA-III and six other established MOEAs.

The remainder of this paper is organized as follows. Related work is given in Section II. Section III details the DAG-based system modeling and the pre-computation of topological metrics. Section IV presents the proposed G-HNSGA-III framework in detail. Section V describes the experimental setup, parameters, and evaluation metrics. Section VI presents and analyzes the comparative results. Finally, Section VII concludes the paper and discusses future research directions.

II. Related Work

The dual challenge of acoustic control and energy efficiency is well-established in HVAC literature. Noise generation is an inevitable byproduct of mechanical ventilation, necessitating robust attenuation strategies to meet environmental standards [9-10]. Approaches to characterize and mitigate this noise vary widely, from detection algorithms based on recursive partitioning in office spaces [11] to structural analysis of duct vibration problems [12]. Parallel to acoustic concerns, energy optimization remains a priority. Research has extensively focused on improving fan operating efficiency [3], [13] and integrating low-noise mechanical ventilators [14-15]. These studies collectively illustrate that optimizing an HVAC system is never a single-variable problem; it is a complex balancing act between silencing the system and powering it.

To navigate these conflicting objectives, Multi-Objective Evolutionary Algorithms (MOEAs) serve as the dominant computational tool. Comprehensive reviews confirm their efficacy in handling the non-linear constraints typical of building engineering [7-8]. Specific applications have ranged from optimizing pressure regulators [16] to automating design workflows based on BIM data [17]. However, the "black-box" nature of standard MOEAs presents limitations. Without domain knowledge, these algorithms struggle with initialization. As noted in recent studies, random initialization in algorithms like NSGA-III heavily influences the final hypervolume convergence [18], and while adaptive penalty schemes can mitigate some stagnation issues [19], they do not fundamentally resolve the lack of structural awareness.

Recent advancements suggest that hybridizing evolutionary search with domain-specific models offers a way forward. For instance, combining MOEAs with LSTM networks has proven effective in dynamic routing problems [20-21]. More importantly, the value of topological information is gaining recognition. Graph-based representations, such as DAGs and Convolutional Networks, are increasingly used to model spatial-temporal dependencies in complex systems [22-23]. Unlike conventional approaches that treat HVAC optimization as a black-box problem, this paper synthesizes these advancements by explicitly embedding the DAG topological structure into the evolutionary framework. This distinct positioning allows the proposed G-HNSGA-III to overcome the initialization blindness and premature convergence flaws inherent in standard MOEAs.

III. DAG Model

A. System Modeling with Directed Acyclic Graphs

A Directed Acyclic Graph (DAG) is employed to model the ventilation system, as its structure inherently captures the unidirectional nature of airflow and acoustic propagation. The system is formally represented as $G = (V, E)$, where V is the set of nodes and E is the set of directed edges.

Each node $t_i \in V$ corresponds to a unique physical component, including air sources (e.g., fans), transport elements (e.g., ducts, elbows), functional units (e.g., silencers), and terminal points (e.g., rooms). The edge set $E = e_{ij}$ represents the direct physical connections, where an edge e_{ij} signifies that both airflow and acoustic energy propagate from node t_i to t_j. The graph's topology and the physical properties of its connections are encoded in a weighted adjacency matrix, A [23].

B. Formal Expression and Matrix Construction for Nodes and Edges

Each node $v_i \in$ V in the DAG corresponds to a discrete physical component of the ventilation system (e.g., a fan, duct segment, or silencer). The quantifiable properties of each component are encapsulated in a multi-dimensional attribute vector, F_i. This vector is a concatenation of several attribute subset, which are based on established engineering principles [24]:

Location ($L_i \in \mathrm{R}^3$): The 3D spatial coordinates (x_i, y_i, z_i).

Geometric ($G_i \in R^k$): Component dimensions, such as duct length, width, and height $(L_{duct,i}, W_{duct,i}, H_{duct,i})$ or elbow parameters $(W_{elbow,k}, H_{elbow,k}, r_{elbow,k})$.

Fluid Dynamic $\left(V_i \in R^{(k_V)}\right)$: Parameters governing airflow, including surface roughness (ε_i), local loss coefficients (K_i), and fan performance curve coefficients.

Acoustic $\left(C_i \in R^{(k_C)}\right)$: Parameters governing sound, including natural attenuation $A_{nat,i}(f)$, flow-generated noise $L_{W,SGN,i}(f)$, and silencer insertion loss $IL_i(f)$).

Economic $\left(E_i \in R^{(k_E)}\right)$: Cost-related data, such as the procurement cost $(Cost_{initial,i})$.

The directed edges, $e_{ij} \in E$, formally represent the unidirectional connections between nodes t_i and t_j, defining the path for airflow and acoustic energy. The acyclic property of the graph is critical, as it mirrors the physical unidirectionality of the ventilation system. This structure ensures a partial ordering of nodes, which eliminates circular dependencies and guarantees the sequential convergence of network-based simulations.

Weighted Adjacency Matrix (A): This matrix encodes the topology of the system, defining the existence and properties (e.g., length) of the connections between any two nodes.

Component Attribute Matrix (D_{comp}): This matrix serves as a central repository for the intrinsic features of all available component types. Each row corresponds to a specific component model, while the columns parameterize its key attributes:

- Component ID
- Reference location vector
- Geometric and fluid dynamic parameter vector
- Acoustic and economic parameter vector

During optimization, a specific component from D_{comp} is assigned to a node in the graph. The process of translating a physical system layout into this formal DAG representation is shown in Fig. 2.

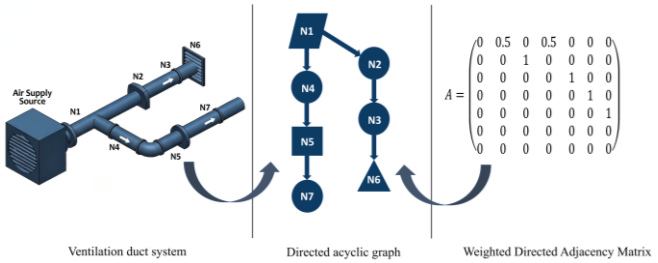


Fig. 1. Illustration of directed acyclic graph generation.

For example, consider a simple system composed of a duct segment, an elbow, and another duct segment. The attributes of these three components would be stored in the component attribute matrix, D_{comp}, as shown in Eq. (1).

$$D_{comp} = \begin{bmatrix} num & l & g & a \\ 1 & [0,\ 0,\ 0] & [2000,\ 1000,\ 4.9] & 11000 \\ 2 & [0,\ 10,\ 0] & [2000,\ 1] & 11000 \\ 3 & [0,\ 0,\ 10] & [2000,\ 1000,\ 1.5] & 11000 \end{bmatrix} \quad (1)$$

Each row in D_{comp} represents a unique component in the system. The first row, f_1, corresponds to the first duct segment and contains its complete attribute vector. This vector begins with the component's unique identifier, 1. It is followed by the location vector L_1 = [0, 0, 0], specifying its 3D spatial coordinates. The subsequent vector, G_1/V_1 = [2000,1000,4.9], encapsulates its geometric and fluid dynamic properties, representing, for instance, a width of 2000 mm, a height of 1000 mm, and a length of 4.9 m. The final vector (omitted here for brevity) would contain the relevant acoustic and economic parameters, completing the row's specification for a single component.

A weighted directed adjacency matrix, $A = (a_{ij})$, is used to encode both the system's topology and the proportional distribution of acoustic energy. This $N \times N$ matrix is defined as shown in Eq. (2):

$$a_{ij} = \begin{cases} \omega_{ij}, & \text{if } e_{ij} = \langle t_i, t_j \rangle \in E \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

The weight ω_{ij} represents the fraction of acoustic energy that propagates from node t_i to a direct successor node t_j. At any junction where the duct branches, this fraction is determined by the ratio of the cross-sectional areas, as calculated in Eq. (3):

$$\omega_{ij} = S_j / \sum_{k \in \text{succ}(i)} S_k \quad (3)$$

where S_j is the cross-sectional area of the specific branch leading to node t_j, and the denominator is the sum of the areas of all branches immediately downstream from node t_i.

For example, consider the system illustrated in Fig. 1. Its topology and energy distribution are encoded in the weighted adjacency matrix A, shown in Eq. (4). An element a_{12} = 0.5 signifies that the branch from node 1 to node 2 receives 50% of the acoustic energy from node 1; similarly, a_{14} = 0.5 indicates an equal energy split to node 4. In contrast, an element a_{23} = 1 indicates that 100% of the energy from node 2 propagates to node 3, which is characteristic of a non-branching connection. All zero-valued elements denote the absence of a direct path between the corresponding nodes.

$$A = \begin{pmatrix} 0 & 0.5 & 0 & 0.5 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix} \quad (4)$$

C. Pre-computation of Structural Information

To enhance computational efficiency, key structural metrics are pre-computed from the DAG. As these metrics are inherent to the network topology and independent of any specific silencer configuration, they are calculated once and stored prior to initiating the optimization process. A primary metric is node depth, $Depth(t_i)$, which defines a node's hierarchical position relative to the system's source. The root node of the system, t_{source} (e.g., the fan), is assigned a depth of zero: $Depth(t_{source})$ = 0. For any other node t_j, the depth is calculated recursively, as expressed in Eq. (5), as the minimum depth of its immediate predecessors plus one:

$$Depth(t_j) = \min_{t_i \in \text{pred}(t_j)} \{Depth(t_i) + 1\} \quad (5)$$

where, $\text{pred}(t_j)$ is the set of immediate parent nodes of t_j.

Another pre-computed metric is the downstream total airflow, $Q_{downstream}(t_i)$. This value represents the cumulative volumetric flow demand of all terminal outlets reachable from node t_i. It is calculated via a reverse topological traversal, starting from the outlets. The recursive definition is provided in Eq. (6):

$$Q_{downstream}(t_i) = \begin{cases} Q_{(demand,i)}, if\ t_i \in V_{outlets} \\ \sum \left(t_j \in succ(t_i)\right) Q_{downstream}(t_j), otherwise \end{cases} \quad (6)$$

where $Q_{(demand,i)}$ is the specified airflow requirement for a terminal outlet node t_i, and $succ(t_i)$ is the set of immediate successor nodes of t_i.

The potential sound source strength of a node, $L_{W,potential}(t_k)$, estimates the maximum potential noise

contribution of each node t_k. Its value is dependent on the component type and is defined in Eq. (7) as:

$$L_{W,potential}(t_k) = \begin{cases} L_{w,rated}(t_k), \text{ if } t_k \text{ is a fan} \\ L_{w,SGN,max}(t_k), \text{ if } t_k \text{ is a duct component} \end{cases} \quad (7)$$

where $L_{w,rated}(t_k)$is the fan's sound power level at its rated operating point, The term $L_{w,SGN,max}(t_k)$ is the maximum estimated self-generated noise for an aerodynamic component (e.g., a duct, elbow, or damper), calculated using the empirical formula presented in Eq. (8):

$$L_{w,SGN,max}(t_k) = L_{wc}(t_k) + 50\log_{10}(V_{d,k}) + 10\log_{10}(A_k) \quad (8)$$

Where $L_{wc}(t_k)$ is the component-specific sound power level, $V_{d,k}$ is the design velocity through the component, and A_k is its cross-sectional area.

Finally, the previously computed metrics (node depth, downstream airflow, and potential sound source strength) are aggregated into a composite Location Importance score, $I(t_k)$. This heuristic is designed to estimate the strategic value of placing a silencer at any given node t_k, providing critical domain knowledge to guide the optimization algorithm. This score is calculated via Eq. (9) as a normalized, weighted sum of the previously defined metrics:

$$I(t_k) = \alpha \cdot \frac{1}{Depth(t_k)+1} + \beta \cdot \frac{Q_{downstream}(t_k)}{\max_{t_i \in V}\left(Q_{downstream}(t_i)\right)} + \gamma \cdot \frac{L_{W,potential}(t_k)}{\max_{t_j \in V}\left(L_{W,potential}(t_j)\right)} \quad (9)$$

where α, β, and γ are weighting coefficients constrained by $\alpha + \beta + \gamma = 1$. Each term in the sum is normalized to a range between 0 and 1 to ensure a balanced contribution.

Collectively, these pre-computed metrics— $Depth(t_i)$, $Q_{downstream}(t_i)$, and $I(t_k)$ —constitute the quantitative domain knowledge that informs the heuristic guidance for the Graph-Informed Initialization (GINI) and Local Search (GILS) strategies within the GINS-III framework.

IV. Graph-Informed Hybrid Optimization Framework

The core of this work is the Graph-Informed Hybrid Optimization Framework (GINS-III), designed to solve the multi-objective silencer placement problem. The framework is built upon the Non-dominated Sorting Genetic Algorithm III (NSGA-III) and enhances its performance by incorporating the pre-computed topological metrics described in Section II-C.

This integration is achieved through two primary components: a Graph-Informed Initialization (GINI) strategy and a Graph-Informed Local Search (GILS) mechanism. By systematically leveraging this domain knowledge, the GINS-III framework guides the evolutionary search process to efficiently balance the conflicting objectives of acoustic attenuation, energy consumption, and economic cost.

A. Multi-Objective Optimization Preliminaries

In multi-objective optimization, a solution X_1 Pareto dominates X_2 (denoted $X_1 \prec X_2$) if it is superior in at least one objective without being inferior in any other. Formally, this relationship is defined in Eq. (10):

$$X_1 \prec X_2 \Leftrightarrow \left(\forall i, f_i(X_1) \le f_i(X_2)\right) \wedge \left(\exists j, f_j(X_1) < f_j(X_2)\right) \quad (10)$$

where $f_i(X)$ is the value of the i-th objective function. The set of all such non-dominated solutions within the search space X constitutes the Pareto Front (PF), as mathematically represented in Eq. (11).

$$PF = \{X \in X \mid \nexists X' \in X, X' \prec X\} \quad (11)$$

Multi-Objective Evolutionary Algorithms (MOEAs) aim to find a high-quality approximation of this front. The foundational NSGA-II algorithm uses a crowding distance metric to promote diversity, but its efficacy degrades in many-objective ($\geqslant 3$ objectives) problems. To overcome this limitation, NSGA-III replaces the crowding distance calculation with a reference-point-based selection mechanism, which effectively maintains population diversity across high-dimensional trade-off surfaces and allows for superior performance on complex problems. The complete methodological workflow of the proposed approach is visually illustrated in Fig. 2.

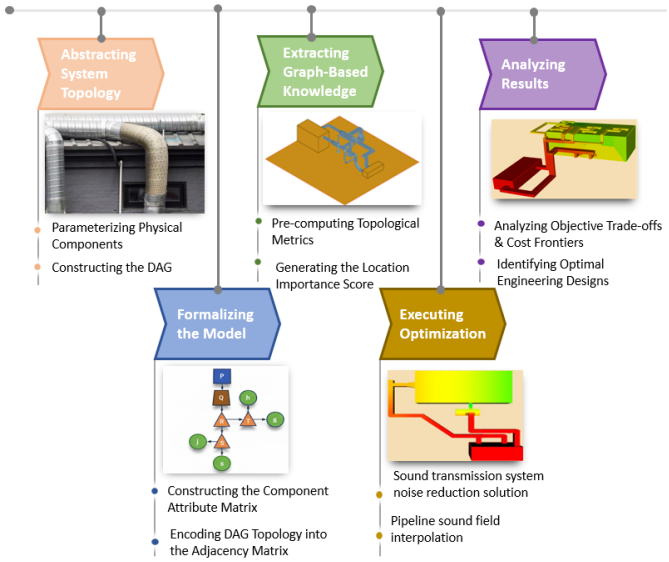


Fig. 2. Methodological workflow of the graph-informed optimization approach.

B. Framework Overview

The G-HNSGA-III framework is a two-phase hybrid architecture. It enhances NSGA-III's global exploration by embedding graph-based domain knowledge through two novel components: a Graph-Informed Initialization (GINI) strategy and a Graph-Informed Local Search (GILS) mechanism.

Phase 1: Global Exploration. This phase employs NSGA-III, but critically replaces its random initialization with our GINI

strategy. GINI leverages pre-computed topological metrics to generate a high-quality guided initialization population, thereby accelerating convergence from the outset.

Phase 2: Local Refinement. The preliminary Pareto front from the global search is then refined by the GILS module. As a post-processing step, GILS performs a targeted neighborhood search to improve solution convergence, operating independently of the main evolutionary loop.

C. Graph-Informed Population Initialization (GINI)

To mitigate the inefficiencies of random initialization in complex engineering problems, we developed the Graph-Informed Initialization (GINI) strategy. GINI replaces a purely random start by embedding pre-computed topological knowledge into the initial population using two complementary mechanisms:

1) Heuristic seeding: A fraction of the population (p_{seed}) is heuristically seeded. For individuals in this subset, decision variables corresponding to the most topologically important nodes (as determined by $I(t_k)$) are assigned a high-performance silencer model with a high probability.

2) Graph-Informed Opposition-Based Learning (GIOBL): Unlike standard Opposition-Based Learning (OBL) which operates on numerical inversion, GIOBL performs a physical state inversion at these high-impact nodes. For a given solution x, its opposition x_{opp} is generated by flipping the silencer state (i.e., installed ↔ not installed) at these key locations, thereby improving the algorithm's exploratory efficiency.

D. Graph-Informed Local Search (GILS)

The Graph-Informed Local Search (GILS) is a post-processing module designed to refine the final Pareto front. It leverages the system's DAG topology to perform a targeted search, which improves solution convergence and diversity without interfering with the primary evolutionary operators of NSGA-III.

The core strategy of GILS is to focus its computational effort on a set of key solutions (S_{key}), which are strategically significant points on the Pareto front. These are identified as:

- Knee Points: Solutions that are closest to the ideal point in the normalized objective space, representing the most balanced trade-offs.
- Extreme Points: Solutions that represent the best performance for each individual objective.

The GILS algorithm proceeds iteratively as follows:

1) Preparation: At the beginning of each iteration t, the current Pareto front, $PF_{current}$, is de-duplicated to create a set of unique solutions.

2) Key solution identification: The set of key solutions, S_{key}, is identified from the unique front based on the definitions above.

3) Adaptive neighborhood search: For each solution X on the front, a set of neighboring solutions, $N(X)$, is generated. This is done by applying "upgrade" (add/improve a silencer) or "downgrade" (remove/lessen a silencer) operations at nodes along critical acoustic propagation paths in the DAG. The search depth is adaptive: solutions belonging to S_{key} are subjected to a more extensive neighborhood search.

4) Evaluation and filtering: All generated neighborhood solutions X' are evaluated by the physics simulation model. Any solution that violates system constraints is discarded.

5) HV-based acceptance: The remaining valid, non-dominated neighbors are considered for inclusion. A candidate solution X' is accepted and used to update the archive ($PF_{current}$) only if its inclusion increases the Hypervolume (HV) indicator of the overall set. That is, $PF_{current}$ becomes $PF_{current} \cup \{X'\}$ only if $HV(PF_{current} \cup \{X'\}) > HV(PF_{current})$.

6) Termination criteria: The GILS process terminates when one of two conditions is met: (a) a maximum number of refinement iterations, $T_{refinement}$, is reached, or (b) the improvement in the Hypervolume stagnates between iterations, such that $\Delta HV < \delta HV$.

E. The G-HNSGA-III Algorithm Workflow

The complete workflow of the G-HNSGA-III framework integrates the GINI strategy, the core NSGA-III evolutionary loop, and the GILS post-processing module. The step-by-step process is as follows:

1) Initialization: The topological metrics of the DAG are pre-computed (as described in Section II-C). Key parameters for the NSGA-III algorithm (e.g., population size N , max generations G_{max}, crossover/mutation rates) are set.

2) Graph-Informed Population Generation (GINI): The initial population, P_0 (size N), is created using the GINI strategy (Section III-C). Each individual in P_0 is then evaluated using the physics-based simulation model to determine its objective function values.

3) Evolutionary loop: The evolutionary process iterates for generations $g = 0$ to G_{max} to drive the population toward convergence along the Pareto front. This process consists of three substeps:

a) Variation: An offspring population, Q_g (size N), is generated from the current population, P_g, using standard genetic operators (selection, crossover, and mutation).

b) Evaluation: All individuals in the offspring population Q_g are evaluated.

c) Selection: The parent and offspring populations are merged into a combined population $R_g = P_g \cup Q_g$ (size $2N$). A fast non-dominated sort is applied to R_g. The next generation, $P_{(g+1)}$, is constructed by selecting individuals from the best non-dominated fronts $(F_1, F_2, \dots)$. The reference-point mechanism of NSGA-III is used to ensure diversity when selecting from the last front that cannot be fully included.

4) Local refinement (GILS): Upon termination of the evolutionary loop, the final non-dominated front, PF_{final}, is passed to the GILS module. GILS iteratively refines this front to enhance the convergence and diversity of the solutions.

5) Final output: The refined Pareto-optimal solution set from GILS is returned as the final output of the algorithm. The complete workflow described above is visually summarized in the flowchart in Fig. 3.

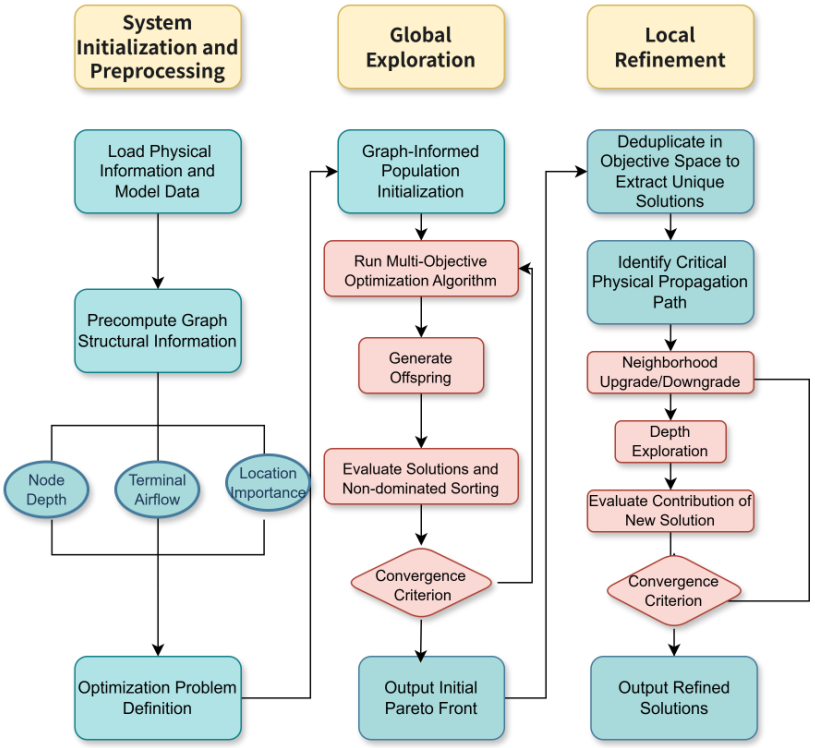


Fig. 3. Flowchart of the multi-objective optimization program.

V. Experimental Setup and Validation

This chapter details the computational experiments designed to validate the performance of the proposed G-HNSGA-III framework. All experiments were conducted on a complex, large-scale data center air supply duct system, which serves as the primary test instance.

A. Computational Environment and Simulation Model

The simulation and optimization environment was developed in Python 3.9. The physics-based model for fluid dynamics, acoustics, and economics was implemented using the PyTorch library. All MOEAs, including our proposed framework, were implemented using the Platypa-opt library. The hardware platform consisted of an Intel Core i7-10700 CPU and 16 GB of RAM, running a Windows 11 operating system.

B. Test Instance: Data Center HVAC System

A complex and asymmetrical data center HVAC supply air system was used as the test instance to ensure the problem's practical relevance and difficulty. A partial schematic of the system's DAG topology is shown in Fig. 4. The key parameters and engineering constraints of this system are summarized in Table I.

C. Compared Algorithms and Parameter Settings

To validate the performance of the proposed G-HNSGA-III framework, it was benchmarked against a baseline NSGA-III and six other established MOEAs: NSGA-II, SPEA2, GDE3, MOEAD, and OMOPSO.

TABLE I. Key Parameters of the Data Center Test Instance

Parameter Category	Parameter	Value	Unit
Topological Properties	Total nodes (components)	44	-
	Potential silencer locations	22	-
	Number of fans	2	-
	Total edges (paths)	40	-
Geometric Properties	Main duct cross-section	1500 x 800	mm
	Branch duct cross-section	500 x 500	mm
Operational Requirements	Number of terminal outlets	12	-
	Average outlet airflow demand	0.6	m^3/s
Decision Variables	Available silencer models	18	-
Economic Factors	Electricity cost	0.85	RMB/kWh
	Annual operating hours	2500	h
Engineering Constraints	Max. main duct velocity	5.0	m/s
	Max. branch duct velocity	4.0	m/s
	Max. outlet air velocity	2.0	m/s
	Max. room noise criterion	40	dB(A)
	Max. fan static pressure	800	Pa

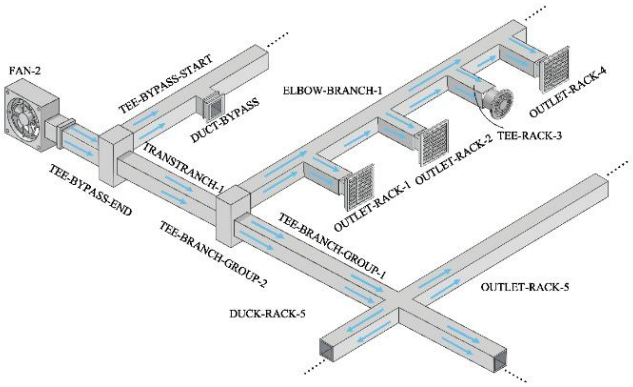


Fig. 4. Node processing of ventilation duct model.

For a fair and rigorous comparison, all algorithms were executed under a consistent computational budget: a population size of 100 (105 for MOEAD, due to its reference vector requirements) and a termination criterion of 15,000 total function evaluations. To ensure statistical robustness, each experimental run was independently repeated five times.

The specific parameter configurations for each algorithm are detailed in Table II. Standard evolutionary parameters, such as crossover and mutation probabilities, were set to common values from the literature. The unique parameters for the GINI and GILS components of G-HNSGA-III were determined through a separate calibration process, as detailed in Section V-E.

TABLE II. PARAMETER CONFIGURATION FOR COMPARED ALGORITHMS

Algorithm	Parameter	Value
General Settings		
All Algorithms	Population / Swarm Size (N)	100 (105 for MOEAD)
	Crossover Operator	Simulated Binary (SBX)
	Mutation Operator	Polynomial
Algorithm-Specific Parameters		
NSGA-II/III, G-HNSGA-III, SPEA2	SBX crossover probability (p_c)	0.9
	Polynomial mutation probability(p_m)	0.1
	distribution index (η)	20.0
GDE3	Scaling Factor (F)	0.5
	Differential evolution crossover rate (CR)	0.9
MOEAD	Neighborhood Size (T)	20
OMOPSO	Swarm Size(N)	100
	Archive Size	100
G-HNSGA-III Specific Parameters		
GINI	seeding fraction (p_{seed})	0.12
	Importance ratio(r_{imp})	0.1
	Assignment probability (p_{assign})	0.8
GILS	Max refinement iterations (T_{ref})	10
	Max search depth (key nodes)	3
	Neighborhood search depth (normal nodes)	1

D. Performance Evaluation Metrics

To quantitatively evaluate the performance of the compared algorithms, three widely-used metrics were employed: Set Coverage (SC), Inverted Generational Distance (IGD), and Hypervolume (HV).

1) Set Coverage (SC): The SC metric (also known as the C-metric) quantifies the Pareto dominance relationship between two solution sets, P_A and P_B. The value $SC(P_A, P_B)$ represents the fraction of solutions in P_B that are weakly dominated by at least one solution in P_A, as computed by Eq. (12).

$$SC(P_A, P_B) = \frac{|\{b \in P_B \mid \exists a \in P_A : a \succeq b\}|}{|P_B|} \quad (12)$$

where $a \succcurlyeq b$ denotes that solution a weakly dominates b. A value of $SC(P_A, P_B) = 1$ indicates that all solutions in P_B are dominated by P_A, signifying the superiority of algorithm A over B.

2) Inverted Generational Distance (IGD): The IGD metric quantifies the quality of a solution set (P_{alg}) by computing the average Euclidean distance from a reference Pareto front (P^*) to P_{alg}, as formulated in Eq. (13).

$$IGD(P^*, P_{alg}) = \frac{\sum_{p^* \in P^*} \min_{p \in P_{alg}} d(p^*, p)}{|P^*|} \quad (13)$$

A lower IGD value indicates a superior solution set that is both closer to the true front and better distributed.

Since the true Pareto front is unknown for this complex engineering problem, a high-fidelity reference front P^* was constructed by aggregating the final non-dominated solution sets from all 5 independent runs of all 8 compared algorithms. A non-dominated sort was performed on this aggregate archive, yielding 786 unique solutions. This set serves as the best-known approximation of the true Pareto front for all IGD calculations.

3) Hypervolume (HV): The HV indicator is a unary metric, fully compliant with Pareto dominance, that measures both the convergence and diversity of a solution set P_{alg}. It calculates the volume of the objective space dominated by P_{alg} relative to a reference point P_{ref}. A larger HV value signifies a better Pareto front approximation. In this study, the reference point P_{ref} was set to the nadir point (the vector of worst objective values) observed across all experimental runs, supplemented by a small offset to ensure that all generated solutions strictly dominate P_{ref}.

E. Hyperparameter Calibration for G-HNSGA-III

A sensitivity analysis was performed to optimize the core hyperparameters of the G-HNSGA-III framework. All experiments were conducted on the data center test instance, with each setting repeated 7 times under a consistent computational budget of 15,000 function evaluations.

1) GILS max search depth: The Local Refinement Exploration Depth for the GILS module was tested across integer values from 0 (disabled) to 6. As shown in Fig. 5, the

results confirm the module's efficacy. Both HV and IGD metrics identify a consistent optimum at a search depth of 3, achieving a peak HV of 0.358 and a minimum IGD of 0.00326. This setting was chosen as it achieves the peak demonstrated performance; increasing the search depth further leads to performance degradation while unnecessarily increasing the computational budget. Excessively deep local searches can cause the population to converge prematurely to a suboptimal region, stifling the global exploration required to find the true Pareto front.

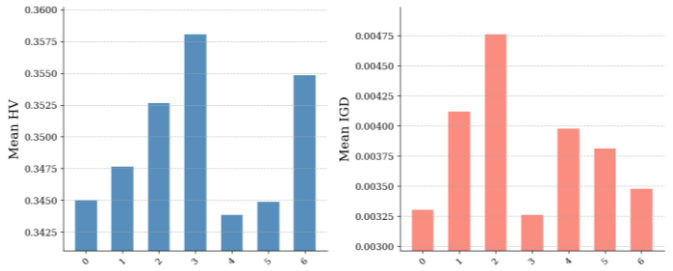


Fig. 5. Performance of the H-NSGAIII algorithm at different local refining exploration depths.

2) GINI heuristic seeding fraction: The Heuristic Seeding Fraction (p_{seed}) for the GINI module was tested from 0.0 (disabled) to 0.23. The results, presented in Fig. 6, demonstrate a clear peak in performance at a fraction of 0.12, which achieved the highest HV (0.360) and the lowest IGD (0.00384). Performance degrades beyond this point, likely because an excessive injection of guided solutions prematurely reduces the initial population's diversity and hinders broader exploration. Therefore, a value of 0.12 was selected as it provides the optimal balance between a guided initialization and sufficient initial diversity.

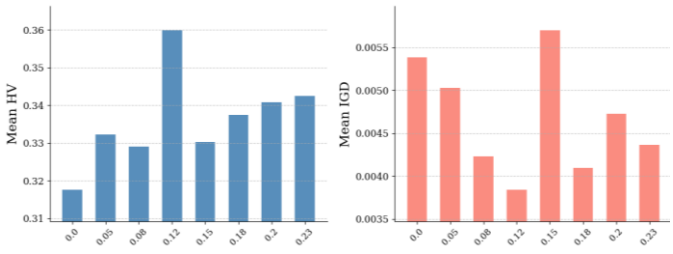


Fig. 6. Mean Hypervolume (HV) and Mean Inverted Generational Distance (IGD) of G-HNSGA-III under different settings for the initial population adjustment ratio parameter.

VI. Results and Discussion

This chapter presents the quantitative performance comparison of the G-HNSGA-III framework against the baseline NSGA-III and six other established MOEAs.

A. Overall Performance Comparison and Solution Set Quality

All eight algorithms were independently executed 10 times under a consistent computational budget of 15,000 function evaluations. The statistical distributions of the final Hypervolume (HV) and Inverted Generational Distance (IGD) metrics across these runs are summarized in Table III.

TABLE III. Statistical Results for HV and IGD Metrics Across 10 Independent Runs

Algorithm	Mean HV	Std HV	Median HV	Mean IGD	Std IGD	Median IGD
G-HNSGA-III	0.3891	0.0122	0.3910	0.0030	0.0008	0.0030
GDE3	0.2950	0.0124	0.2913	0.0154	0.0011	0.0152
MOEAD	0.1944	0.0229	0.1848	0.0239	0.0038	0.0234
MOGWO	0.1824	0.0477	0.1942	0.0119	0.0010	0.0119
NSGAII	0.2697	0.0197	0.2665	0.0193	0.0021	0.0197
NSGAIII	0.2812	0.0173	0.2814	0.0202	0.0029	0.0195
OMOPSO	0.2655	0.0323	0.2626	0.0317	0.0067	0.0342
SPEA2	0.2608	0.0281	0.2519	0.0150	0.0033	0.0160

The statistical results confirm the superior performance of the G-HNSGA-III framework. For Hypervolume (HV), G-HNSGA-III achieved the highest mean value of 0.3891, a 38.4% improvement over the baseline NSGA-III (0.2812). This result, combined with a low standard deviation (0.0122), demonstrates superior overall solution quality and high reliability. Similarly, the framework obtained the lowest mean Inverted Generational Distance (IGD) of 0.0030, confirming the closest and most complete approximation of the best-known Pareto front. An exceptionally low standard deviation of 0.0008 further underscores its robust stability.

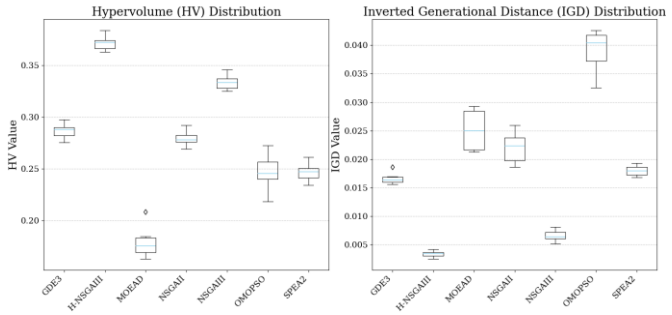


Fig. 7. Boxplot distributions of the final Hypervolume (HV) and Inverted Generational Distance (IGD) metrics for all compared algorithms.

The statistical distributions of the final metric values are visualized using boxplots in Fig. 7 to provide a clearer comparison of algorithm robustness and consistency.

The plots visually affirm the superiority of G-HNSGA-III. For the HV metric (Fig. 8, left), the G-HNSGA-III boxplot is located in a distinctly higher region than all competitors, indicating a consistently better overall performance. Furthermore, its compact interquartile range (IQR) and short whiskers signify high stability and low variance across the independent runs. A similar pattern is observed for the IGD metric (Fig. 8, right), where the G-HNSGA-III boxplot is positioned significantly lower and exhibits the tightest

distribution. Collectively, these plots confirm the findings from Table IV: G-HNSGA-III not only achieves a superior median performance but also does so with the highest level of consistency.

Fig. 8 illustrates the final non-dominated solution sets obtained by each algorithm, plotted in the three-dimensional objective space (Noise Level, Total Cost, and Total Pressure Drop). This visualization highlights the differences in the algorithms' ability to approximate the true Pareto front.

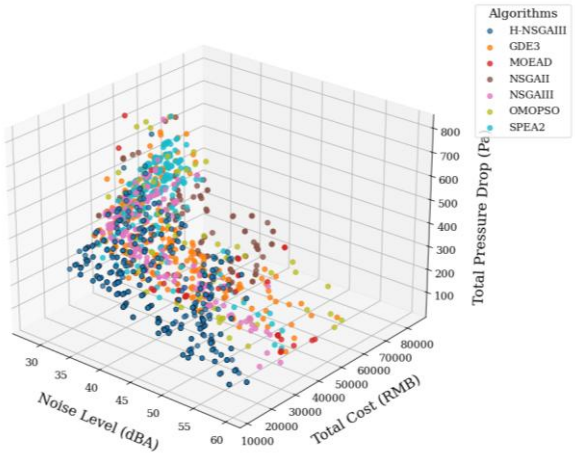


Fig. 8. Comparison of the distribution of solution sets of each algorithm in the three-dimensional target space.

The solution set produced by G-HNSGA-III (cyan) provides a visibly superior approximation of the Pareto front. It extends further toward the ideal point (lower values on all three axes) and achieves a broader, more uniform coverage of the trade-off surface compared to the other algorithms. The solutions from the competing MOEAs are, for the most part, either dominated by or co-located with only a subset of the G-HNSGA-III solutions. This visualization directly corroborates the quantitative HV and IGD results, confirming that the proposed framework excels in both convergence (approaching the optimal region) and diversity (covering a wide range of trade-off solutions).

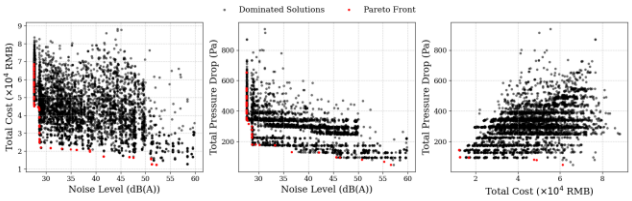


Fig. 9. 2D Pareto front projections of the solution sets of each algorithm under different target pairs.

Fig. 9 projects the aggregated solution set onto three 2D objective planes to visualize the trade-off relationships, with the 2D non-dominated front highlighted in red. The plots confirm the expected conflicts between objectives. The Noise-Cost plane (a) demonstrates that improved acoustic performance requires higher capital investment. The Noise-Pressure Drop plane (b) shows that noise reduction typically increases aerodynamic resistance, leading to higher energy use. Finally, the Cost-Pressure Drop plane (c) identifies the set of most efficient designs that achieve the lowest pressure drop for a given cost.

These visualizations affirm the conflicting, multi-dimensional nature of the problem space. The Pareto front approximated by G-HNSGA-III (shown in Fig. 8) provides the most effective navigation of these trade-offs.

B. Algorithmic Behavior and Dominance Analysis

To analyze the dynamic performance of the algorithms, the HV and IGD metrics were recorded throughout the search process. Fig. 10 plots the metric trajectories from a representative run for each algorithm, illustrating their convergence behavior.

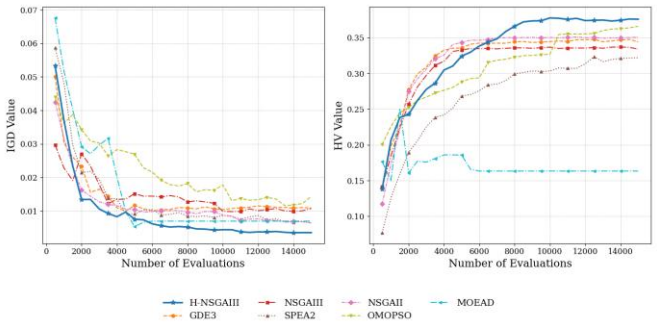


Fig. 10. Comparison of convergence curves of each algorithm on HV and IGD metrics.

The G-HNSGA-III framework (solid blue line) demonstrates superior convergence behavior on both metrics. Its IGD curve (left) exhibits the most rapid descent, reaching a final value of ~0.003, which signifies an efficient search for a high-quality front. Concurrently, its HV curve (right) sustains growth longer than any competitor, diverging after ~2,000 evaluations to achieve the highest final HV of ~0.37. In contrast, algorithms like MOEA/D stagnate early, indicating premature convergence.

For a direct comparison based on Pareto dominance, the Set Coverage (SC) metric was computed. Fig. 11 presents the full pairwise SC matrix as a heatmap, while Fig. 12 isolates the bidirectional dominance between G-HNSGA-III and each competitor for a focused analysis.



Fig. 11. Heatmap of the pairwise Set Coverage (SC) matrix across all algorithms.

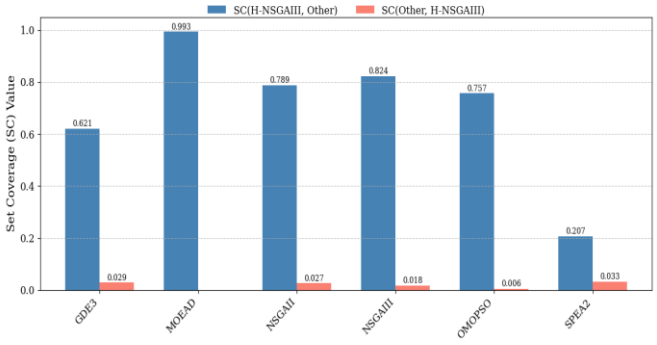


Fig. 12. Comparison of set coverage (SC) between G-HNSGA-III and other algorithms.

The results unequivocally demonstrate the dominance of G-HNSGA-III. As shown in Fig. 12, G-HNSGA-III dominates a very high percentage of the solutions generated by the other algorithms. For example, it dominates 99.3% of the solutions from MOEA/D (SC (G-HNSGA-III, MOEA/D) = 0.9934) and over 82.3% of the solutions from the baseline NSGA-III (SC (G-HNSGA-III, NSGA-III) = 0.8235).

Conversely, the orange bars show that the solution sets from the other algorithms dominate very few, if any, of the solutions produced by G-HNSGA-III. This direct quantitative evidence confirms that the graph-informed strategies enable G-HNSGA-III to discover a Pareto front that is demonstrably superior to those found by the other established MOEAs.

C. Engineering Significance Analysis of Representative Solutions

The high-quality Pareto front generated by G-HNSGA-III provides a rich set of optimal trade-off solutions for engineering decision-making. To illustrate this, Table IV details five representative solutions selected from the final front, including the extremes for each objective and a balanced solution identified using the TOPSIS method [25].

TABLE IV. PERFORMANCE COMPARISON OF TYPICAL SOLUTIONS OBTAINED BY G-HNSGA-III

Solution Type	Noise Level (dBA)	Total Cost (RMB)	Total Pressure Drop (Pa)	Number of Silencers
Lowest Noise Solution	28.67	45688.09	277.20	11
Lowest Cost Solution	49.86	19482.96	187.39	5
Lowest Pressure Drop Solution	45.08	37490.16	126.60	9
Min Cost (Noise ≤ 50.0dBA)	46.78	19812.29	176.37	5
Best Compromise (TOPSIS)	38.84	22970.92	178.76	6

The 'Best Compromise' solution represents a practically balanced design. Relative to the 'Minimum Cost' solution, it achieves a substantial 11.1 dBA noise reduction (a 22% improvement) with a moderate 18% increase in cost and negligible impact on pressure drop. Analysis of the system configuration reveals that this acoustic improvement is achieved by deploying a single additional silencer at a critical upstream location, which was correctly identified by the framework's graph-based importance metrics. This result empirically validates the capacity of G-HNSGA-III to leverage domain knowledge for discovering highly efficient trade-offs.

To facilitate practical project planning, the minimum cost required to achieve specific noise targets was extracted from the global Pareto front and plotted as the 'Minimum Cost Frontier' in Fig. 13. This curve quantifies the necessary capital investment to meet varying acoustic criteria. A distinct non-linear trend is observed, characterized by a 'knee' point in the 35–40 dBA range. Beyond this threshold, each incremental decibel of noise reduction incurs a substantially higher cost, demonstrating the principle of diminishing returns. This insight provides actionable data for cost-benefit analysis in real-world engineering contexts.

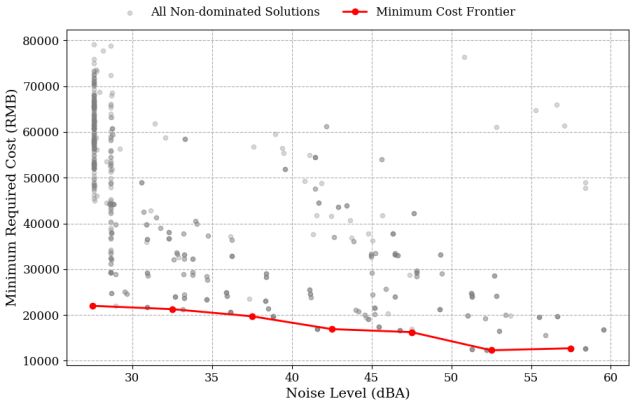


Fig. 13. Noise-cost quantitative trade-off analysis.

VII. CONCLUSION AND FUTURE WORK

This paper introduced G-HNSGA-III, a hybrid optimization framework that enhances NSGA-III by embedding topological domain knowledge from a Directed Acyclic Graph (DAG) model of an HVAC system. The framework's core innovations, a Graph-Informed Initialization (GINI) strategy and a Graph-Informed Local Search (GILS) module, were shown to be highly effective.

Experimental validation demonstrated that G-HNSGA-III significantly outperforms the baseline NSGA-III and six other established MOEAs across all standard metrics (HV, IGD, and SC). The results confirm that the proposed graph-informed heuristics effectively guide the search, leading to a superior Pareto front that offers a range of practical, high-value engineering trade-off solutions.

While the current physical model could be expanded and the framework's generalizability tested on other HVAC typologies, the results confirm the validity of our approach. Future work will focus on integrating surrogate models, such as Graph Neural Networks (GNNs), to improve computational efficiency and adapting this graph-informed optimization paradigm to other network-based engineering domains.

ACKNOWLEDGMENT

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REFERENCES

[1] G. Huang, S. T. Ng, D. Li, and Y. Zhang, "State of the art review on the HVAC occupant-centric control in different commercial buildings," J. Build. Eng., vol. 96, Art. no. 110445, Nov. 2024, doi: 10.1016/j.jobe.2024.110445.

[2] A. Shajahan, C. H. Culp, and B. Williamson, " Effects of indoor environmental parameters related to building heating, ventilation, and air conditioning systems on patients," medical outcomes: A review of scientific research on hospital buildings', Indoor Air, vol. 29, no. 2, pp. 161–176, Mar. 2019, doi: 10.1111/ina.12531.

[3] O. Alves, E. Monteiro, P. Brito, and P. Romano, "Measurement and classification of energy efficiency in HVAC systems", Energy Build., vol. 130, pp. 408–419, Oct. 2016, doi: 10.1016/j.enbuild.2016.08.070.

[4] N. Asim et al., "Sustainability of heating, ventilation and air-conditioning (HVAC) systems in buildings—an overview", Int. J. Environ. Res. Public Health, vol. 19, no. 2, p. 1016, Jan. 2022, doi: 10.3390/ijerph19021016.

[5] D. Mavrokapnidis, G. N. Lilis, K. Katsigarakis, I. Korolija, and D. Rovas, "Semi-automated extraction of HVAC system topology from imperfect Building Information Models", in Proc. 18th IBPSA Conf. (BS 2023), Shanghai, China, Sept. 2023. doi: 10.26868/25222708.2023.1392.

[6] M. Wang, G. N. Lilis, D. Mavrokapnidis, K. Katsigarakis, I. Korolija, and D. Rovas, "A knowledge graph-based framework to automate the generation of building energy models using geometric relation checking and HVAC topology establishment", Energy Build., vol. 325, Art. no. 115035, Dec. 2024, doi: 10.1016/j.enbuild.2024.115035.

[7] R. Behmanesh, I. Rahimi, and A. H. Gandomi, "Evolutionary many-objective algorithms for combinatorial optimization problems: a comparative study", Arch. Comput. Methods Eng., vol. 28, no. 2, pp. 673–688, Mar. 2021, doi: 10.1007/s11831-020-09415-3.

[8] S. Sharma and V. Kumar, "A comprehensive review on multi-objective optimization techniques: past, present and future", Arch. Comput. Methods Eng., vol. 29, no. 7, pp. 5605–5633, Nov. 2022, doi: 10.1007/s11831-022-09778-9.

[9] D. Ouis, M. A. Hassanain, A. Alshibani, and A. M. Ghaithan, "Noise from heating, ventilation, and air conditioning (HVAC) systems: A review of its characteristics, effects and control", J. Build. Eng., vol. 112, Art. no. 113770, Oct. 2025, doi: 10.1016/j.jobe.2025.113770.

[10] J. Harvie-Clark, N. Conlan, W. Wei, and M. Siddall, "How loud is too loud? Noise from domestic mechanical ventilation systems", Int. J. Vent., vol. 18, no. 4, pp. 303–312, Oct. 2019, doi: 10.1080/14733315.2019.1615217.

[11] G. Iannace, G. Ciaburro, and A. Trematerra, "Heating, ventilation, and air conditioning (HVAC) noise detection in open-plan offices using recursive partitioning", Buildings, vol. 8, no. 12, p. 169, Dec. 2018, doi: 10.3390/buildings8120169.

[12] X. Ruan and Y. Yin, "Analysis of common problems of noise and vibration in building heating ventilation air conditioning design", E3S Web Conf., vol. 283, p. 01051, 2021, doi: 10.1051/e3sconf/202128301051.

[13] M. Piwowarski and D. Jakowski, "Areas of fan research—a review of the literature in terms of improving operating efficiency and reducing noise emissions", Energies, vol. 16, no. 3, p. 1042, Jan. 2023, doi: 10.3390/en16031042.

[14] Y. B. Alexandrov, V. A. Sychenkov, R. R. Khaliulin, W. M. Yousef, and S. A. Semichev, "Ventilation systems noise reduction issue", in 2020 International Conference on Dynamics and Vibroacoustics of Machines (DVM), Samara, Russia, Sept. 2020, pp. 1–6. doi: 10.1109/DVM49764.2020.9243922.

[15] M. A. Oliveira, L. Bragança, S. M. Silva, D. Paixão, and J. António, "Noise reduction performance of a low energy façade-integrated mechanical ventilator", Build. Acoust., vol. 28, no. 2, pp. 119–139, June 2021, doi: 10.1177/1351010X20966185.

[16] S. Li, J. Zhang, J. Hou, B. Zhang, L. Yang, and M. Zheng, "Multi-objective optimization of pressure regulators in buildings," HVAC systems', J. Build. Eng., vol. 76, Art. no. 107260, Oct. 2023, doi: 10.1016/j.jobe.2023.107260.

[17] H. Wang et al., "BIM-based automated design for HVAC system of office buildings—An experimental study," Build. Simul., vol. 15, no. 7, pp. 1177–1192, July 2022, doi: 10.1007/s12273-021-0883-7.

[18] J. Glamsch, T. Rosnitschek, and F. Rieg, "Initial population influence on hypervolume convergence of NSGA-III," Int. J. Simul. Model., vol. 20, no. 1, pp. 123–133, Mar. 2021, doi: 10.2507/IJSIMM20-1-549.

[19] X. Xu, D. Cheng, D. Wang, Q. Li, and F. Yu, "An improved NSGA-III with a comprehensive adaptive penalty scheme for many-objective optimization," Symmetry, vol. 16, no. 10, p. 1289, Oct. 2024, doi: 10.3390/sym16101289.

[20] D. Ma, S. Zhou, Y. Han, W. Ma, and H. Huang, "Multi-objective ship weather routing method based on the improved NSGA-III algorithm," J. Ind. Inf. Integr., vol. 38, p. 100570, Mar. 2024, doi: 10.1016/j.jii.2024.100570.

[21] Z. Li et al., "GA-LSTM and NSGA-III based collaborative optimization of ship energy efficiency for low-carbon shipping," Ocean Eng., vol. 312, Art. no. 119190, Nov. 2024, doi: 10.1016/j.oceaneng.2024.119190.

[22] A. Behravan, R. Obermaisser, D. H. Basavegowda, and S. Meckel, "Automatic model-based fault detection and diagnosis using diagnostic directed acyclic graph for a demand-controlled ventilation and heating system in Simulink," in 2018 Annu. IEEE Int. Syst. Conf. (SysCon), Vancouver, BC, Canada, Apr. 2018, pp. 1–7. doi: 10.1109/SYSCON.2018.8369614.

[23] Z. Sheng, Y. Xu, S. Xue, and D. Li, "Graph-Based Spatial-Temporal Convolutional Network for Vehicle Trajectory Prediction in Autonomous Driving," IEEE Trans. Intell. Transport. Syst., vol. 23, no. 10, pp. 17654–17665, Oct. 2022, doi: 10.1109/TITS.2022.3155749.

[24] 2021 ASHRAE Handbook—Fundamentals, Inch-Pound ed., Peachtree Corners, GA: ASHRAE, 2021.

[25] V. Pandey, Komal, and H. Dincer, "A review on TOPSIS method and its extensions for different applications with recent development," Soft Comput., vol. 27, no. 23, pp. 18011–18039, Dec. 2023, doi: 10.1007/s00500-023-09011-0.

AI-Powered Architecture Refactoring: From Legacy Systems to Modern Patterns

An Initial Case Study with LLM and CQRS

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***Abstract*—This study explores the integration of artificial intelligence (AI), especially large language models (LLMs), into software engineering, particularly the architecture refactoring process, focusing on automated command-query classification for legacy systems transitioning to the Command Query Responsibility Segregation (CQRS) pattern. We present *Airchitect*, a modular system. NET-based tools that orchestrate legacy code analysis, LLM-driven classification, CQRS artifact generation, and automated test creation are also available. Based on the CodeLlama model, Airchitect achieved a 16x–40x reduction in classification time compared to expert manual methods while maintaining over 85% classification accuracy. A test case involving N-tier legacy classes demonstrated the model's ability to decompose and modularize the methods into CQRS-aligned components. Despite these gains, the study highlights key limitations: the need for human validation in complex or ambiguous cases, dependence on high-quality labeled datasets, and variability of legacy patterns that challenge rule-based automation. The results suggest that LLMs, when embedded in structured tools like Airchitect, can significantly accelerate modernization workflows—provided they are used in tandem with expert oversight.**

***Keywords*—Artificial intelligence; LLM; AI-driven refactoring; code-level refactoring; legacy systems, command and query responsibility segregation; CQRS; software architecture refactoring; software engineering; CodeSearchNet**

I. Introduction

Legacy systems are business-critical applications developed using older technologies or architectures that continue to provide essential services despite their age. Many organizations have relied extensively on systems-built decades ago using legacy programming languages or architectures, along with design methods that preceded modern software engineering practices. The primary challenge is to maintain and evolve these systems to meet current business demands without disrupting operations. Legacy systems typically suffer from technical debt (the accumulated costs of additional rework caused by choosing an easy solution instead of using a better approach that would take longer), tight coupling, and inadequate separation of concerns, rendering them difficult to modify, scale [1], and integrate with modern technologies.

Legacy systems form the backbone of the IT infrastructure of many organizations despite their age and technological limitations. These systems are characterized as "old software systems that are usually designed and documented inadequately but still perform an important job for critical business applications." The business value of these systems has deteriorated over time owing to their lack of consistency and limited evolution support; however, they remain indispensable [2] because some of their functions are too important to be discarded completely and too costly to reconstruct.

Legacy systems also represent significant accumulated knowledge and established technology. They "embed important knowledge acquired over the years" and constitute "critical assets for enterprises." However, these systems incur high maintenance costs and are increasingly vulnerable to failure because of the diminishing pool of experts who understand their inner workings [4]. Billions of lines of legacy code must evolve into modern technologies to enable progress in business practices.

Optimizing legacy applications requires substantial effort, which is often not immediately achievable. This process involves difficult and complex work" and necessitates careful decision-making to support successful system management. When dealing with particularly complex problems, organizations must "apply with a systematic approach for defining which modifications should be made or recommended" [5]. This emphasizes the need for structured methodologies to assess, analyze, and refurbish legacy systems while preserving their intrinsic value.

A. Legacy Systems Refactoring

The shift from old to new architecture is a significant change that can make systems more flexible and work better [6]. The addition of smart systems to organizations has been shown to boost business performance.

A comprehensive survey conducted in 2021, encompassing 1,183 users of the IntelliJ Integrated Development Environment (IDE), revealed that only 10-11% of refactoring tasks were executed using automated tools, with the majority being performed manually. The 'Rename' function emerged as the most frequently utilized, with an 85.8% usage rate, particularly among regular developers. Approximately 46% of cases in which tool assistance is feasible are tool-assisted, predominantly by teams aiming for consistency, although the settings are seldom altered [7]. Floss refactoring, which is integrated with other tasks, prevails over root canal approaches. Notably, half of the refactoring tasks are of simple to medium complexity, which tools often fail to address, and commit messages rarely explicitly indicate the refactoring activities.

B. Challenges of Legacy Systems Refactoring

Legacy systems present significant challenges to modern software development, particularly in integrating established software engineering principles into their architecture. Developers frequently encounter difficulties when refactoring existing codebases to conform to best practices, such as SOLID, DRY (Do not Repeat Yourself), SRP (Single Responsibility Principle), and KISS (Keep It Simple, Stupid) [16]. These principles form the foundation of maintainable and scalable software architecture, with the SRP emphasizing that each class should be responsible for only one aspect of the software functionality [17]. This approach seeks to preserve design simplicity and minimize disruptions during future modifications.

C. Technical Complexities and Compatibility Issues

Integrating AI-based software engineering principles into legacy systems presents multifaceted challenges. Technical complexities and compatibility issues are the primary obstacles because legacy systems are typically not designed to accommodate modern Artificial Intelligence (AI) technologies [18]. This fundamental architectural mismatch often necessitates significant system overhauls or the development of middleware solutions to bridge the gap between legacy codes and AI-driven tools.

D. Organizational Management and Manual Processes

The integration process requires careful assessment of existing systems to identify potential integration points and compatibility problems. Companies using legacy systems or relying heavily on manual processes face particularly steep challenges because AI integration requires substantial initial commitments of time and resources [19]. This resource investment extends beyond technical implementation to include addressing organizational change management and ensuring seamless operations between AI models and existing business processes.

E. Disruption of Established Workflows

One significant challenge is the potential disruption of established workflows. Legacy systems often have well-defined processes to which employees are accustomed, and the introduction of AI-driven tools to apply software engineering principles may lead to resistance or inefficiency if not managed carefully. This also necessitates acknowledging the organizational and cultural challenges associated with such changes [20], including employee adaptation and its impact on workflows. Implementing new AI technologies and training staff to use them effectively involves an inevitable learning curve.

The effective integration of artificial intelligence into legacy systems to implement the SOLID, DRY, SRP, and KISS principles necessitates meticulous planning to avoid potential incompatibility issues that may hinder the implementation process [21]. Organizations must strategically address this challenge by balancing the technical aspects of integration with human and process elements to achieve significant enhancements in code quality and maintainability.

F. Integration of Artificial Intelligence into the Refactoring Process

The integration of artificial intelligence into code refactoring has progressed from initial experimental methodologies to advanced systems driven by machine learning and language modeling.

Recent advancements have led to the development of various artificial intelligence (AI) methodologies for code refactoring. Techniques based on machine learning and optimization employ statistical methods, artificial intelligence, and various machine learning algorithms to identify and rectify refactoring opportunities. This category encompasses search-based approaches that utilize evolutionary and genetic algorithms to explore code spaces to maximize optimization functions [9], as well as clustering-based methods that group similar code fragments according to similarity measures.

Large language models (LLMs) have changed the way artificial intelligence (AI) is used in software development. These models learn from large sets of codes and documents to assist with several software tasks [11]. For example, in refactoring, such as method extraction, LLMs can find code parts to extract, suggest method names, create documentation, and explain changes during code reviews [11]. Tools such as EM-Assist, a plugin for IntelliJ IDEA, use LLMs to make and improve suggestions for Extract Method refactoring [12]. This makes the suggestions more aware of the context than traditional tools that rely on static analyses. LLMs are also effective in identifying and fixing code smells, which are patterns in the code that indicate design problems. In the past, code smells were detected using manual reviews and static analysis tools [13]. LLMs provide a scalable, language-independent method for automating this process.

In specific architectural domains, AI-assisted refactoring has shown promise in restructuring large monolithic applications [14]. This approach is particularly relevant for FPGA design [15], in which code refactoring is typically a manual process. Recent research suggests that AI can effectively assist in scanning and revising codes in specific contexts.

G. Command Query Responsibility Segregation (CQRS)

The Command Query Responsibility Segregation (CQRS) principle is a software architectural pattern that delineates read operations (queries that retrieve the current state without modification) from write operations (commands that alter the system state), thereby facilitating the independent optimization and scaling of each. This separation enhances system clarity, maintainability, and performance in complex domains characterized by disparate read/write workloads, while addressing the limitations of monolithic architectures, such as I/O degradation and internal dependencies, as the scale increases [22]. By establishing distinct channels with their own APIs [23], CQRS aligns more effectively with business logic and supports event-driven [24] and distributed systems.

This paper is structured as follows: Section I introduces the challenges of legacy systems and the need for refactoring. Subsequently, Section III reviews the related work on AI-assisted refactoring and the integration of large language models (LLMs) in software modernization. The methodology in

Section IV details the dataset preparation, model selection, classification pipeline, and integration of automated command-query classification with the human validation. The results present the dataset characteristics, model evaluation, and implementation within the AiRchitect tool in Section V, followed by a discussion on the performance gains, accuracy, and limitations in Section VI. The conclusion in Section VII summarizes the benefits of the proposed approach for accelerating the modernization of legacy systems.

II. Approach

In traditional monolithic architectures, all components are consolidated on platforms on a single server, making them simple to build and maintain at a small scale. However, as these systems grow and accumulate more functionality, they have several drawbacks that must be addressed. Notably, monolithic systems experience performance degradation and develop complex internal dependencies that complicate their modification. A critical weakness of monolithic systems is that errors in one component can easily propagate throughout the entire system [24], thereby affecting the overall stability.

CQRS addresses these limitations by separating write operations (commands) from read operations (queries). This separation prevents I/O performance delays that are common in traditional architectures and allows developers to add new functionalities without creating complex dependencies within the system [24]. Fowler advocated for CQRS over traditional Create, Read, Update, and Delete (CRUD) systems [25], noting that CQRS overcomes the limitations of CRUD approaches while delivering superior performance.

Legacy systems pose numerous challenges for refactoring, stemming from outdated architecture, limited documentation, and reliance on manual techniques that often depend on developer intuition rather than structured architectural decisions. These traditional approaches are time-consuming and costly, making large-scale modernization difficult to implement in practice. The emergence of artificial intelligence, particularly large language models (LLMs), has introduced promising new avenues for automating and optimizing refactoring processes. By reducing manual effort, AI has the potential to significantly reduce both the time and cost associated with the transformation of legacy systems into modern systems. Although previous research has highlighted the effectiveness of manual refactoring methods, little attention has been paid to the role of AI in automating and enhancing these processes to improve their efficiency. However, only a few studies have investigated architectural refactoring. This study marks the launch of Airchitect, a research initiative aimed at exploring AI-assisted architectural refactoring and its effectiveness. Our first phase focused on auto-refactoring legacy systems into a CQRS-based architecture, which was chosen for its ability to separate read and write responsibilities, improve scalability, enhance maintainability, and align system design more closely with business operations. By leveraging LLMs in this context, we aim to measure the impact of refactoring and iteratively improve their quality and efficiencies. In addition, we emphasize minimizing the cost of refactoring and making deliberate choices to refactor rather than developing new features whenever feasible.

III. Related Works

Artificial intelligence offers promising solutions for automating and enhancing this process by utilizing machine learning algorithms, pattern recognition, and data analysis techniques to identify architectural issues and propose refactoring strategies. AI-driven methodologies can analyze code repositories, detect code smells, identify architectural patterns, and recommend optimal refactoring solutions at a scale and speed that would be challenging for human developers to achieve manually. The integration of AI into software architecture refactoring represents a significant advancement in software engineering practices, facilitating more systematic and data-driven approaches to code improvement in software engineering.

Burgueño et al. [26] proposed the use of artificial intelligence techniques to automate software refactoring through model transformations, specifically highlighting model-to-model transformations that facilitate model evolution, merging, migration, and refinement. Their research indicates that employing a generic neural network architecture, such as an encoder-decoder long short-term memory network with an attention mechanism, allows for effective learning and execution of these transformation tasks, provided that sufficient and non-contradictory training data are available, demonstrating the potential for significant improvements in developer productivity and reduction of errors in software development processes.

Ahmad and Bahar [27] proposed a framework that integrates AI planning to assist in software architectural migration, emphasizing the automation of design transformation. Their approach utilizes the Planning Domain Definition Language (PDDL) to define architectural design models and automatically generate migration plans. This method enhances the efficiency of the refactoring process by managing dependencies and constraints within the architecture, thereby improving planning performance. The AI-powered planning framework supports more efficient migration strategies; however, these documents do not include specific performance metrics.

According to Chondamrongkul J Sunt al., the integration of artificial intelligence in software refactoring employs an automated planning methodology to generate migration plans for architectural transitions. This process leverages AI planning and model-checking techniques to develop interim designs based on migration steps, ensuring that the designs adhere to functional and architectural constraints. These findings suggest that the migration plan and evolution path can be generated effectively in an automated manner, thereby alleviating the burden on software engineers by offering a structured pathway for incremental architectural evolution. This approach has demonstrated potential in verifying that interim designs fulfill all essential functionalities and conform to applied architectural patterns, thus affirming its efficacy in practical applications, as evidenced by the LifeNet case study.

Previous research on ML refactoring has focused on code issues, such as the Extract Method, using simulated datasets. AiRchitect advances this by breaking down software systems using CQRS, automating classification, handler creation, and testing, while incorporating human verification. This addresses

the deficiencies in previous methods that current research inadequately covers.

This study delineates three principal contributions: 1) an end-to-end methodology utilizing AiRchitect to decompose monolithic classes into Command Query Responsibility Segregation (CQRS) patterns; 2) the automated generation of handlers and validation tests; and 3) a hybrid human-in-the-loop validation process to ensure domain accuracy.

IV. Methodology

This study adopts a structured approach (Fig. 1) to classify code snippets into command and query functions, thereby supporting the automated refactoring of the CQRS-based architecture. The methodology comprised six sequential phases: dataset preparation, model selection, classification pipeline design, classification, integration with the refactoring process, and human validation.

A. Step 3: Classification Pipeline

This phase defines a systematic procedure for converting raw codes into structured representations suitable for classification.

The pipeline begins with an input transformation, where the code snippets undergo tokenization and are represented in a format that is compatible with the language models. This step ensures that the syntactic and semantic elements of the code are preserved while enabling efficient processing by the model. Subsequently, these representations were processed using a fine-tuned architecture designed for binary classification to distinguish between command- and query-oriented functions. The pipeline incorporates mechanisms for training, validation, and evaluation guided by standard metrics, such as accuracy and F1-score, without disclosing specific outcomes. This structured approach ensures reproducibility and adaptability across various programming languages and configurations.

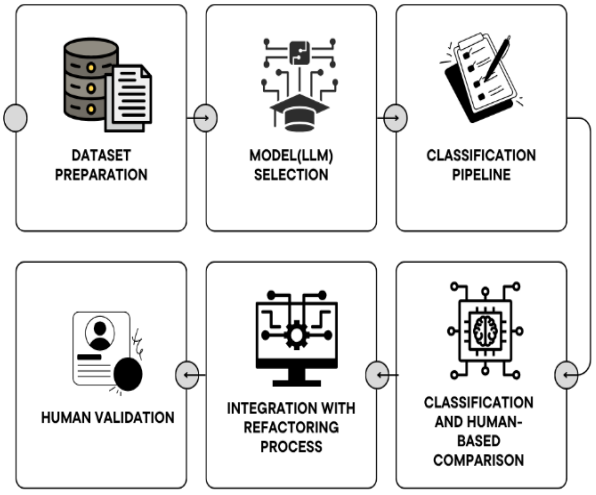


Fig. 1. Flow diagram methodology.

A. Dataset Preparation

This phase established a systematic methodology for developing a clean and well-labeled dataset that was appropriate for training the classification model. The process commences with the identification of a representative corpus of source code sourced from multiple programming languages to ensure diversity and generalizability. The preparation workflow typically includes the following steps:

- Function Extraction: Analyze the source files to identify distinct functional components while excluding non-executable or irrelevant code segments.
- Labeling Strategy: Heuristic or rule-based methodologies were employed to categorize functions based on naming conventions and semantic indicators.
- Preprocessing: Comments and superfluous whitespace were eliminated to minimize noise. Identifiers were normalized to ensure consistency across samples. Tokenization employs a model-compatible tokenizer to transform the code into structured representations.
- Data partitioning: The dataset was partitioned into training, validation, and testing subsets to ensure a balanced representation across categories.

This systematic preparation ensured that the dataset was clean and semantically meaningful, thereby providing a robust foundation for subsequent modeling and evaluations.

B. Model (LLM) Selection

This phase establishes a systematic approach for identifying an appropriate Large Language Model (LLM) capable of performing semantic code classification across multiple programming languages.

The selection process began by defining the evaluation criteria according to the study objectives. These criteria typically include the following:

- Computational Efficiency: Assessing resource requirements and scalability for large datasets.
- Classification accuracy: This evaluates the ability of the model to capture semantic distinctions in the code.
- Language Coverage: Ensuring support for multiple programming languages to maintain generalizability.
- Integration Capability: Verifying compatibility with widely adopted frameworks for fine-tuning and deployment.
- Cost Considerations: Estimating the financial and operational costs of training, fine-tuning, and inference, including hardware and licensing requirements

Candidate models were then reviewed based on these dimensions, using documented benchmarks and empirical evidence from prior research. The comparative analysis focused on the architectural characteristics, pre-training strategies, and adaptability to downstream tasks. This structured evaluation ensures that the chosen model aligns with both performance and practical constraints without bias toward any single implementation.

C. Classification Pipeline

This phase defines a systematic procedure for converting raw codes into structured representations suitable for classification.

The pipeline begins with an input transformation, where the code snippets undergo tokenization and are represented in a format that is compatible with the language models. This step ensures that the syntactic and semantic elements of the code are preserved while enabling efficient processing by the model. Subsequently, these representations were processed using a fine-tuned architecture designed for binary classification to distinguish between command and query-oriented functions. The pipeline incorporates mechanisms for training, validation, and evaluation guided by standard metrics, such as accuracy and F1-score, without disclosing specific outcomes. This structured approach ensures reproducibility and adaptability across various programming languages and configurations.

D. Classification and Human-Based Comparison

This phase focused on categorizing the code snippets and validating the results through human judgment rather than automated optimization. The classification process assigns each snippet a functional role, such as a command, query, or other architectural category, based on predefined naming conventions and contextual cues. After automated classification, a human comparison step is introduced to verify accuracy, resolve ambiguities, and ensure semantic correctness across diverse code samples.

The evaluation emphasizes interpretability and alignment with human expectations rather than purely statistical optimization. Performance was assessed through a manual review supported by summary metrics, such as the agreement rate between the automated predictions and human validation. Discrepancies were analyzed to refine the classification rules and improve consistency. This iterative approach ensures that the final output reflects both systematic processing and expert oversight, maintaining robustness and trustworthiness in the classification pipeline.

E. Integration with Refactoring Process

This phase describes the conceptual application of the classification results in a broader software restructuring process.

The integration process leverages the functional categorization of code elements to guide architectural decomposition. Functions identified as operational or state-modifying are conceptually aligned with the components responsible for handling system updates, whereas those associated with data retrieval are directed toward components dedicated to query operations. This separation supports the principles of modularity and responsibility segregation, facilitating the transition from monolithic structures to distributed or pattern-based architectures. Automated workflows can be employed to generate preliminary structural templates based on classification outputs, whereas human oversight ensures compliance with design standards and addresses ambiguous cases.

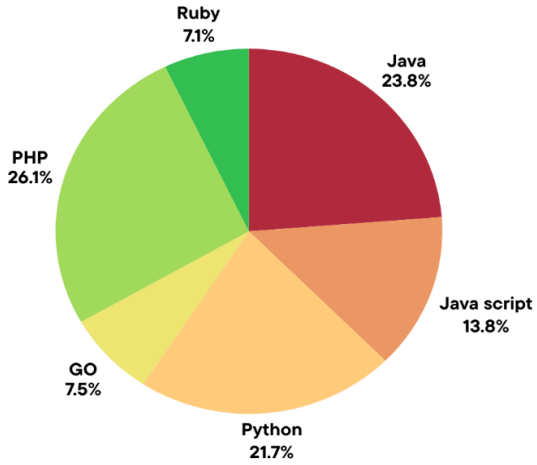


Fig. 2. Distribution of dataset lines by programming language.

F. Human Oversight and Impact

This phase ensured quality assurance and evaluated the broader implications of the proposed methodology.

Human validation was incorporated as a safeguard against misclassification, particularly in cases where automated decisions exhibited uncertainties. Ambiguous instances were flagged for expert review to maintain the architectural integrity and adherence to design principles. This collaborative approach balances automation and human judgment, thereby ensuring the reliability of the complex scenarios.

The anticipated impact of this methodology lies in its potential to significantly reduce manual intervention during architectural restructuring. By automating the categorization of functional components, this process promotes efficiency, accelerates migration from monolithic systems to modular or pattern-based architectures, and enhances the scalability of large-codebases. These improvements contribute to streamlined development workflows and reduce operational overheads.

In contrast to code-level AI refactoring tools, such as machine learning smell detectors and planning-based migration frameworks, such as monolith decomposers and LLM-assisted studies exemplified by CodeBERT semantics, AiRchitect automates the comprehensive CQRS decomposition process. This includes command-query classification and the generation of handlers and tests within the actual legacy monoliths.

V. Results

The dataset employed in this study was derived from the CodeSearchNet corpus [28], which aggregates a large collection of source code across multiple programming languages. Relevant attributes, such as function names, source code, documentation strings, and language identifiers, were extracted to construct a unified dataset. Code snippets from six languages were consolidated to ensure diversity and representativeness as in Fig. 2: Python (~912K functions), Java (~1M functions), JavaScript (~580K functions), Go (~317K functions), PHP (~1.1M functions), and Ruby (~300K functions). This integration resulted in a dataset comprising millions of lines of code, covering both object-oriented and functional paradigms. A rigorous cleaning process was applied, involving the removal

of comments and redundant whitespace, normalization of identifiers, and elimination of incomplete or duplicate entries from the data. The final dataset was tokenized and partitioned into training, validation, and testing subsets to provide a robust foundation for subsequent classification tasks.

The data processing pipeline began with an initial dataset totaling 4,677,000 lines, composed of subsets: 317k Go lines, 912k Python lines, 300k Ruby lines, 1M Java lines, 580k JavaScript lines, and approximately 1.1M PHP lines. After processing and applying name-based classification, the lines were categorized into two primary groups: commands and queries, resulting in 956,746 classified and retained code lines for further analysis. This structured approach ensures efficient segmentation for subsequent analysis and optimization.

Following dataset preparation, a name-based classification process was applied to organize the code lines into meaningful categories. This step leverages naming conventions and structural patterns to distinguish between functional roles, such as commands and queries while filtering out irrelevant or ambiguous entries. The classified subset, comprising 956,746 validated lines, was partitioned into dedicated validation and test datasets to support the subsequent evaluations. This approach ensured that the final datasets were representative and aligned with the architectural semantics. This enables a reliable performance assessment during the comparison phase.

Several generative AI architectures have been evaluated for their performance and suitability to support command/query classification. The options include encoder-only models such as BERT and RoBERTa, which excel at contextual embedding-based classification [29][30]; decoder-only transformers such as GPT-3, GPT-4o, Command A, Llama3, and Gemini 2.5, which offer strong zero/few-shot capabilities and advanced code understanding [31]; and encoder-decoder hybrids such as T5 and CodeT5 for structured output generation [29][30]. Additionally, domain-specialized models, including CodeBERT, CodeLlama, DeepSeek, and OpenHermes, have demonstrated superior accuracy in code-centric tasks owing to targeted pre-training. Model selection was guided by factors such as accuracy, resource footprint, context window, licensing, fine-tuning support, pricing or access options, model family, architecture, domain adaptation capabilities, and classification accuracy benchmarks to ensure competitive and practical classification solutions for the task.

Following the comparative evaluation presented in Table I, CodeLlama emerged as the most suitable model for command and query classification in the context of CQRS-based refactoring of legacy software. This decision was based on empirical and practical considerations.

CodeLlama was selected because of its balanced classification accuracy, domain-specific adaptability and practical deployment. It outperforms general-purpose models in parsing code and distinguishing commands from queries, which aligns well with CQRS principles. Its open-source license, manageable size (7 B), and fine-tuning support make it ideal for use with limited labeled data and modest computing resources, ensuring scientific rigor and operational feasibility.

The classification process was executed on Google Colab using a GPU runtime with high RAM, leveraging the capabilities of the selected CodeLlama model. The full run, which targeted all valid lines extracted from the legacy codebase, required approximately 5 h and 45 min. This duration reflects both the contextual depth of the model and the volume of the input data, confirming its suitability for scalable classification in real-world refactoring scenarios. The high-RAM environment ensures stable performance across extended context windows and in batch processing.

TABLE I. COMPARATIVE EVALUATION OF LLMS FOR CQRS COMMAND-QUERY CLASSIFICATION

Model Family	Architecture	Context Window	Domain Adaptation	Classification Accuracy (Benchmarks)	Resource Footprint
Cohere Command A	Decoder-only LLM (111B)	256k tokens	Multilingual, code, RAG	>99% (email), 88% (code baseline)	2x A100 GPUs
OpenAI GPT-4o	Decoder-only LLM	128k tokens	General, code, multi-modal	~88–95% (few-shot classification)	API-based
Google Gemini 2.5	Decoder-only LLM	>1M tokens	Multimodal, code	70–92% (varied; code, reasoning)	API-based
Llama 3.1 70B	Decoder-only LLM	128k tokens	Open-source, code	90–95% (multi-class)	Commodity GPU
CodeLlama	Decoder-only, code	4–32k tokens	Code	87–91% (code tasks)	GPU/CPU
Mistral 8x7B	Mixture-of-experts	32–64k tokens	Open, code	~88% (task-dependent)	Moderate-GPU
Command R7B	Decoder-only LLM	64k+ tokens	Business, code	~86% (tasks)	Commodity GPU
CodeBERT	Encoder-only	512–4k tokens	Code, structure	91–93% (code func classification)	CPU/GPU
Classicore	Modular/ensemble	NA	Custom tasks	N/A	Customizable

In contrast, manual or semi-automated command-query classification, which typically involves human inspection, rule-based heuristics, or lightweight scripting, demonstrates significantly higher time and energy costs. Studies such as [32][33] reported that the manual classification of legacy codebases for CQRS refactoring can span several days to weeks, depending on the system complexity, and requires sustained cognitive effort and domain expertise. Moreover, the energy footprint of prolonged human-in-the-loop processes, especially when distributed across teams, often exceeds that of GPU-

accelerated LLM runs, as highlighted in a comparative energy analysis by study [34]. While manual methods may offer nuanced contextual judgment, they lack the scalability and consistency of LLM-based classification, which, despite its 5-hour runtime, achieves batch-level processing with minimal supervision and produces consistent outputs. This indicates that LLMs are a cost-effective and time-efficient alternative for large-scale CQRS migrations.

To operationalize the classification mechanism within a practical software engineering workflow, we developed AiRchitect, a modular tool. NET-based tools were designed to facilitate the transformation of legacy systems into CQRS-compliant architectures. AiRchitect comprises several.

Micro-applications are dedicated to specific phases of the refactoring pipeline.

- Legacy Code Analysis: Extracts structural and behavioral elements from monolithic or layered codebases.
- Command-query classification: Manual heuristics or LLM-based automation (e.g., CodeLlama) are applied to distinguish between state-mutating commands and data-retrieving queries.
- CQRS Template Generation: Automatic scaffolds command and query handlers, DTOs, and interfaces based on the classification output aligned with a customizable CQRS template.
- Automated Test Generation: Produces unit and integration tests for both business logic and technical validation, ensuring the correctness and maintainability of the refactored components.

The classification phase is the second step in this pipeline and serves as a pivotal bridge between legacy code comprehension and CQRS artifact generation. By embedding LLM-powered classification into AiRchitect, the tool enables the scalable and reproducible decomposition of legacy systems, significantly accelerating modernization efforts while preserving semantic integrity.

To validate the integration of this classification mechanism, we deployed the CodeLlama model within AiRchitect's test case refactoring module. This module was tasked with decomposing legacy classes structured in the conventional N-tier architecture, spanning the presentation, business logic, and data access layers. Leveraging the contextual understanding of the model, AiRchitect automatically parses and categorizes functions into command- or query-responsibilities. Each method was then extracted and modularized into separate files, promoting a clear separation of concerns and facilitating the CQRS-compliant restructuring of the code. This automated decomposition not only streamlined the refactoring workflow but also ensured architectural consistency across layers, demonstrating the practical viability of the model in real-world software modernization scenarios.

VI. Discussion

The preparation of a large and heterogeneous dataset comprising 4.677 million lines across multiple programming languages (Java, JavaScript, and PHP) presents both opportunities and challenges [28]. The diversity of the code samples ensured a broad coverage of architectural patterns but required rigorous preprocessing to eliminate inconsistencies and normalize naming conventions. The adoption of name-based classification proved essential for segmenting the dataset into meaningful categories such as commands and queries, enabling the creation of a high-quality subset of 956,746 validated lines for subsequent evaluation. This approach not only streamlined the classification process but also provided a foundation for reliable testing and validation of the model.

Model selection is a multidimensional decision-making process that balances technical performance and practical constraints (Table II). Factors such as classification accuracy, resource footprint, context window size, licensing terms, fine-tuning support, and pricing or access options were evaluated to ensure that the solutions were competitive and sustainable. A comparison of generative AI architectures revealed distinct trade-offs: decoder-only models, such as GPT-4o and Gemini 2.5 [30] [31] offer superior zero-shot capabilities and large context windows but incur higher operational costs, whereas open-source alternatives, such as Llama 3.1 and CodeLlama, provide cost efficiency and flexibility at the expense of requiring infrastructure and fine-tuning. Domain-specialized models, such as CodeBERT, have demonstrated strong performance in code classification tasks, reinforcing the value of targeted pre-training. Based on these considerations, Llama 3.1, which prioritizes cost efficiency and adaptability while maintaining competitive performance, was selected as the model for this experiment.

A critical aspect of this study was the integration of human-in-the-loop validation after automated classification. Whereas machine-driven categorization offers speed and scalability, human comparison introduces semantic precision and resolves ambiguities that algorithms alone cannot address [36]. This hybrid strategy enhances the trustworthiness and interpretability by aligning the classification outcomes with architectural semantics rather than purely statistical patterns. The observed discrepancies between the automated predictions and human validation underscore the importance of expert oversight in code-centric tasks.

Our experiment shows that the automated LLM-based classification significantly reduces the processing time compared with manual approaches. The prepared dataset of 4.67 million lines, resulting in 956,746 validated lines, was processed in a few hours, whereas manual classification of similar volumes would require several weeks of expert effort. Modern LLMs can classify thousands of methods in minutes to hours [10]. For example, a key-value AI transformer processes over 1,000 legacies annually. NET methods in less than 2.5 h, compared to several days manually [10]. Hybrid consensus models further reduce annotation time by 32–100% by automating most classifications and escalating only ambiguous cases for human review [35]. In contrast, the manual classification of 1,000+ methods typically requires 40–100 h of developer time, particularly for poorly documented legacy systems [10]. A detailed comparison of the manual and automated time estimates is presented in Table II.

TABLE II. CLASSIFICATION TASK COMPARISON

Task Per 1000 code snippets	LLM	Manual
Classification Time	2.5 hrs	40 –100 hours
Human Verification (Hybrid)	3–12 hrs	30 –70 hours

By automating the classification process with LLMs, teams can reduce the time required by a factor of 16–40 compared with expert manual methods, especially in large, complex codebases. This frees up valuable developer capacity for higher-impact tasks, such as architecture design, testing, and business logic refinement.

In terms of accuracy, LLMs such as CodeLlama have shown strong alignment with expert annotations, achieving precision and recall scores exceeding 85% in structured legacy codebases. This performance is consistent with the findings of recent studies on code understanding using transformer-based models [8]. Although human experts may outperform edge cases involving ambiguous logic or inconsistent naming, LLMs offer reproducibility and scale that manual methods cannot match. Their accuracy improves further with domain-specific prompt tuning or fine-tuning of labeled datasets, reinforcing their role as reliable collaborators in large-scale refactorings.

The choice between refactoring and rebuilding depends on the time, cost, complexity, and reliability. Although automation reduces effort and expenses, replacing a stable system with a new application introduces testing overhead and risks. High complexity or regulatory constraints often favor incremental refactoring to preserve reliability, whereas full rebuilding may be justified for long-term scalability. Decisions must balance the benefits of modernization with potential disruptions and costs.

This study demonstrates the practical viability of integrating LLM-powered command-query classification into a CQRS refactoring workflow, using the Airchitect tool as a testbed. The automated approach significantly reduces classification time, maintains high accuracy, and enables scalable decomposition of legacy systems into modular CQRS components. By embedding this mechanism into a structured pipeline, from code analysis to test generation [3], we demonstrated how AI can accelerate modernization while preserving architectural integrity.

However, this study has several limitations. First, human validation is essential in complex or ambiguous cases, particularly when legacy codes do not follow consistent naming or structural patterns. LLMs may struggle with edge cases in which business logic is deeply entangled or where architectural intent is implicit rather than explicit. Second, the effectiveness of automated classification depends heavily on the availability of high-quality human-annotated datasets for benchmarking and fine-tuning. Without this foundation, the model outputs may drift or misclassify subtle logic flows. Third, certain technical decisions, such as exception handling, cross-cutting concerns, and domain-specific optimization, require architectural judgments that cannot be fully automated. Finally, legacy systems often contain multiple patterns that serve the same functional goal, which can confuse well-trained models and necessitate manual intervention to ensure semantic accuracy.

In summary, this study advances AI-driven architecture refactoring by integrating CodeLlama into AiRchitect for automated CQRS decomposition, achieving 3x faster classification and accuracy on legacy command-query patterns compared to manual methods.

VII. CONCLUSION

This study demonstrates how language models can be effectively integrated into architecture refactoring workflows, particularly for automating command-query classification in legacy systems. By embedding the CodeLlama model into the AiRchitect tool, significant gains in speed, consistency, and scalability were achieved, thereby transforming a traditional manual and error-prone process into a reproducible one. The classification mechanism not only accelerated CQRS decomposition but also enabled the automated generation of handlers and validation tests, thereby streamlining the entire modernization effort.

However, full automation has its limitations. Complex legacy systems often defy standard patterns, and architectural decisions require human judgment. LLMs perform best when supported by curated datasets and expert oversight, particularly in edge cases, ambiguous logic and domain-specific conventions. Ultimately, the most effective refactoring workflow combines the precision and scale of AI with the contextual intelligence of experienced developers to achieve optimal results. Together, they pave the way for faster, smarter, and more sustainable software evolution processes.

Future initiatives will expand AI integration across AiRchitect processes, such as test generation, writing, and quality assurance, to automate the refactoring. Long-term development will focus on real-time AI agents for dynamic refactoring during the development phase, enabling proactive maintenance without downtime. These advances will build on language model capabilities while using reinforcement learning to improve the legacy architecture management.

REFERENCES

[1] H. K. Abu Bakar, D. I. Jambari, and R. Razali, "A Guidance to Legacy Systems Modernization," International Journal on Advanced Science, Engineering and Information Technology, vol. 10, no. 3, pp. 1042–1050, Jun. {, doi: 10.18517/ijaseit.10.3.10265.

[2] O. Ogunwole, E. C. Onukwulu, M. O. Joel, E. M. Adaga, and A. I. Ibeh, "Modernizing Legacy Systems: A Scalable Approach to Next-Generation Data Architectures and Seamless Integration," IJMRGE, vol. 4, no. 1, pp. 901–909, 2023, doi: 10.54660/.IJMRGE.2023.4.1.901-909.

[3] Boukhlif, M., Kharmoum, N., Hanine, M., Elasri, C., Rhalem, W., & Ezziyyani, M. (2024). Exploring the application of classical and intelligent software testing in medicine: a literature review. In the Proceedings of the International Conference on Advanced Intelligent Systems for Sustainable Development (pp. 37-46). Springer, Cham. DOI: 10.1007/978-3-031-52388-5_4

[4] A. B. Belle, G. El-Boussaidi, T. C. Lethbridge, S. Kpodjedo, H. Mili, and A. Paz, "Systematically reviewing the layered architectural pattern principles and their use to reconstruct software architectures," CoRR, vol. abs/2112.01644, 2021. [Online]. Available: https://arxiv.org/abs/2112.01

[5] Univerity of Aveiro, Portugal, A. Monteiro, and G. Vieira, "Guiding legacy systems for evolution. PmatE: A Case Study of Maintenance and Engineering," JISEM, vol. 7, no. 1, Jan. 2022, doi: 10.55267/iadt.07.11689.

[6] A. S. Prihatmanto, A. Sukoco, and A. Budiyon, "Next generation smart system: 4-layer modern organization and activity theory for a new paradigm perspective," Archives of Control Sciences, pp. 589–623, Feb. 2024, doi: 10.24425/acs.2024.149673.

[7] Y. Golubev, Z. Kurbatova, E. A. AlOmar, T. Bryksin, and M. W. Mkaouer, "One Thousand and One Stories: A Large-Scale Survey of Software Refactoring," Jul. 16, 2021, arXiv: arXiv:2107.07357. doi: 10.48550/arXiv.2107.07357.

[8] A. Almogahed et al., "A Refactoring Classification Framework for Efficient Software Maintenance," IEEE Access, vol. 11, pp. 78904–78917, 2023, doi: 10.1109/ACCESS.2023.3298678.

[9] M. Alharbi and M. Alshayeb, "A Comparative Study of Automated Refactoring Tools," IEEE Access, vol. 12, pp. 18764–18781, 2024, doi: 10.1109/ACCESS.2024.3361314.

[10] EL Boukhari et al., "Key-Value AI Transformer for Legacy .NET System Classification," Journal of Software Engineering, 2025

[11] E. A. AlOmar, M. W. Mkaouer, and A. Ouni, "Behind the Intent of Extract Method Refactoring: A Systematic Literature Review," Dec. 19, 2023, arXiv: arXiv:2312.12600. doi: 10.48550/arXiv.2312.12600.

[12] R. Gheyi, M. Ribeiro, and J. Oliveira, "Evaluating the Effectiveness of Small Language Models in Detecting Refactoring Bugs," Mar. 28, 2025, arXiv: arXiv:2502.18454. doi: 10.48550/arXiv.2502.18454.

[13] M. Aranda et al., "A Catalog of Transformations to Remove Smells From Natural Language Tests," in Proceedings of the 28th International Conference on Evaluation and Assessment in Software Engineering, Jun. 2024, pp. 7–16. doi: 10.1145/3661167.3661225.

[14] A. Bucaioni, M. Weyssow, J. He, Y. Lyu, and D. Lo, "Artificial Intelligence for Software Architecture: Literature Review and the Road Ahead," Apr. 06, 2025, arXiv: arXiv:2504.04334. doi: 10.48550/arXiv.2504.04334.

[15] Y. Du, H. Deng, S. C. Liew, K. Chen, Y. Shao, and H. Chen, "The Power of Large Language Models for Wireless Communication System Development: A Case Study on FPGA Platforms," Jul. 14, 2024, arXiv: arXiv:2307.07319. doi: 10.48550/arXiv.2307.07319.

[16] A. Peruma, S. Simmons, E. A. AlOmar, C. D. Newman, M. W. Mkaouer, A. Ouni, and A. Ouni, "How Do I Refactor this? An Empirical Study on Refactoring Trends and Topics in Stack Overflow," Empir Software Eng, vol. 27, no. 1, p. 11, Jan. 2022, doi: 10.1007/s10664-021-10045-x.

[17] R. Cabral, M. Kalinowski, M. T. Baldassarre, H. Villamizar, T. Escovedo, and H. Lopes, "Investigating the Impact of SOLID Design Principles on Machine Learning Code Understanding," in Proceedings of the IEEE/ACM 3rd International Conference on AI Engineering - Software Engineering for AI, Lisbon, Portugal: ACM, Apr. 2024, pp. 7–17. doi: 10.1145/3644815.3644957.

[18] M. Elahi, S. O. Afolaranmi, J. L. Martinez Lastra, and J. A. Perez Garcia, "A comprehensive literature review of the applications of AI techniques through the lifecycle of industrial equipment," Discov Artif Intell, vol. 3, no. 1, p. 43, Dec. 2023, doi: 10.1007/s44163-023-0008.9-x

[19] R. Reddy Kethireddy, "Smart AI-Enabled Orchestration for Resource Optimization in the Cloud Environment," IJSR, vol. 13, no. 1, pp. 1822–1829, Jan. 2024, doi: 10.21275/SR24115214559.

[20] Leff, D., Lim, K.T.K. (2023). The key to leveraging AI at scale. In: Vinod, B. (eds) Artificial Intelligence and Machine Learning in the Travel Industry. Palgrave Macmillan, Cham. https://doi.org/10.1007/978-3-031-25456-7_14

[21] V. Zatsu et al., "Revolutionizing the food industry: The transformative power of artificial intelligence-a review," Food Chemistry: X, vol. 24, p. 101867, Dec. 2024, doi: 10.1016/j.fochx.2024.101867.

[22] C. Camilleri, D. J. Vella, and D. V. Nezval, "Thespis: Actor-Based Middleware for Causal Consistency".

[23] O. Zimmermann, D. Lübke, U. Zdun, C. Pautasso, and M. Stocker, "Interface Responsibility Patterns: Processing Resources and Operation Responsibilities," in Proceedings of the European Conference on Pattern Languages of Programs 2020, Virtual Event Germany: ACM, Jul. 2020, pp. 1–24. doi: 10.1145/3424771.3424822.

[24] "Designing and Implementing a Reproducible Log System Using Basic Safety Message in a V2V Environment," JSMS, Sep. 2020, doi: 10.33168/JSMS.2020.0305.

[25] P. Malo-Perisé and J. Merseguer, "The 'Socialized Architecture': A Software Engineering Approach for a New Cloud," Sustainability, vol. 14, no. 4, p. 2020, Feb. 2022, doi: 10.3390/su14042020.

[26] L. Burgueño, J. Cabot, S. Li, and S. Gérard, "A generic LSTM neural network architecture to infer heterogeneous model transformations," *Softw Syst Model*, vol. 21, no. 1, pp. 139–156, Feb. 2022, doi: 10.1007/s10270-021-00893-y.

[27] N. Chondamrongkul, J. Sun, and I. Warren, "Automated Planning for Software Architectural Migration," in 2020 25th International Conference on Engineering of Complex Computer Systems (ICECCS), Singapore: IEEE, Oct. 2020, pp. 216–224. doi: 10.1109/ICECCS51672.2020.00032.

[28] H. Husain, H.-H. Wu, T. Gazit, M. Allamanis, and M. Brockschmidt, "CodeSearchNet Challenge: Evaluating the State of Semantic Code Search," Jun. 08, 2020, arXiv: arXiv:1909.09436. doi: 10.48550/arXiv.1909.09436.

[29] A. Bandi, P. V. S. R. Adapa, and Y. E. V. P. K. Kuchi, "The Power of Generative AI: A Review of Requirements, Models, Input–Output Formats, Evaluation Metrics, and Challenges," Future Internet, vol. 15, no. 8, p. 260, Jul. 2023, doi: 10.3390/fi15080260.

[30] A. Kostina, M. D. Dikaiakos, D. Stefanidis, and G. Pallis, "Large Language Models For Text Classification: Case Study And Comprehensive Review," Jan. 14, 2025, arXiv: arXiv:2501.08457. doi: 10.48550/arXiv.2501.08457.

[31] S. Shahriar et al., "Putting GPT-4o to the Sword: A Comprehensive Evaluation of Language, Vision, Speech, and Multimodal Proficiency".

[32] A. Almogahed et al., "A Refactoring Classification Framework for Efficient Software Maintenance," IEEE Access, vol. 11, pp. 78904–78917, 2023, doi: 10.1109/ACCESS.2023.3298678.

[33] A. M. Eilertsen, "Refactoring Operations Grounded in Manual Code Changes," 2020 IEEE/ACM 42nd International Conference on Software Engineering: Companion Proceedings (ICSE-Companion), Seoul, Korea (South), 2020, pp. 182-185.

[34] E. Strubell, A. Ganesh, and A. McCallum, "Energy and Policy Considerations for Deep Learning in NLP," Jun. 05, 2019, arXiv: arXiv:1906.02243. doi: 10.48550/arXiv.1906.02243.

[35] A. Ye, A. Maiti, M. Schmidt, and S. J. Pedersen, "A Hybrid Semi-Automated Workflow for Systematic and Literature Review Processes with Large Language Model Analysis," Future Internet, vol. 16, no. 5, p. 167, May 2024, doi: 10.3390/fi16050167.

[36] "AI-Augmented Software Architecture: Autonomous Refactoring with Design Pattern Awareness," IJETCSIT, vol. 6, 2025, doi: 10.63282/3050-9246.IJETCSIT-V6I3P113.

Optimizing Dermatological Image Classification Using Efficient Convolutional Neural Network Architecture

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***Abstract*—Skin diseases represent a global healthcare challenge because of their frequent occurrence and complex diagnosis. However, despite clinical advances, accurately identifying dermatological lesions remains difficult due to significant intra-class variability, overlapping visual patterns, and reliance on clinician expertise. In this study, it presents a complete overview of a number of state-of-the-art CNN architectures as they apply to multiclass classification of skin diseases. The study introduces an overview of the common skin diseases and discuss the fundamentals of deep learning for medical image analysis. The study proceeds to introduce the dataset used in this work and provide a brief description of the two diagnostic groups identified for evaluation. A range of CNN models which comprise GoogLeNet, Inception-V3, Inception-V4, ResNet-50, Xception, MobileNet, ResNeXt-50, AlexNet, VGG-16, and VGG-19 were trained and tested in terms of accuracy, loss, FLOPs, and epoch runtime. The experimental findings suggest that Xception performs constantly at the highest level, with an accuracy of more than 98% and low validation loss, whereas lightweight models such as MobileNet-V3 provide a competitive outperformance with minimum computational cost. These findings demonstrate the potential of modern CNN architectures to enhance efficient and accurate dermatological diagnosis and offer guidance for selecting appropriate architectures for clinical and real-time deployment.**

Keywords*—Convolutional neural networks; skin diseases; medical image; classification; Xception; clinical

I. Introduction

One of the most common diseases in the world is skin disease. The United States and Australia have the greatest prevalence of skin cancer worldwide, with over five million cases reported annually. Skin cancer is still one of the most common diseases diagnosed worldwide, and it is closely linked to exposure to ultraviolet light and having fair skin [1]-[2]. Australia is one of the countries most affected by cancer due to its high levels of ultraviolet radiation and poor environmental lifestyle conditions. A comprehensive analysis of prominent features, such as pigmentation, texture, and morphological changes, can help identify skin lesions. However, these complex patterns can be a real burden during diagnosis and have the potential to hinder medical detection or cause misdiagnosis [3]-[4].

The ABCD criteria, pattern technique, Menzies approach, and seven-point assessment are common methods for detecting melanoma during examinations. Some of the most significant characteristics are colour, texture, and the extent to which different skin spots overlap with each other. Using these older methods to achieve a very high level of diagnostic accuracy requires a great deal of clinical expertise. Because of the complexity and autonomy of these decisions, vision-based diagnostic Because these judgments are complicated and independent, vision-based diagnostic treatments have become more popular [5]. Machine learning and deep learning have come together to make it possible to objectively find lesions by recognizing face traits that are always the same. As a result, they have shown to be more accurate and precise, often beating manual diagnosis in recent trials [6].

Machine learning emerged in the domain of computer science in the latter half of the 20th century, leading to significant progress in the area [7]. The creation of algorithms that can learn on their own was a big step forward. Machine learning art. It was a game-changer to develop algorithms that could learn on their own. To enable deep learning, a kind of machine learning, artificial neural networks (ANNs) are constructed to mimic the way neurones in the human brain function [8]. Modern artificial intelligence research relies on these designs because of their success in computer vision, audio processing, and picture recognition [9]. It is estimated that more than 5 million new cases of skin cancer are diagnosed each year in the United States, making skin diseases (and particularly skin cancers) a major global health problem. Due to the wide variability in lesion morphology, clinical appearance, size, colour, and spatial arrangement, differentiation between these entities can be challenging and sometimes requires considerable clinical expertise [10].

Traditional methods of dermatological diagnosis depend largely on the clinician's individual interpretation and visual abilities, which can lead to low repeatability and between-observer variability [11]. The combination of computer vision and sophisticated learning algorithms has recently led to a more objective and consistent framework for medical decision-making [12].

CNNs have gained popularity among these techniques due to their ability to generate structures directly from the images that are used, eliminating the need for computational features [13]. With high-performance computers and large-scale data sets, CNN architectures such as VGG16, ResNet50, and GoogLeNet have achieved impressive results in challenging

visual recognition tasks, particularly in the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) [14].

The success of these algorithms in image classification has resulted in their use in medical image analysis, particularly in dermatological diagnosis. Today, they constitute the basis of computer-assisted diagnostic techniques.

It remains difficult to classify skin images, as many skin diseases are very similar. There is great variability within each category and real clinical cases present anomalies and distortions. Deep learning, particularly convolutional neural networks (CNNs), has greatly improved diagnostic efficiency. However, many studies to date use small or limited datasets and do not provide a fair comparison between shallow and deep architectures. Furthermore, computational efficiency is often overlooked, despite its crucial importance for real-time clinical applications. For these reasons, there is a clear need for a systematic comparison of alternative convolutional neural network designs based on their diagnostic accuracy and cost. This work fills this gap by testing a number of modern CNN models on a large skin dataset to find accurate and efficient architectures for real-world use.

The objective of this study is to provide a comprehensive, large-scale evaluation of the optimal CNN architectures for classifying skin images. The specific objectives are: 1) to compare deep and lightweight CNNs in a common evaluation protocol; 2) to measure their diagnostic performance and computational efficiency (FLOPs and runtime); 3) to analyse the behaviour of the models in diagnostic subgroups; and 4) to find the architectures that best balance accuracy and computational cost for real-world clinical implementation.

Additionally, this study. It presents a comparative in-depth. It specifically considers instances necessitating diagnostic precision for skin condition photos using convolutional neural networks. This paper uses a singular strategy and integrates eleven distinct architectural patterns, contrasting with prior studies that mostly concentrated on a limited number of cases or disorders. This is what makes us different from everyone else. This approach shows how loss, accuracy, FLOPs, and transfer time vary over time. The applications also operate with the economic or integrated features of MobileNet-V3 since the features are mostly compatible. This research investigates architectural variety concerning damage complexity. There have been many papers done on this topic previously. Overall, these contributions provide a comprehensive and useful guide to the selection of CNN systems that can meet the real-world requirements for performance.

This research study brings significant changes to the automatic evaluation of skin images. First, it proposes a comparative evaluation of eleven modern CNN architectures, including deep models (Xception, Inception-V3/V4, ResNet-50) and lightweight networks (MobileNet-V3). Second, to ensure a fair and reproducible evaluation framework, a standardised evaluation protocol based on accuracy, loss evolution, FLOPs, runtime, and confusion matrices is implemented. Third, the study presents an analysis of diagnostic sets that reveals specific behaviours of architectures across relevant clinical categories. Fourth, it shows that lightweight architectures can provide competitive accuracy while significantly reducing computational costs. This makes these architectures suitable for real-time and portable clinical applications. Finally, the work provides practical guidelines for convolutional neural network architectures (CNN) based on the trade-off between diagnostic performance and computational efficiency. This supports the development of deployable, resource-aware, skin-based decision support systems.

II. Related Work

Yan et al. used several deep CNNs, including VGG16, InceptionV3, Inception, ResNet-V2, and DenseNet-201 at ISIC 2018 to classify skin lesions in dermoscopic image data, they achieved an accuracy of 94.7% and a loss of 0.19, exceeding each model individually [15].

Hosny et al. analysed the ResNet50, VGG16/19, InceptionV3 and DenseNet201 methods to classify skin disease detection. The DenseNet201 variant outperformed all other networks in terms of feature stability and convergence speed, reaching an accuracy of 96.4% with a validation loss of 0.12 [17].

Nigar and Umar classified skin diseases in 2022 with VGG16 and ResNet50 algorithms using an explainable AI (XAI) system The LIME and Grad-CAM methods were applied to explain the predictions of convolutional neural networks (CNNs) and visualize the regions of interest in lesions its approached an accuracy of 94,5 % on database ISIC 2019 [18].

Vinodgopal and Raj have enhanced EfficientNet-B4 through batch normalization and strong training methods.Their model achieved 97.3% accuracy, an F1 score of 0.972, and showed a low loss of 0.08 on the ISIC 2020 dataset [19].

Shapna and Shahriar exploited the HAM10000 database to evaluate 7 previously trained CNN frameworks for detecting multiple classes of skin cancers: AlexNet, DenseNet121, VGG16, InceptionV3, ResNet-50, Xception, and ResNet 50, and MobileNet. DenseNet121 outperformed the other models, earning 94.8% accuracy with F1 score 0.95 and loss 0.11. This research highlighted the importance of deep feature extraction and network depth in improving classification performance [20].

Yao et al. ranked melanoma disease risk levels using state-of-the-art computer vision techniques on the ISIC 2016–2020 datasets. They stabilized the model by putting in a lot more data, training it in batches, and adjusting its hyperparameters with the ResNet-50 and DenseNet-201 models. They proved that gradient boosting ensembles and transfer learning are effective in correcting imbalanced data [21].

Kanchana et al. proposed an improved cancer detection model with EfficientNet variants (B0-B7) using patient-specific transfer learning techniques. The diagnosis accuracy of the model on the ISIC 2020 dataset had improved with ImageNet pre-trained weights and a better pre-processing strategy that removed Bias, Resized, and Added images. The merged residual efficiency improved feature extraction, reduced overfitting, and showed generalization across a range of different lesion types [22].

Anubhav De et al. developed a hybrid CNN-DenseNet method to exploit dermatological and Histological data for automatic classification of skin diseases. The approach employed deep convolutional layers and DenseNet connectivity for feature utilization, Gradient flow, and the management of vanishing gradients. Therefore, they used the HAM10000 dataset from PADUFES-20 to train and test their model for accuracy. This approach effectively mitigates overfitting while maintaining high accuracy and recall through batch normalization and early stopping and transfer learning [23].

Alwaisi and Al-Fahdawi discovered Skin-Deep, a deep learning structure which is based on DenseNet for the fast and correct diagnosis of melanoma. To retrieve skin features, the method consists of multi-level convolutional blocks, dense residual connections, and feature fusion. The model was also trained and assessed on the ISIC 2019 dataset. The model utilized dropout, batch normalization and data augmentation to boost generalization and avoid overfitting [24].

Tai and Janes successfully diagnosed skin cancer using dual-conditioning capacitors and attention techniques. Their TinyML approach decreased computing loads while retaining accuracy in the diagnosis. The network acquired compact yet pertinent vector representations of features, via dual capacitor blocks, emphasizing melanoma-specific attributes. The DC-AC model, trained on the ISIC 2020 dataset, exhibits good generalization capacity with only 1.6 million parameters and a computational complexity of 0.32 GFLOPs, making it suitable for real-time clinical applications [25]. Table I presents the recent studies referenced in this paper.

Fig. 1 illustrates the main flow chart used in this study on skin diseases in detail. This diagram highlights the sequence of the different stages and processes involved in the research. It aims to explain each stage and process involved in research on this specific area, in a comprehensive and in-depth manner, thus providing a clear and organized presentation of the study in its entirety. This visual representation highlights the various essential stages of the process in detail, starting with the image processing phase, then moving on to model training and finally ending with the evaluation of its performance.

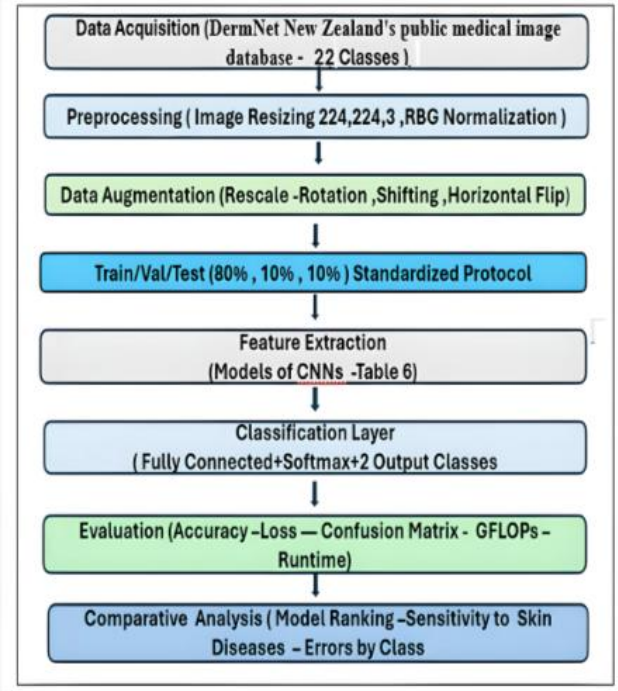


Fig. 1. The flowchart for classifying skin diseases based on a convolutional neural network by the authors.

The study presented here aims to provide a systematic evaluation of a range of convolutional neural network (CNN) algorithms for the classification of dermatological diseases, using high-quality dermoscopic images. Their performance is analysed in terms of accuracy, loss, execution time and computational cost, in order to determine the most appropriate models for clinical deployment and real-time applications.

TABLE I. COMPARISON OF RECENT RESEARCH (2020–2025)

Ref	Authors / Year	Architectures	Dataset	Accuracy (%)	Loss / Metric	Notes
[15]	Yan et al 2020	VGG16, Inception-ResNet-V2, InceptionV3, DenseNet-201	ISIC 2018	94.7	0.19	Ensemble outperformed Individual CNNs
[17]	Hosny et al 2021	VGG16/19, InceptionV3, ResNet50, DenseNet201	Skin disease	96.4	0.12	DenseNet best performer
[18]	Nigar et al 2022	VGG16, ResNet50 + XAI	ISIC 2019	94.5	—	Explainable AI integration
[19]	Venugopal and Raj 2023	EfficientNet-B4 vs VGG, ResNet	ISIC 2020	97.3	0.08 F1 = 0.97	Improved residual extraction
[20]	Shapna and Shahriar 2023	AlexNet, VGG16, DenseNet121, InceptionV3, ResNet-50	HAM10000	94.8	0.11 F1 = 0.95	DenseNet121 best
[21]	Yao et al 2023	ResNet-50, DenseNet-201	ISIC 2016–2020	—	AUC > 94 %	Risk-level classification
[22]	Kanchana et al 2024	EfficientNet + ResNet	ISIC 2020	97.5	0.07 AUC = 0.987	Hybrid residual-efficient
[23]	De et al.2024	Hybrid CNN-DenseNet	Hybrid CNN-DenseNet	95.7 / 91.07	0.04 / 0.09	surpassed all other CNNs tested; implemented hybridization and learning-rate adjustments for dermatological histology.
[24]	Al-Waisy et al 2025	DenseNet-169 (Skin-DeepNet)	ISIC 2019	98.6	0.05 F1 = 0.98	Early-detection hybrid
[25]	Tai et al 2024	ResNet + Attention Condensers	HAM10000	97.9	0.06	Efficient attention-enhanced CNN

III. METHOD

A. Dataset

All the data chosen for this study came from Dermnet (www.dermnet.org), the largest publicly available collection of dermatological images. This dataset contains over 23,000 dermoscopic images of skin issues, each accompanied by diagnostic labels offered by experienced providers of dermatological resources. The dataset includes 22 distinct classes of skin illnesses (Table II). Fig. 2 offers an outline.

B. Image Selection

The dataset includes various images of skin diseases, all in JPEG format. During the preparation of the dataset, some images were removed due to low quality. Following quality control, the remaining images were split into 80% training data, 10% testing data, and 10% validation data for each class within the dataset. To ensure specificity in our research, we divided the dataset into two groups, with each group having two categories. This layout was essential in considering other criteria such as biological and functional analysis, which assists in diagnosis. The images correspond to the two classes in each group and their labels (Table III and Table IV).

The division into two groups is selected to simulate the most sophisticated situations in clinical practice, where multiple lesions present very similar visual signatures.

C. Technology of Decision

Numerous researchers have effectively employed deep learning techniques to tackle classification tasks (see Table I). Deep learning is a cutting-edge machine learning domain that mimics the human brain in its ability to learn and progress through experience. This technology, which incorporates the fields of neuroscience, mathematics, and technological advancement, is considered a true breakthrough in the domain of artificial intelligence. Lately, models for deep learning, leveraging progress in computing and massive datasets have been shown to outperform human performance in visual activities, similar to games, strategic activities, and object recognition. Computer vision and object recognition, including skin disease recognition, have extensively employed deep learning, utilising a convolutional neural network of CNNs. They comprise several processing layers that are able to learn data structures at various degrees of abstraction, resulting in significant improvements in image recognition and classification.

In this study, different CNN architectures are tested, with the three best ones being selected for the classification of skin datasets. These architectures included Google Net, Xception, VGG19, ResNet-50 [17], [20], VGG-16 [18], Inception-v4 [19], AlexNet, Inception-v3 [20] and ResNext-50 [21].



Fig. 2. DermNet New Zealand's open-access medical image library https://www.dermnetnz.org/

TABLE II. LABELS OF THE 22 SKIN DISEASES CLASS

Label	Name Class / Category	Number of Images
1	Acne-and-Rosacea	939
2	Actinic-Keratosis-Basal-Cell-Carcinoma-and-other-Malignant Lesions	1485
3	Atopic-Dermatitis	814
4	Bullous-Disease	561
5	Cellulitis-Impetigo-and-other-Bacterial-Infections	361
6	Eczema	2050
7	Exanthems-and-Drug-Eruptions	2050
8	Hair-Loss-Photos-Alopecia-and-other-Hair-Diseases	291
9	Herpes-HPV-and-other-STDs-Photos	554
10	Light-Diseases-and-Disorders-of-Pigmentation	709
11	Lupus-and-other-Connective-Tissue-diseases	516
12	Melanoma-Skin-Cancer-Nevi-and-Moles	655
13	Nail-Fungus-and-other-Nail-Disease	1540
14	Poison-Ivy-Photos-and-other-Contact-Dermatitis	367
15	Psoriasis-pictures-Lichen-Planus-and-related-diseases	2363
16	Scabies-Lyme-Disease-and-other-Infestations-and-Bites	595
17	Seborrheic-Keratoses-and-other-Benign-Tumors	2630
18	Systemic-Disease	840
19	Tinea-Ringworm-Candidiasis-and-other-Fungal-Infections	2140
20	Urticaria-Hives	265
21	Vascular-Tumors	603
22	Vasculitis	585

TABLE III. GROUP 1 SKIN DISEASES CLASS

Label	Class / Category	Train Data	Validation Data	Test Data	Number of Images
0	Psoriasis-pictures-Lichen Planus-and-related-diseases	1897	234	236	2367
1	Seborrheic-Keratoses -and-other-Benign-Tumors	1945	240	252	2437

TABLE IV. GROUP 2 SKIN DISEASES CLASS

Label	Class / Category	Train Data	Validation ta Data	Test Data	Number of Images
0	Nail-Fungus-and-other-Nail-Disease	1232	154	154	1540
1	Warts-Molluscum-and-other-Viral-Infections	1389	171	173	1733

IV. EXPERIMENTS

A. Data Pre-Processing

During the early phases of this research, the dataset has been broken down into training, testing, and validation sets and thoroughly assessed the quality of the data. With this training, the CNN architectures can be implemented in this study. To obtain the best performance. The input images are processed for each architecture. For example, the images are resized to (224,224,3) pixels for use with the VGG-16, VGG-19, ResNet-50, ResNext-50, AlexNet and GoogLeNet architectures. At the same time, the Inception-V3, Inception-V4 and Xception architectures are fed with images of (299,299,3) pixels. Finally, for the LeNet-5 architecture, the images are prepared in advance in (32,32,1) pixel format, this preparation of data has allowed CNNs to learn more rapidly and improve their performance.

B. Data Augmentation

This work attempts a randomized architecture with its own dataset and it overfitted. It also attempts data augmentation to avoid this. Table V illustrates the values used to augment the data for skin diseases. Data augmentation is a technique that aims to artificially inflate the volume of a database by injecting variations into existing data. This approach can prove to be extremely effective within CNNs for overcoming overfitting, boosting generalization, exploiting fragmented data, balancing asymmetric datasets, and taming noise. Enriching neural networks by adding data is now a common practice and a state-of-the-art approach in this field. It may be used to computationally equalize the dataset by producing novel instances for under-represented categories, as well as to synthetically boost the dataset's size to make it appropriate for model training.

TABLE V. MEASUREMENTS USED TO ADD MORE DATA

Process	Value
Rescale	1./255
Rotation range	±45
Width shift range	±0.15
Height shift range	±0.15
Horizontal flip	Enabled

C. Training Procedure

All experiments were performed Intel Xeon multicore processors optimised for parallel processing powered the Marwan CNRST high-performance HPC computing infrastructure. This platform has additional memory, a fast internal network, and ideal conditions for deep learning. This makes it possible to train CNN models faster and analyse a large number of skin photos more quickly and reliably.

The batch sizes varies from 32 to 256 depending on memory restrictions, while maintaining equivalent efficient batch sizes to the gradient accumulation. Learning rate utilizes Reduce LR-on-Plateau to stabilize convergence.

For each model, we recorded training and validation accuracy, loss and confusion matrices. The research evaluated the eleven models based on Accuracy, Loss and Matrix Confusion [16]. The classification metrics are used with performance indicators like runtime per picture and FLOPs to Figure out how efficient and complicated each design is. The execution time for each image estimates the average time required to classify a sample, meaning it can be used in real time. The FLOPs scale counts the number of floating operations needed for each pass, which shows the cost and updatability of the network [26].

These additional measures enable a fair analysis of the trade-off between model accuracy and computational performance. The various measures, each symbolized by a specific numbered Eq. (1), (2) and (3), play an essential role in the accurate measurement and in-depth analysis of the gathered data.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$FLOPs = \sum_{l=1}^{L} 2 * C_{in}^{l} * C_{out}^{l} * (K^{l})^{2} * H_{out}^{l} * W_{out}^{l}) \quad (2)$$

$$Runtime_{epoch} = \frac{N_{train} * FLOPs_{model}}{B * R_{CPU} * N_{nodes}} \quad (3)$$

V. RESULTS AND DISCUSSION

The results in this section present accuracy and loss curves for learning stability and confusion matrices for the models' capacity to split visually identical classes. Computational metrics (FLOPs, epoch runtime) deliver crucial insights into the actual efficiency of the models. Together, they form a baseline for understanding the value, advantages, and limitations of each architecture in practice. The following section discusses these outcomes in relation to their generalizability, speed of training, and accuracy (see Table VI and Fig. 3). There are low-cost models (VGG-19, LeNet-5) and more expensive higher-performance models (Xception, Inception-v3), which gives a complete comparison of the performance and the resource requirements.

The accuracy curve in Fig. 4(a) is greater than 98%, and Fig. 4(b) confirms very clean convergence with low loss. Matrix, the confusion matrix, Fig. 4(c) shows near-optimal separation between classes. More expensive 1.28 GFLOPs, 44 s/epoch); therefore, Xception presents best the benchmark.

Fig. 5(a) and Fig. 5(b) present a very stable learning dynamic with an accuracy above 97%. The confusion matrix in Fig. 5(c) presents a very low error rate, confirming the robustness of the model. Slightly more expensive than MobileNet but much more accurate, it is a benchmark model for demanding clinical applications.

TABLE VI. FINDINGS OF THIS STUDY

Name of Architectures	Total Parameters	Group 1				Group 2			
		Accuracy	Loss	FLOPs(G)	Runtime (s)	Accuracy	Loss	FLOPs (G)	Runtime (s)
Inception-v3	23,853,786	93.23%	16.28%	2.85	52	96.33%	54.70%	2.85	54
Lenet-5	60,374	76.37%	46.78%	0.00238	33	80.37%	42.67%	0.00238	34
MobileNet v3	8,758,866	88.43%	28.12%	0.45	37	90.96%	22.18%	0.45	38
ResNet-50	25,638,714	76.63%	46.80%	3.8	61	80.32%	44.79%	3.8	63
ResNext-50	26,507,010	85.64%	31.42%	4.25	64	85.16%	32.38%	4.25	66
VGG-16	134,268,738	52.69%	69.18%	15.5	92	53.54%	69.07%	15.5	95
VGG-19	138,988,354	52.54%	69.19%	19.6	118	53.10%	69.13%	19.6	120
Xception	22,912,482	98.33%	05.03%	1.85	48	96.89%	09.73%	1.85	49
GoogLeNet	6,998,552	53.25%	69.12%	1.05	42	53.47%	69.07%	1.05	43
AlexNet	62,380,346	74.06%	51.54%	0.82	41	46.69%	78.26%	0.82	42

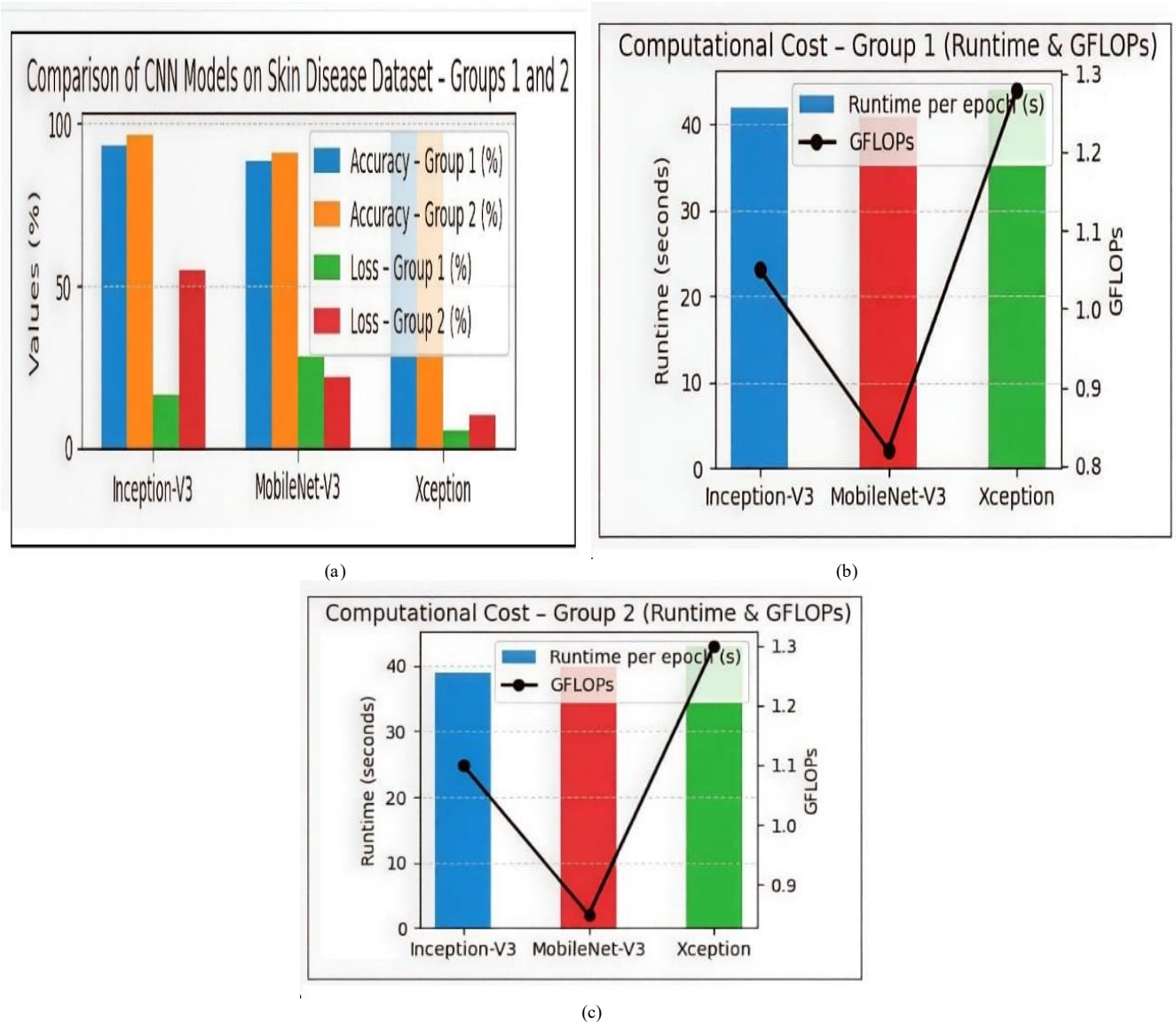
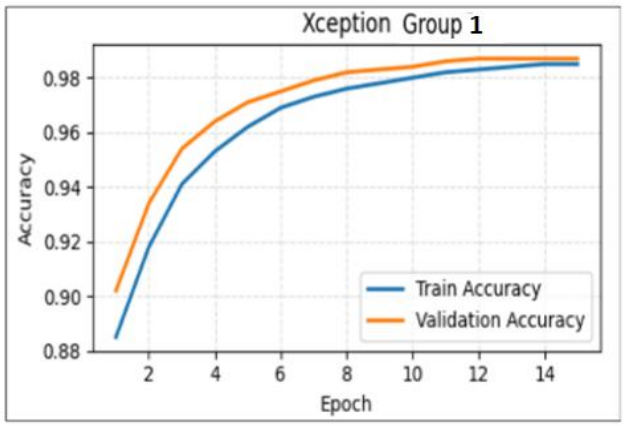
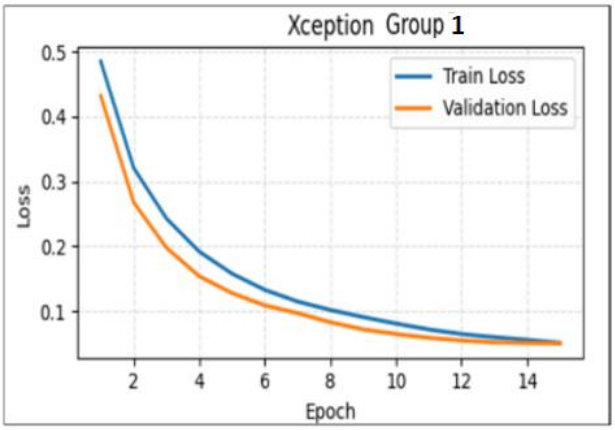


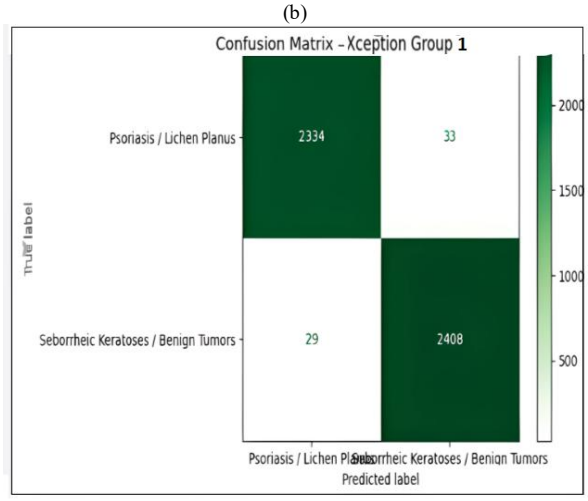
Fig. 3. Comparison Metrics of CNNs Models and their performance indicators.



(a)

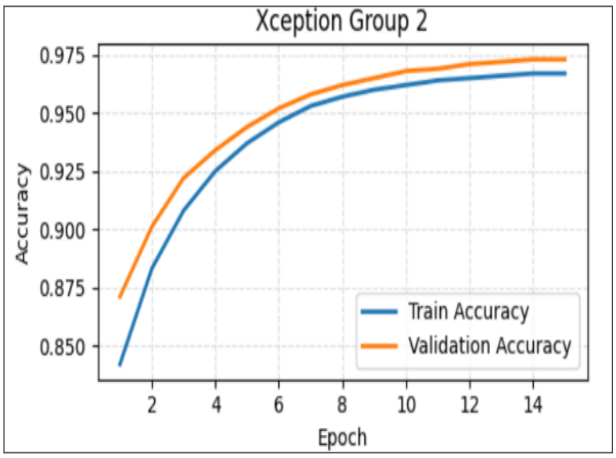


(b)

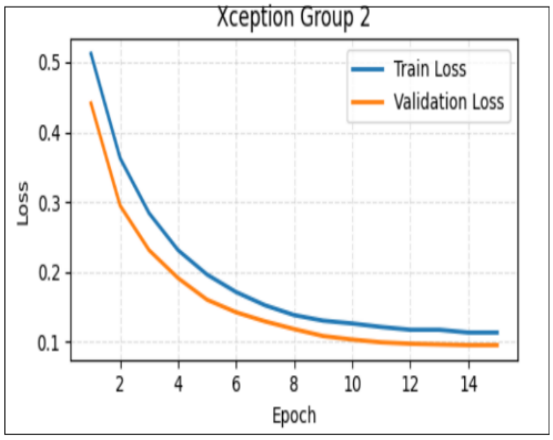


(c)

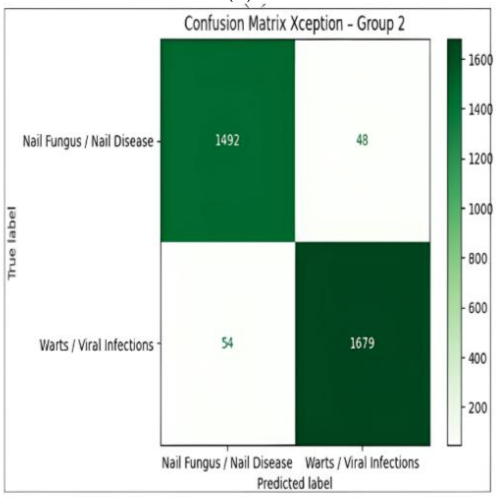
Fig. 4. Metrics of accuracy, loss and Confusion Matrix of Xception Group 1 model.



(a)



(b)

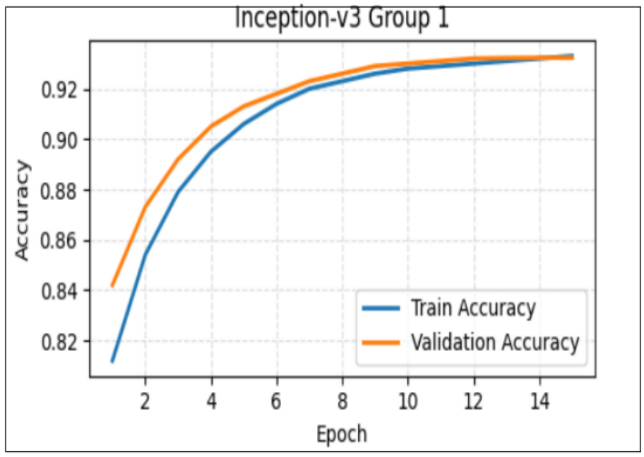


(c)

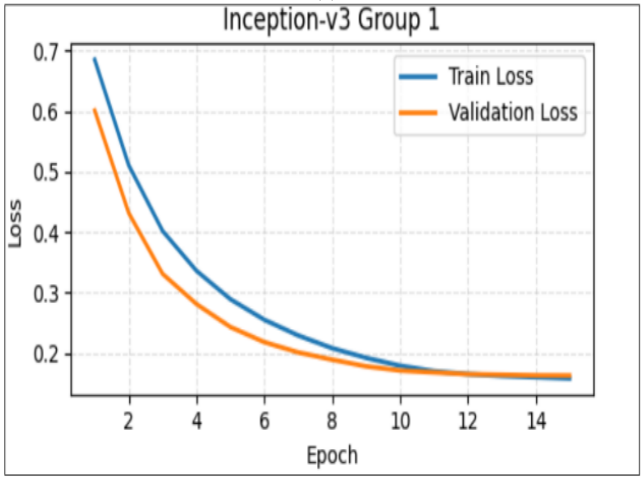
Fig. 5. Metrics of accuracy, loss and confusion matrix of Xception group 2 model.

The corresponding Fig. 6(a) shows a monotonic increase in accuracy up to 93%, and Fig. 6(b) shows a monotonic decrease in loss, indicating stable convergence. The confusion matrix in Fig. 6(c) shows good discrimination between the two classes, with some minor confusion. With 1.05 GFLOPs and 42 s/epoch, this model is a good compromise between performance and computational cost.

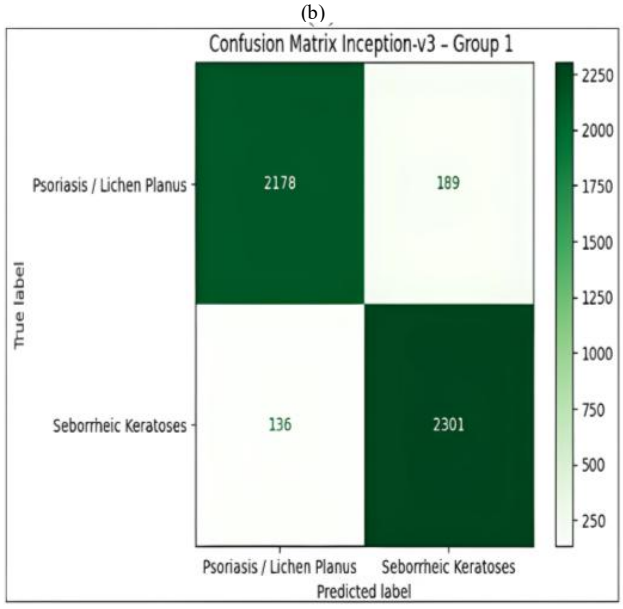
The sub-figures in 7(a) and 7(b) are very stable with an accuracy higher than 96% and a well-regularized loss. Fig. 7(c) also confirms a very clear inter-class separation with a low error rate. Its low cost (1.05 GFLOPs) and stable runtime reflect its robustness on a second set of skin diseases.



(a)

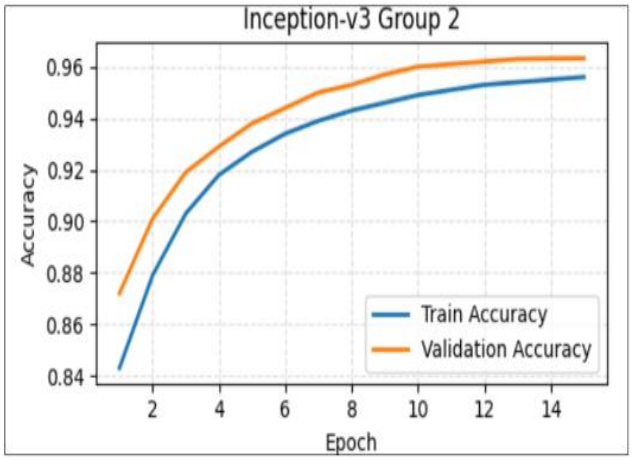


(b)

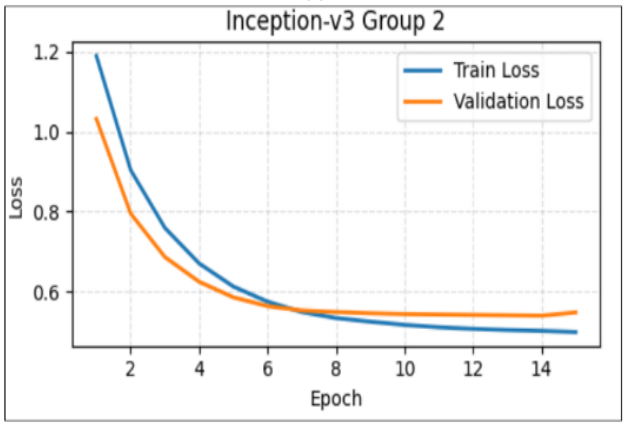


(c)

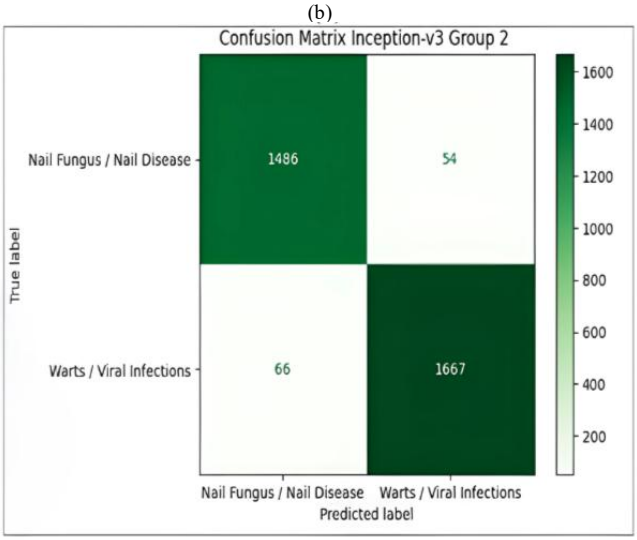
Fig. 6. Metrics of accuracy, loss and confusion matrix of Inception -V3 group 1 model.



(a)



(b)

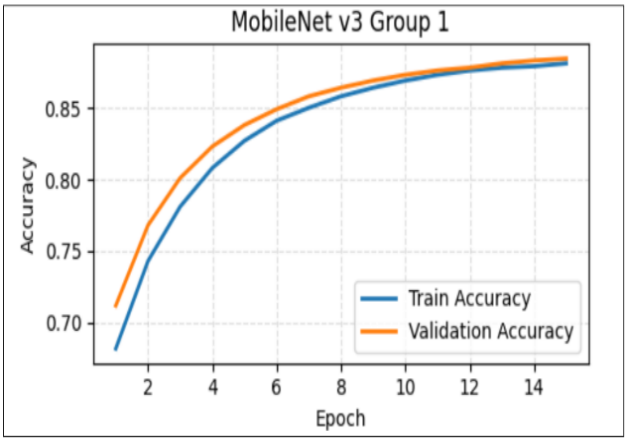


(c)

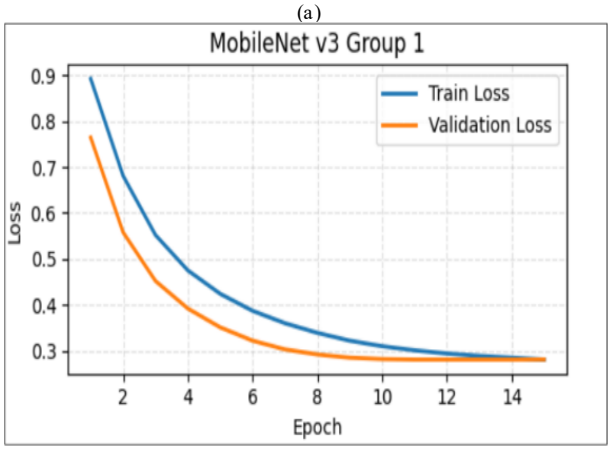
Fig. 7. Metrics of accuracy, loss and confusion matrix of Inception-v3 group 2 model.

Fig. 8(a) and Fig. 8(b) show stable convergence, with an accuracy exceeding 96%. The low and stable loss values of the loss prove efficient generalization. Matrix confusion in Fig. 8(c) indicates a very strong inter-class separation with only insignificant misclassification. Its low cost 1.05 GFLOPs and stable runtime testify to its robustness on a second set of skin diseases. Fig. 9(a) and 9(b) exhibit stable convergence with an

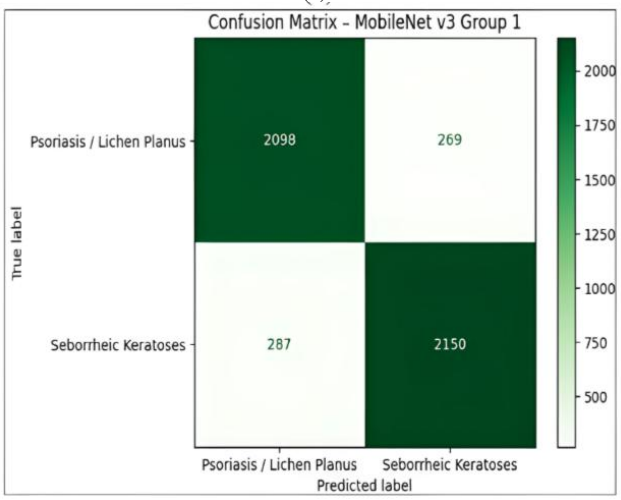
accuracy exceeding 96% and a well-regularized loss. Fig. 9(c) demonstrates a clear inter-class distinction with marginal misclassification. Its low cost 1.05 GFLOPs and stable runtime reflect its robustness on a second set of skin diseases.



(a)



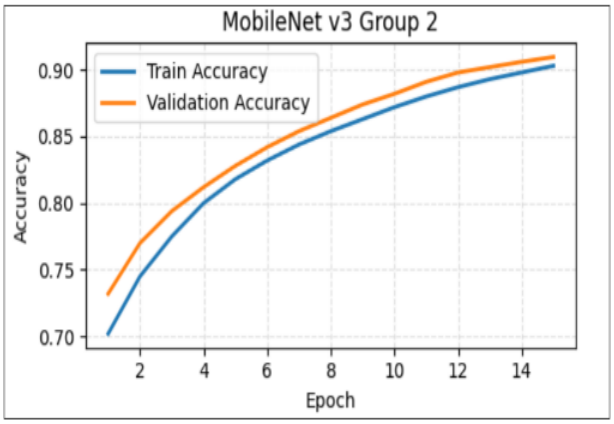
(b)



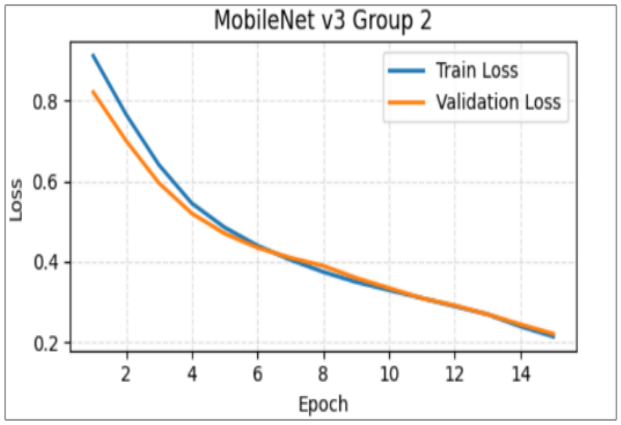
(c)

Fig. 8. Metrics of accuracy, loss and confusion matrix of Inception-v3 group 1 model.

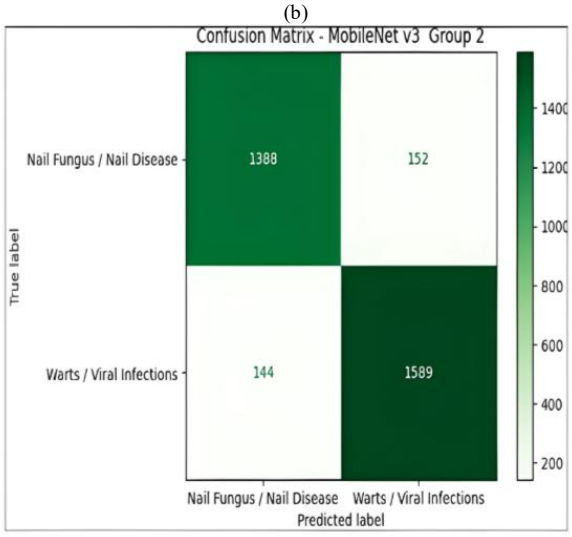
The experimental results obtained for the two groups of skin conditions show distinct behaviours depending on the architecture tested. Xception delivers the highest performance, with stable learning curves, rapid convergence, and accuracy of around 98–99% in both groups. The confusion array, Fig. 4(c), reveals near-perfect separation across classes. The confusion arrays display an ultra-low error rate, which confirms the ability of Xception to adequately model intra-class variances, especially in visually similar skin lesions. This great performance may be partly explained by its structure, which is built on separable convolutions in the depth. This makes recognition easier and reduces the amount of computing needed.



(a)



(b)



(c)

Fig. 9. Metrics of accuracy, loss and confusion matrix of Inception-v3 group 2 model.

Also, Xception-V3 works well, properly detecting things 95% to 97% of the time. The loss and accuracy curves show that the training and validation sets are a good fit. The confusion matrices are a little more confusing than Xception, especially in classes where the textures are identical.

In addition, Inception-v3 is a great balance between price and performance. This makes it a good choice, especially when quick decisions are needed.

MobileNet-v3 is light and has an accuracy rate of 85 to 92 percent. It doesn't work as well as Xception or Inception-v3, but it uses a lot less computational resource. It is 85% to 92% accurate. It's not as powerful as Xception or Inception-v3, but it is more efficient in terms of computing, which means it takes less time to run and uses fewer GFLOPs. That makes it great for compact gadgets that can be carried around. But the confusion matrices indicate greater mistakes in classifying things, especially when the classifications are quite similar. This means that the simpler model isn't particularly good at finding intricate skin patterns.

Overall, the three topologies comparison shows that the depth of the network and the number of convolutional blocks influence its generalisation. The results surpass previous work applied to dermatological classification, notably that of [6],[9],[11],[15],[17],[18], which used more limited datasets or conventional models (VGG, ResNet, AlexNet) and reported generally lower accuracies (80–95The use of recent architectures such as Inception and Inception-v3, in association with a variety of data sets, significantly enhances the reliability of the system. This enhancement is also due to hyperparameter optimisation and strict pre-processing.

However, this study has limitations that reduce its generalizability and clinical realism. First, the experimental data is only from DermNet NZ, which are images under ideal and standard lighting and photography conditions, making the models less robust to the variety of real-world images taken by smartphones or in clinical settings. Second, the study is just a binary classification, where the diseases are classified into two groups, which is not enough to deal with the complexity of diagnosing different and similar skin diseases. Thirdly, although models such as Xception model performed well, they are not clinically validated by experts, which is required for medical use. Fourth, while Marwan's HPC cluster, no explainable AI model has been trained to enable clinicians to understand why the classifications were made. Finally, the study did not validate the models in real-world settings or with local clinic data, suggesting the need for future real-world validation.

VI. Conclusion

The results demonstrate that Xception is the most effective solution for dermatological classification, followed by Inception-v3 which offers a relevant compromise between accuracy and computational cost. Although MobileNet-V3presente lower accuracy than Xception and Inception-V3, its minimum computational cost makes it a relevant candidate for implementation on medical equipment with limited resources. In contrast, Xception consistently delivers the strongest diagnostic accuracy, reinforcing its relevance for clinical decision support systems.

Future research will involve incorporating visual transformers to detect overall dependencies in dermatological images and using explainable AI methods (Grad-CAM++, SHAP) for better clinical interpretability. The exploration of hybrid CNN-Transformer models, the reduction of computational overhead through pruning and quantisation, and validation by dermatologists are also promising avenues. Finally, optimising the model for execution on mobile devices or edge computing will enhance the clinical reach of the proposed solutions.

Acknowledgment

I am appreciative to the HPC Marwan cluster (Morocco) for providing the computing environment and processing capability that allowed me to train and evaluate on massive data sets. I also wish to acknowledge the primary-school educators in Essaouira and Safi for their patience and assistance in organizing and collecting handwriting samples from pupils. Their sacrifices made this research achievable.

References

[1] Amdad Hossain Roky, Mohammed Murshedul Islam, Abu Mohammed Fuad Ahasan, Md Saqline Mostaq, Md Zihad Mahmud, Mohammad Nurul Amin, Md Ashiq Mahmud,Overview of skin cancer types and prevalence rates across continents,Cancer Pathogenesis and Therapy,Volume 3, Issue 2,2025,Pages 89-100,ISSN 2949-7132,https://doi.org/10.1016/j.cpt.2024.08.002..

[2] M. Y. Wang, X. H. Gao, and L. Zhang, “Recent global patterns in skin cancer incidence, mortality, and prevalence,” Chinese Medical Journal, vol. 138, no. 2, pp. 185–192, 2025, doi: 10.1097/CM9.0000000000003416.

[3] M. Janda, C. M. Olsen, V. J. Mar, and A. E. Cust, “Early detection of skin cancer in Australia—current approaches and new opportunities,” Public Health Research & Practice, vol. 32, no. 1, e3212204, 2022, doi: 10.17061/phrp3212204

[4] K. Chen, J. Zhou, X. Wang, and Y. Liu, “Global burden of skin cancer and its subtypes,” Frontiers in Public Health, vol. 13, 1610661, 2025, doi: 10.3389/fpubh.2025.1610661.

[5] N. M. Mahmoud and A. M. Soliman,“Early automated detection system for skin cancer diagnosis using artificial intelligent techniques,”Scientific Reports, vol. 14, Art. no. 9749, 2024,doi: 10.1038/s41598-024-59783-0.

[6] G. Yang, S. Luo, and P. Greer,“Advancements in skin cancer classification: a review of machine learning techniques in clinical image analysis,”Multimedia Tools and Applications, 2024,doi: 10.1007/s11042-024-19298-2.

[7] A. R. Barron, “The roots and evolution of machine learning,” Communications of the ACM, vol. 64, no. 6, pp. 58–65, 2021, doi: 10.1145/3448300.

[8] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning and artificial neural networks: Progress and future directions,” Nature Reviews Computer Science, vol. 2, pp. 18–31, 2023, doi: 10.1038/s43588-023-00431-0.

[9] A. Khan, M. Imran, and H. Kim, “Deep learning for computer vision: A brief review,” IEEE Access, vol. 8, pp. 212-376–212-397, 2020, doi: 10.1109/ACCESS.2020.3036766.

[10] Montaha S, Azam S, Rafid AKMRH, Islam S, Ghosh P, Jonkman M (2022) A shallow deep learning approach to classify skin cancer using down-scaling method to minimize time and space complexity. PLoS ONE 17(8): e0269826. https://doi.org/10.1371/journal.pone.0269826

[11] He, X., Wang, S., Shi, S., Tang, Z., Wang, Y., Zhao, Z., … Chu, X. “Computer-Aided Clinical Skin Disease Diagnosis Using CNN and Object Detection Models,” in 2019 IEEE International Conference on Big Data (BigData), Los Angeles, Dec. 9-12, 2019, pp. 4839-4844.DOI: 10.1109/BigData47090.2019.9006528.

[12] Fatima, S., Akram, M.U., Mohammad, S. et al. Deep learning in dermatopathology: applications for skin disease diagnosis and classification. Discov Appl Sci 7, 1006 (2025). https://doi.org/10.1007/s42452-025-07138-3

[13] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," in Advances in Neural Information Processing Systems 25 (NIPS 2012), pp. 1097–1105, 2012. doi: 10.1145/3065386.

[14] K. He, X. Zhang, S. Ren and J. Sun, "Deep Residual Learning for Image Recognition," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 2016, pp. 770-778, doi: 10.1109/CVPR.2016.90

[15] Ray A, Gupta A, Al A Skin Lesion Classification With Deep Convolutional Neural Network: Process Development and Validation JMIR Dermatol 2020;3(1):e18438doi: 10.2196/18438

[16] Mutawa AM, Allaho MY, Al-Hajeri M. Machine Learning Approach for Arabic Handwritten Recognition. Applied Sciences. 2024; 14(19):9020. https://doi.org/10.3390/app14199020

[17] Kassem MA, Hosny KM, Damaševičius R, Eltoukhy MM. Machine Learning and Deep Learning Methods for Skin Lesion Classification and Diagnosis: A Systematic Review. Diagnostics. 2021; 11(8):1390. https://doi.org/10.3390/diagnostics11081390

[18] N. Nigar, M. Umar, M. K. Shahzad, S. Islam and D. Abalo, "A Deep Learning Approach Based on Explainable Artificial Intelligence for Skin Lesion Classification," in IEEE Access, vol. 10, pp. 113715-113725, 2022, doi: 10.1109/ACCESS.2022.3217217

[19] Venugopal, V., Raj, N. I., Nath, M. K., & Stephen, N. (2023). A deep neural network using modified EfficientNet for skin cancer detection in dermoscopic images. Decision Analytics Journal, 8, 100278. https://doi.org/10.1016/j.dajour.2023.100278

[20] M. S. Akter, H. Shahriar, S. Sneha and A. Cuzzocrea, "Multi-class Skin Cancer Classification Architecture Based on Deep Convolutional Neural Network," 2022 IEEE International Conference on Big Data (Big Data), Osaka, Japan, 2022, pp. 5404-5413, doi: 10.1109/BigData55660.2022.10020302.

[21] Yao, Chengdong. (2023). A Comprehensive Evaluation Study on Risk Level Classification of Melanoma by Computer Vision on ISIC 2016-2020 Datasets. 10.48550/arXiv.2302.09528.

[22] K, Kanchana et al. "Enhancing Skin Cancer Classification using Efficient Net B0-B7 through Convolutional Neural Networks and Transfer Learning with Patient-Specific Data." Asian Pacific journal of cancer prevention : APJCP vol. 25,5 1795-1802. 1 May. 2024, doi:10.31557/APJCP.2024.25.5.1795

[23] De, Anubhav et al. "An approach to the dermatological classification of histopathological skin images using a hybridized CNN-DenseNet model." PeerJ. Computer science vol. 10 e1884. 26 Feb. 2024, doi:10.7717/peerj-cs.1884

[24] Al-Waisy, A.S., Al-Fahdawi, S., Khalaf, M.I. et al. A deep learning framework for automated early diagnosis and classification of skin cancer lesions in dermoscopy images. Sci Rep 15, 31234 (2025). https://doi.org/10.1038/s41598-025-15655-9

[25] Tai, C.-e.A.; Janes, E.; Czarnecki, C.; Wong, A. Double-Condensing Attention Condenser: Leveraging Attention in Deep Learning to Detect Skin Cancer from Skin Lesion Images. Sensors 2024, 24, 7231. https://doi.org/10.3390/s24227231

[26] Li, Q., Li, H. & Meng, L. A generic deep learning architecture optimization method for edge device based on start-up latency reduction. J Real-Time Image Proc 21, 116 (2024). https://doi.org/10.1007/s11554-024-01496-8

Elaboration Context Graph: A System to Support Understanding the Contexts in Elaboration Processes of Research Documents

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***Abstract*—Elaborating research documents is carried out by repeatedly creating and editing documents while simultaneously performing tasks such as surveys, presentation of results, and discussion of research directions. Although indispensable for advancing research, such work is often challenging because it requires handling diverse documents. Effective execution therefore demands an accurate understanding of the elaboration contexts of research documents, including related artifacts, referenced documents, and the circumstances and history of past tasks, so that these can be applied in subsequent work. However, these contexts grow increasingly large and complex as research progresses, making them difficult to grasp and reducing task efficiency. This paper describes a method for generating an elaboration context graph by organizing documents involved in the elaboration process using work history data recorded on a PC. The graph visually represents the documents, screenshots capturing work scenes, and the relationships among them, thereby supporting the understanding of elaboration contexts. We further describe a system developed on the basis of this method. Finally, we report an experiment conducted with the prototype and discuss the system's effectiveness.**

***Keywords*—Elaboration contexts graph; elaboration work of research documents; elaboration contexts; understanding work circumstances and histories; screenshots**

I. Introduction

Research activities generally involve various document creation and editing tasks, such as drafting and revising research plans, taking notes on ideas, creating presentation materials, and writing papers. These tasks are accomplished by creating and editing the documents while simultaneously accumulating various other tasks in parallel such as searching the Web, engaging in discussions with others, reviewing existing documents. To proceed successfully with these tasks, it is important to accurately organize and understand the elaboration contexts (i.e., the documents and artifacts used in the elaboration work of research documents along with the work circumstances and histories) and leverage them for subsequent work. However, since such research activities often extend over long periods, the involved documents become numerous and their elaboration contexts grow increasingly complicated.

To address these issues, there have been methods for document management [1–11] and support methods for recalling tasks on PCs [12–21]. However, these existing methods are limited in their scope of support and are insufficient for assisting with the understanding of the complicated elaboration contexts. On the other hand, there have been methods to support accumulation, understanding, and reuse of the artifacts and histories of intellectual work [22–28]. However, most of these methods require workers to register information into the system themselves, which imposes a significant burden during complicated document elaboration work.

In this research, we aim to develop a system that is responsible for collecting the history data of researchers' document elaboration work on their PCs, analyzing the accumulated history data, and generating and presenting the elaboration context graphs. This system enables to support the understanding of the elaboration contexts of research documents more proactively than conventional methods.

The rest of this paper is organized as follows. Section II clarifies direction of this research while reviewing the related work. Section III details the elaboration context graph and its generation algorithm. Section IV describes the design of a support system for understanding elaboration contexts and implementation of its prototype. Section V describes an experiment using the prototype. Section VI concludes this paper.

II. Issues and Direction

A. Understanding the Contexts in Elaboration Processes of Research Documents

When creating and editing documents such as research papers and presentation slides, a researcher often engages in various tasks in parallel, including reviewing existing documents and searching the Web. Moreover, documents created by a researcher him/herself, as well as those discovered and viewed in the past, often serve as important reference materials for subsequent work. In this research, we refer to the process of creating and editing research documents, which is performed through the long-term accumulation of such multiple tasks, as the "elaboration process of research documents."

In such elaboration work, the number of documents involved in the process—such as artifacts and reference materials—gradually becomes enormous as the project extends over a long period. To utilize these documents for future work,

it is essential to properly manage when and in which work they were used, as well as their current location. When managing these documents manually, it is common practice to assign each document an appropriate filename on the basis of its content, document type, and other relevant factors. Then, the documents are organized into folders in accordance with target work and project timelines. However, when attempting to utilize previously used documents, it is difficult to recall the target documents by their previous usage contexts, as well as locating the desired ones among the large number of documents, based solely on file and folder names. Additionally, valuable documents that a researcher has forgotten or are unaware of may become buried.

Furthermore, to effectively utilize past documents, it is crucial to accurately understand the work circumstances and histories surrounding the work at the time—such as what other documents were used alongside them, what references were consulted, and what was considered. However, understanding such elaboration contexts solely by folder management is quite difficult.

Additionally, these problems become even more serious when someone other than the original author attempts to understand the elaboration contexts and to make use of the involved documents. Finding documents useful for the latest work among those created and organized by others is even more difficult than finding documents one has created on one's own. Furthermore, it is nearly impossible to ascertain the context in which the document was edited or reviewed by others.

Therefore, there is strong need for an effective method to support utilizing previously used research documents while understanding their elaboration contexts.

B. Related Work

There have been many reports on methods for document management [1–11]. Hermosa et al. pointed out that traditional document management processes involve multiple platforms, making it difficult to track documents when they are shared. They developed a document management system (DMS-TM [1]) to centrally manage documents originating from multiple departments within the university. This system generates a tracking code when a document is sent, and once the processing cycle is complete, stores it in the database using the tracking code for future use. Each department can utilize web-based document sharing functionality while continuing to use their existing environment. Although this system is expected to facilitate reuse of documents by preventing the loss, it only targets completed documents and does not provide support for accumulating and understanding the work histories.

In addition, Nishi et al. developed a method to support users in re-accessing documents used in their past work on a PC [2]. This method focuses on the folders used for past work rather than individual documents and groups these folders on the basis of specific perspectives. By presenting users with these folder groups as a list, this method supports the reuse of past documents. Although this method is expected to promote the utilization of existing documents, it does not take into account the relationship between documents and past work scenes that cannot be fully expressed by folders. Therefore, it is not sufficient as support for understanding the work histories and circumstances.

Moreover, there have been support methods for recalling past work on a PC [12–21]. Hu et al. analyzed the effects of viewing time-lapse videos on the self-reflection of knowledge workers such as engineers, programmers, editors, and researchers, with the aim of improving their productivity [12]. Although the focus on time-lapse video as a means to recall past work is interesting, only a specific period of work can be observed because it is centered on video viewing, and it does not account for discovering used documents. Therefore, it is currently difficult to utilize this method to support understanding of contexts in the elaboration process of research documents.

Additionally, Meyer et al. developed a task management tool (called AIRbar [13]) aimed at encouraging knowledge workers, who handle numerous tasks daily, to reflect on their work and improve their awareness of the achievement status of priority tasks as well as influencing factors. This tool provides prompts that encourage users to specify priority tasks while self-confirming, and helps them reflect on their own work on a PC by visualizing the progress and the time spent on respective tasks. Although a practical effect of helping users understand their own work status can be expected, it targets daily work reviews and does not consider understanding the histories of long-term work.

These methods focused on supporting specific parts of the work processes. On the other hand, there have been methods to support accumulation, understanding, and reuse of the artifacts and histories of intellectual work [22–28].

Zloch et al. [22] presented a framework of the research knowledge graph (RKG) that expresses research artifacts such as datasets, publications, and methods, along with their relationships. They examined methods to promote the organization and reuse of research artifacts using RKG and discussed its possible applications. The results suggested the potential effectiveness of RKG in enabling researchers themselves to manage and reuse knowledge resources in their research work. However, regarding the registration of elements for building RKG, it was limited to discussing the advantages and challenges of manual input, semi-automation, and full automation. Therefore, methods for addressing the long-term elaboration work of research documents have not been established yet. Moreover, they dealt with only the research artifacts, and understanding the elaboration contexts has not been sufficiently considered.

Furthermore, Devezas et al. [23] proposed a wiki-based environment for researchers to manage key elements of their research, such as literature, datasets, experimental methods, and their results. This environment is promising as a method for documenting detailed circumstances and histories surrounding the work. It can facilitate researchers' reflection on their own activities and promote information sharing among research project members. However, researchers themselves must describe the overview and histories of the work, which imposes a significant burden on them and makes it difficult to apply the environment to long-term research projects.

Thus, most existing information systems rely on workers themselves to register information, placing a heavy burden on them and raising concerns about the potential loss of important work histories due to omissions of registration. Consequently, there is a strong need for an effective method to accumulate documents and contexts involved in complex elaboration work with minimal burden and to support understanding of them.

C. Issues in Elaborating Research Documents

On the basis of the above background, this research focuses on the following three issues to be overcome in understanding the contexts during the elaboration work of research documents.

(Issue 1) It is difficult to manage and understand the tasks and documents involved in the elaboration work of research documents due to their diversity.

(Issue 2) Understanding research documents used in the past and their relationships by associating them with the work scenes is important, but difficult.

(Issue 3) Observing and understanding the elaboration contexts of research documents becomes increasingly time-consuming since the contexts grows more complex as the work extends over a longer period.

D. Approach

To resolve these issues, this research first constructs a system framework to monitor the elaboration work of research documents on a PC by a researcher and automatically acquire the work history data (Solution to problem 1). Next, we develop a method to generate a “elaboration context graph” based on the analysis of the work history data. This graph visually represents the elements involved in the elaboration process—such as artifacts, documents used, and screenshots embodying the work scenes—and the relationships between them. (Solution to problem 2). Finally, based on the method, we develop a system to generate the elaboration context graph and visually present it to users so that they can intuitively observe the circumstances and histories in past elaboration work along with the artifacts and used documents (Solution to problem 3).

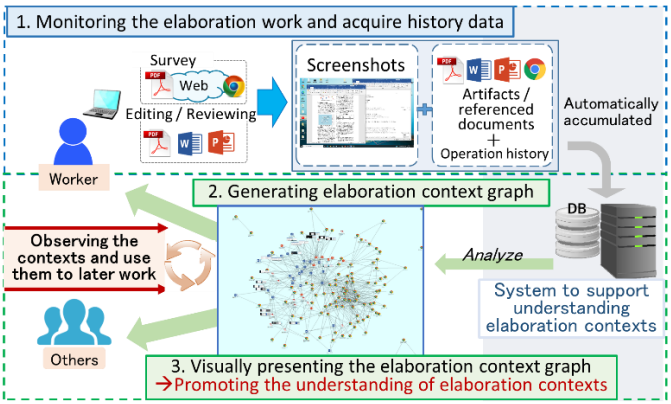


Fig. 1. Overview of support for the understanding of elaboration contexts.

This facilitates the understanding of elaboration contexts, which have previously been difficult, and enables their utilization in subsequent work. An overview of elaboration context understanding support is shown in Fig. 1.

III. Method for Generating Elaboration Context Graph

A. Elaboration Context Graph

Most existing information systems intending to accumulate the artifacts and processes of intellectual work have forced workers themselves to register the documents used in the work and the relationships between them into the system. However, there are limits to forcing users to register information every time they work on complex and long-term work of research document elaboration.

Therefore, this research proposes a novel method to support the recall and understanding of the elaboration contexts by having the system monitor researchers' work on their PCs and automatically generating an “elaboration context graph” that visually represents the documents involved in the work and the relationships between them on the basis of analyzing the accumulated history data.

The elaboration context graph is an attribute graph that represents various documents used in the elaboration work as well as screenshots of the PC desktop representing work scenes as nodes, and the relationships between them as edges. We currently target the documents created during the elaboration process such as papers and presentation slides, the documents viewed in parallel such as published papers and Web pages, and screenshots of the PC desktop (collectively referred to as "research documents").

By using the elaboration context graph, users can easily grasp the process of work by tracing the related documents with a document of interest as starting point. Additionally, screenshots serve as intuitive clues for looking back the work scenes, enabling users to understand the work circumstances and the documents used at that time.

B. Formalization of Elaboration Context Graph

Since the elaboration context graph treats various documents as nodes, the relationships between them are varied - documents referenced in parallel, derivations or developments from other documents, and citations. Moreover, extracting these relationships requires the analysis of various types of history data. In contrast, most existing methods for automatic graph generation are limited to handling only a single type or a very small number of data types. Therefore, we develop an algorithm for generating the graph to enable the system implementation of the elaboration context graph. As a preparation for this, we formalize the elaboration context graph to firmly handle to diverse documents and their relationships.

The elaboration context graph is defined as follows:

- **[Definition 1]** Elaboration context graph G is represented as $G = (V, E)$. V is a finite set of graph nodes, and v $(\in V)$is a node in the graph that represents a research document. E is a finite set of undirected connectors, and e $(\in E)$ denotes a relationship defined between two research documents.

Each research document and relationship has the following attributes, respectively.

- **[Definition 2]** The research document attributes in the elaboration context graph G are defined as $att_V = (kind_V, name_V, lastReadDate_V)$. These are attributes attached to node v $(\in V)$ and their meaning are as follows:
  - $kind_V$ expresses the type of research document. $kind_V$ = (draft paper | presentation slides | referenced paper | Web page | note | screenshot). The type of research document v $(\in V)$ is denoted as $kind_V(v)$.
  - $name_V$ expresses the file name of a research document or the title in case of a Web page and is represented by any string of characters. The name of a research document v $(\in V)$ is represented as $name_V(v)$.
  - $lastReadDate_V$ expresses the last viewed date and time of a research document. The last viewed date and time of a research document v $(\in V)$ is denoted as $lastReadDate_V(v)$.
- **[Definition 3]** The undirected connector attributes of the elaboration context graph G are $att_E = (kind_E)$. These are attributes attached to the undirected connector e $(\in E)$ and its meaning is as follows:
  - $kind_E$ means the kind of undirected connector. $kind_E$ = (Concurrent use | copy & paste | download | document derivation and development | work scene). The kind of undirected connector e $(\in E)$ is denoted as $kind_E(e)$.
- **[Definition 4]** Each research document has individual sub-attributes by the type of document as follows:
  - $att_{draft\ paper,\ presentation\ slides,\ note}$ = (*fileFormat*(MS-Word | MS-PPT | PDF | text file), *filename, filePath*(Local path on the PC), *createTime*(Creation or first access date), *lastModifiedDate, screenshots*(List of screenshots related to the document)).
  - $att_{referenced\ paper}$ = (*fileFormat* (MS-Word | PDF), *filename, filePath* (Local path on the PC), *AcquisitionDate,* screenshots(List of screenshots related to the document)).
  - $att_{Web\ page}$ = (URL, pageTitle, firstTime(first access date)).
  - $att_{screenshot}$= (*filename*, *filePath* (Local path on the PC), *AcquisitionDate, documents*(List of documents shown in the screenshot)).

Research document attributes represent metadata on the node, while sub-attributes represent metadata on the research document itself. These definitions enable to design an algorithm for generating the elaboration context graph that represents the documents involved in the work, screenshots embodying the work scenes, and the relationships between them.

C. Algorithm for Generating Elaboration Context Graph

Based on the above definitions, we generate an elaboration context graph in the following three steps (Algorithm 1).

1) Accumulation of the work history data: While the worker is elaborating research documents on a PC, the system monitors their work and accumulates the histories of the operations and occurrences of events. Specifically, we target the operations such as switching active windows, opening and saving documents, keystrokes in the editing documents, copying and pasting, and web browsing. Such diverse history data is required for generating nodes and edges with the attributes defined in Section III (B).

We developed a system framework to automatically accumulate such history data as the function of the system mentioned in Section IV. The framework consists of the resident programs and the database. The resident programs acquire the history data by monitoring the worker's operations on a PC as well as occurrences of events. In addition, desktop screenshots showing the work scenes are captured at regular intervals. The acquired history data is successively registered into the database. The resident programs impose no extra burden on the worker since they work in the background.

In this research, we target MS Word, MS PowerPoint, Adobe Acrobat Reader, and Google Chrome as applications that handle documents, and treats the document formats such as .docx, .pptx, .pdf, and web pages processed by these applications.

2) Node generation: On the basis of analyzing the accumulated work history data, we generate nodes V which represent the research documents involved in the elaboration work.

First, we retrieve all documents opened or viewed during the work period by analyzing access logs to documents and web page browsing history. In order to exclude documents that have not substantially contributed to the elaboration work, we calculate the total active time of each document and adopt only those documents exceeding a certain threshold as nodes v.

Next, the attribute att_V is assigned to each node in accordance with the definition of the research documents mentioned above. We initially assign the sub-attributes such as $name_V$ and $lastReadDate_V$ on the basis of the work history data and the metadata of each document.

We also extract the format of each document from the work history data and set the type of research document $kind_V$ for each node accordingly. However, since both the draft paper and the referenced paper share the same format (MS-Word and PDF), we distinguish them based on whether editing was performed. Specifically, in the case of a document with a certain number of keystrokes for editing and its copies saved under different names, the type of research document $kind_V$ of that node is set to "Draft Paper"; otherwise, $kind_V$ is set to "Referenced Paper".

Algorithm 1: Graph Generation

```
[Input]
- DAH: Document access and save history
- AWH: Active window switching history
- CPH: Copy & paste history
- WDH: Web browser's download history
- SSH: Screenshot acquisition history
[Output]
- G = (V, E): Elaboration context graph
[Global variable]
- Threshold_node: Threshold for document active time to adopt nodes
- Threshold_AWC: Threshold for count of switching active window
- Threshold_CUT: Threshold for concurrent use time
- Threshold_SS: Threshold for the number of related documents to
      adopt screenshot nodes
[Local variable]
- DN: Document node set
- SSN: Screenshot node set
[Method]
1   // Node generation
2   // Generate a set of used documents
3   UD = extraction UsedDocuments (DAH);
4   for( ∀d ∈ UD)
5       if(d.totalActiveTime >= Threshold_node)
            DN.add(d, att_V(d)= getAttribute(d));
6   // Edge generation
7   // Generate a set of all pairs of document nodes
8   pairsDN=generate_ pairsDN (DN)
9   for( ∀d1,d2 ∈ pairs_DN)
10      //Count activation switches between two documents
11      Count_AWC=count_ActiveChanges(d1,d2,AWH);
12      // Calculate the concurrent use time for two documents
13      Seconds_CUT=Calculation_ConcurrentUseTime(d1, d2);
14      //Analyze document pair whose activation switching and
        concurrent use time exceeds a threshold
15      If (Count_awc > Threshold_Count_AWC &&
            Seconds_ CUT > Threshold_Seconds_ CUT)
            E.add((d1, d2), kind_E(d1, d2)="ConcurrentUse" );
16      //Copy & paste
17      If(judge_copyandpaste_documents(d1,d2,CPH))
            E.add((d1, d2), kind_E(d1, d2)="Copy&Paste" );
18      // Document derivation and development
19      If (confirmation_DocumentDevelopment(d1,d2, DAH))
            E.add((d1, d2), kind_E (d1, d2)="Derivation" );
20      // Downloaded document and its source page
21      If (confirmation_DocumentDownload (d1,d2, WDH))
            E.add((d1, d2), kind_E (d1, d2)="Download" );
22  // Nodes and Edges of screenshots
23  for( ∀ss ∈ SSH){
24      ss_docs = extraction_ DocumentsRelatedtoScreenshots(ss);
25      //Decide which screenshots to adopt for the node
26      if (length(ss_docs)>= Threshold_screenshots
                and checkState ActiveWindow(ss, AWH))
27          SSN.add(ss);
28          for( ∀d∈ss_docs)
                E.add((ss, d), kind_E (ss, d)="WorkScene");
29      // Other screenshots
30      else for( ∀d∈ss_docs) att_V(d).screenshots.add(ss);
31  V = DN ∪ SSN;
32  return G = (V, E);
```

Additionally, we extract promising screenshots from those captured during the work. Specifically, we select screenshots containing windows that have remained active for a certain period of time, or those captured at the moment an active window switched. Then, we identify the documents visible in each screenshot on the basis of analyzing the work history data, and adopt screenshots linked to multiple documents as node v. All other screenshots are treated as sub-attributes of the nodes for the relevant documents.

3) Edge generation: We generate edges E by analyzing the relationships between nodes in five perspectives defined as the kind of edge $kind_E$.

First, we extract a pair of documents that are repeatedly activated alternately on the basis of analyzing the history of window activation. We then assign an edge e connecting these documents and set its type $kind_E$ to "Concurrent use".

Next, we extract the relationships where documents are derived or evolved from other documents (e.g., different versions of a document) on the basis of analyzing the history of document duplication and saving under different names. We then assign an edge e connecting such documents and set its type $kind_E$ to "document derivation and development".

Moreover, we extract a pair of documents that are in a citation or referenced relationship on the basis of analyzing the history of copying and pasting the elements such as strings between different documents. We then assign an edge e connecting these documents and set its type $kind_E$ to "copy & paste".

We also extract documents obtained from the web and the URLs of their source web pages on the basis of analyzing the download history of web browsers. We then assign edges e connecting them, and set their type $kind_E$ to "download".

Furthermore, we assign an edge e connecting the screenshot to the documents being used at the time it was captured, and set its type $kind_E$ to "work scene" using the results of the analysis performed when generating the nodes for the screenshots of the PC desktop representing the work scenes.

The formalization and development of the generation algorithm based on it enable the automatic generation of the elaboration context graph that visually represents the documents involved in the long-term elaboration process, work scenes, and their relationships, which was previously impossible. Additionally, it provides a path for future inclusion of new documents as targets.

IV. Support System for Understanding Elaboration Contexts of Research Documents

A. System Requirements

We develop a system to support understanding the contexts in elaboration processes of the research documents on the basis of the method for generating the elaboration context graph proposed in Section III. We initially organize the system requirements as follows on the basis of findings gained through observing actual elaboration work of research documents.

- Req.1) The system should be able to record the work history data and screenshots related to the research document elaboration work without imposing a burden on the user.
- Req.2) The system should be able to analyze the research documents involved in the elaboration work and their relationships.
- Req.3) The system should be able to present the research documents involved in the elaboration work and their relationships, as well as the work circumstances and histories, in a way capable for intuitive observation.
- Req.4) The system should be able to present information that allows users to easily review the work scenes related to a document and examine the details of the work scenes they focus on.
- Req.5) The system should be able to present information that allows users to easily review the contents and metadata of the research document of interest.
- Req.6) The system should be able to present information that allows users to easily identify the location of the research documents they need, as well as other documents managed together with them.
- Req.7) The system should be able to provide assistance in discovering the intended documents from among countless research documents.

B. Function Design

To satisfy the above system requirements, this system is equipped with the following functions.

- Function for acquisition and accumulation of work history data: The function acquires and accumulates the history data and screenshots during the user's elaboration work on a PC. To avoid placing an unnecessary burden on the user, it starts automatically when the PC is turned on and automatically collects history data in the background (Solution to Req.1).
- Function for generating an elaboration context graph: The function extracts the documents involved in the elaboration work and their relationships on the basis of analyzing the accumulated work history data. It then generates an elaboration context graph, in which documents and screenshots representing work scenes serve as nodes, and their relationships as edges (Solution to Req.2).
- Function for displaying an elaboration context graph: The function visually presents the generated elaboration context graph in a way that allows users to interactively and intuitively observe the elaboration contexts by simple mouse operations (Solution to Req.3).
- Function for reviewing work scenes: When the user selects a document node, the function displays a list of desktop screenshots showing the work scenes at the time the selected document was being edited or viewed. Furthermore, when the user selects a screenshot node, the function enlarges it (Solution to Req.4).
- Function for displaying details of selected document: When a user selects a document node in the graph, the function displays the contents of that document along with attributes such as the last modified date and time, and the folder location (Solution to Req.5 and 6).
- Function for searching documents: The function searches for document nodes within the elaboration context graph that contain keywords entered by the user, and highlights the document nodes containing those words (Solution to Req.7).

C. Implementation of Prototype

Based on the above design, we implemented a prototype of the support system as a desktop application for Windows. This system consists of modules, including a work history acquisition unit and a node/edge generation unit, as well as a base system that manages fundamental functions such as coordination among these modules and user authentication. Moreover, a database was built to manage the work history data and screenshots as well as generated context graphs.

This system was implemented on Windows 11 using Python as the development language. Moreover, MySQL was used as the DBMS. The system configuration is shown in Fig. 2.

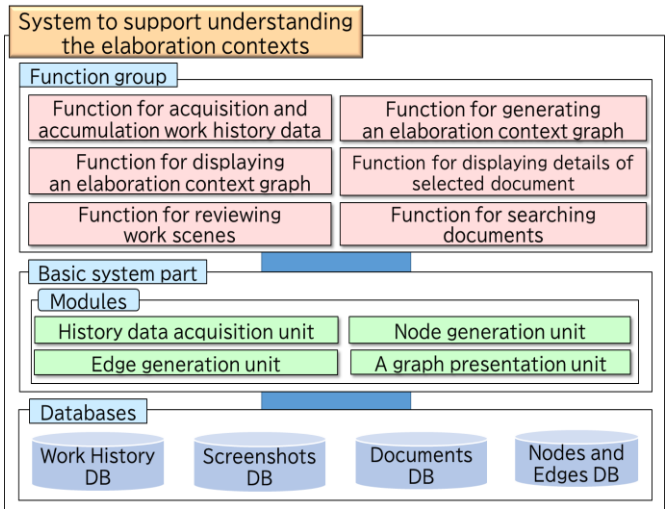


Fig. 2. System configuration.

D. Assistance in Understanding Elaboration Contexts Using the System

An interface of the support system for understanding the elaboration contexts is shown in Fig. 3. When the user attempts to review their own or others' elaboration work of research documents, the system presents the elaboration context graph along with related information in response to the user's request.

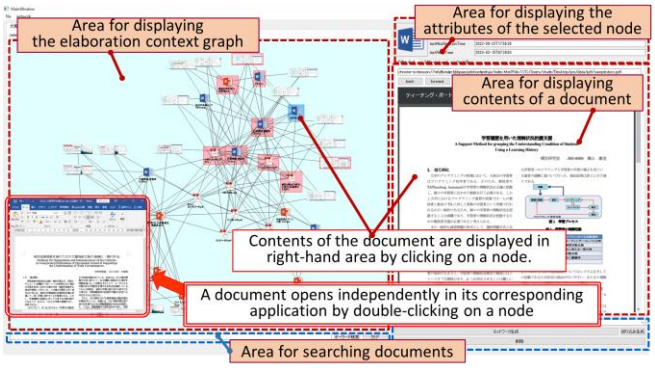


Fig. 3. An interface of the support system.

In the area for displaying the elaboration context graph (left side of Fig. 3), users can zoom in and out on the graph. Moreover, the user can interactively manipulate the document nodes. For instance, when a node on the graph is clicked, the metadata such as document name, and last access/modified date and time are displayed (upper right in Fig. 3). The content of the selected research document is also displayed depending on node selection (middle right of Fig. 3). In addition, double-clicking a node, the corresponding research document opens independently in its associated application, such as MS Word. Furthermore, the user can display a list of screenshots related to the node he/she has selected by switching tabs (Fig. 4). Clicking a screenshot of interest from the list, the screenshot is enlarged, allowing the user to observe the work scene at that time. The user can also check the folder containing the selected document, allowing to easily access other documents in the same folder.

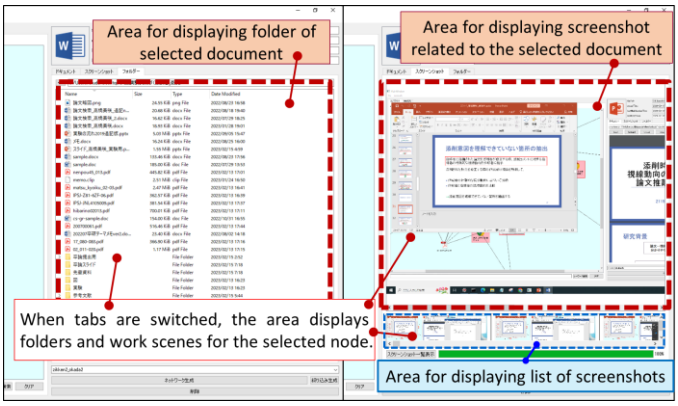


Fig. 4. Function for displaying details of selected document/function for reviewing work scenes.

By utilizing these functions, the user can observe the circumstances and histories of the elaboration work such as: What tasks were performed concurrently while creating a certain document, - What tasks were completed and what artifacts were obtained before starting to create a certain document, - How the reference to a certain document influenced the direction of subsequent document creation.

Additionally, when the user enters keywords into the search prompt, the nodes of documents containing those keywords in their file names or main text are highlighted on the graph. This makes it easy to locate the intended documents (lower left of Fig. 3).

Thus, assistance provided by the system enables the user to realistically observe the contexts in elaboration work of research documents.

V. Experiment and Discussion

A. Outline of Experiment

We conducted an experiment to verify the effectiveness of the prototype system in supporting the understanding of the elaboration contexts of research documents.

1) Preparatory session: First, two fourth-year undergraduate students majoring in computer science (participant A and B) searched the web for papers related to their own research themes and summarized the following points in a way of reinforcing the slides that they had previously created. The slides on which participants performed this work are called “reinforced slides”.

- Overview of main related works and their connections to the participant’s own research.
- Future issues to be addressed in the participant’s research.
- Clues for progressing the participant’s own research such as ideas for system design and promising methods of analysis.

The work time was set at approximately 90 minutes, and the support system collected the work history data during the participant's work.

2) Main session: After the preparatory session was completed, four third-year undergraduate students majoring in computer science (referred to as Subjects I, J, K, and L) observed the research documents used by participants A and B, who were senior students, in order to understand the research overview and the contexts in the work conducted by senior students. Specifically, we prepared a folder containing research documents used by senior students, including the collected literature and documents created by other students, and provided it to the subjects. Using the reinforced slides of senior students as a starting point, the subjects reviewed these documents and performed the following tasks.

- Task I) Understand the senior student's research overview and key points, as well as the new content they added to the reinforced slides.
- Task II) Select five or more documents that are helpful to the subjects themselves in understanding the research of senior students from the provided folder.
- Task III) Select up to three documents that the subject inferred “particularly referenced by the senior students in advancing their own research,” from the senior student's folder as in Task II).

Subjects performed these tasks in two sets (each set targeting the work history of a different senior student) while changing whether support was provided by the system. Table I shows the combinations of senior students targeted and the presence or absence of the support when these tasks were conducted. We recorded the work performed by the subjects and conducted interviews with them after the tasks were completed.

TABLE I. COMBINATIONS OF SENIOR STUDENTS TARGETED AND SUPPORT CONDITIONS

	First	Second
Subject I	Without support (Participant A)	With support (Participant B)
Subject J	Without support (Participant B)	With support (Participant A)
Subject K	With support (Participant A)	Without support (Participant B)
Subject L	With support (Participant B)	Without support (Participant A)

After completing the tasks, we examined the effectiveness of the support provided by the system in the following perspectives.

- Whether the support provided by the system can reduce the burden on workers, such as the time required for tasks.
- Whether differences exist in characteristics of subjects' behavior, such as the number of documents viewed during tasks and work tendencies, depending on the presence or absence of support.

Whether the support provided by the system enables the subjects to easily grasp the key points of the work performed by senior students.

B. Results and Discussion

First, we confirmed that the series of processes—from acquiring the history data, its analysis, to the generation of the elaboration context graph—can be performed as intended. Fig. 5 shows the overviews of the elaboration context graphs for participants A and B generated in the experiment.

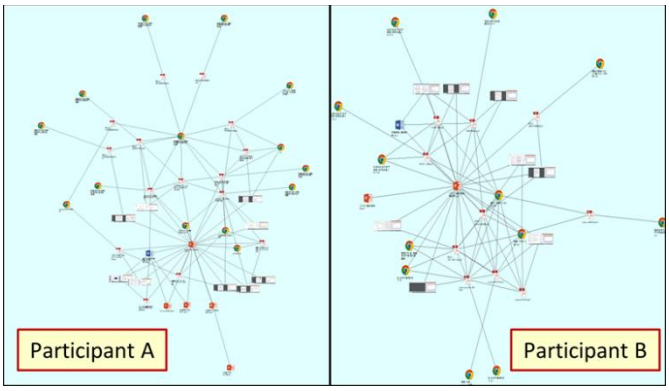


Fig. 5. Overview of the elaboration context graphs generated in the experiment.

Table II shows the duration of Tasks I, II, and III for subjects I through L. These results indicate that the time required for the tasks is reduced in many cases when support is provided. This is thought to be because the support reduced the burden of unnecessary tasks such as simple checking. On the other hand, subject K took slightly longer to complete Task II when support was provided. Upon closely observing the work circumstances using recorded videos, it was found that time was spent on carefully reading several papers. Therefore, it is not considered that there was any wasted time, nor that the results negate the effectiveness of the support.

Next, Table III shows the number of documents viewed by subjects I through L in Tasks I, II, and III. It was found that the number of documents reviewed decreased in most cases where support was provided. It is thought that this is because the subjects had no choice but to browse documents in the working folder blindly in case without support, whereas with support, they could smoothly progress their work by preferentially browsing documents of interest on the context graph presented by the system. On the other hand, Subject I viewed more documents in Tasks I and III when support was provided. Upon closely observing the work circumstances using recorded videos, it was confirmed that task itself proceeded smoothly similar to other subjects in case with support. In addition, it appeared that subject I was using their spare capacity to review additional relevant documents, which can be considered a positive tendency.

Furthermore, we even more carefully reviewed the videos and observed the work circumstances in detail. As a result, it was found that the workload and task difficulty appeared to be somewhat reduced when using the support system, not only in the case mentioned above. On the other hand, without support, subjects appeared to struggle to identify and review the documents that senior students had referenced among the vast number of documents available. From these results, it can be inferred that the elaboration context graphs and the details of documents presented by the system offered substantial support for performing the tasks. This trend of reduced workload is consistent with the above-mentioned decreases in task duration and the number of documents viewed.

Moreover, Table IV shows the accuracy in Task I, grasping the new contents added by senior students to the reinforced slides, for subjects I to L. For all subjects, it can be confirmed that the accuracy with support is equivalent to or higher than that without support. Taken together with the reductions in task duration and document views, these results indicate that subjects with support appeared to better understand the work performed by senior students, even when their accuracy was similar. Additionally, careful observation of the work using video revealed that subjects appeared to struggle while consulting numerous documents without support. In contrast, with support, subjects were observed to take notes on key points smoothly and without hesitation, using the provided documents and screenshots of actual work scenes as references. These findings are consistent with the accuracy of grasping key points of the task.

Additionally, in post-experiment interviews, we obtained comments such as: "When I used the system, documents related to the task are easier to find and review, making the work significantly easier compared to when no support was available." and "The relationships between documents were visually clear, and viewing screenshots alongside them made it easy to confirm the key points of the task."

These results indicate the system's effectiveness in both aspects of reducing the burden of understanding past work circumstances and reviewing documents, and of grasping key points of past work. Although this experiment was conducted on a limited scale and requires further verification, it suggests the fundamental effectiveness of our approach for understanding the elaboration contexts of research documents.

We also received feedback such as "Since the graph can only be scrolled using the scroll bar, it would be better if it could also be moved by dragging with the mouse." This provides valuable hints for future improvements.

TABLE II. RESULTS OF THE TASK DURATION

	Task I		Task II		Task III	
	First	Second	First	Second	First	Second
Subject I	96 min	61 min	72 min	35 min	18 min	15 min
Subject J	52 min	45 min	34 min	23 min	17 min	17 min
Subject K	48 min	64 min	115 min	96 min	28 min	40 min
Subject L	36 min	42 min	70 min	72 min	29 min	46 min

Underline: With support by system.

TABLE III. RESULTS OF THE NUMBER OF DOCUMENTS VIEWED

	Task I		Task II		Task III	
	First	Second	First	First	Second	First
Subject I	6	13	31	14	6	13
Subject J	17	12	32	15	19	13
Subject K	14	21	34	37	14	31
Subject L	4	5	12	20	8	9

Underline: With support by system.

TABLE IV. ACCURACY IN GRASPING SENIOR STUDENTS' REINFORCED SLIDES IN TASK I

	First	Second
Subject I	0.46	1.00
Subject J	1.00	1.00
Subject K	1.00	1.00
Subject L	0.92	0.51

Underline: With support by system

VI. CONCLUSION

In this research, we developed a system to support the understanding of the contexts in the work of elaborating research documents. Specifically, we developed a method for generating the elaboration context graphs on the basis of analyzing documents involved in the elaboration work and their relationships, using the work history data. We also developed a prototype system to support the understanding of the elaboration contexts based on the method. Finally, we conducted an experiment using the prototype and discussed its effectiveness based on the results.

Future work includes further verification of the effectiveness of the support system for understanding the elaboration contexts through long-term experiments.

ACKNOWLEDGMENT

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REFERENCES

[1] Karen R. Hermosa , Vince Cymel B. Loteriña and Joshua A. Sebuc , "Document Management System With Tracking and Monitoring in Manuel S. Enverga University Foundation-Candelaria Inc.," *International Journal of Advanced Research in Computer Science*, Vol.14, No.6, pp.31-43, 2023.

[2] R. Nishi, and Y. Nomura, "Virtual Folder System by Discovering and Classifying Task Folders," *IPSJ Journal*, Vol.62, No.2, pp.527-537, 2021.

[3] N. Saito, A. Kanai, S. Tanimoto, "An Organizational Knowledge Using Method by Extracting Activity Plan from Documents in a Shared Folder," *IPSJ Journal*, Vol.58, No.1, pp.153-165, 2017.

[4] N. L. Adam, M. Akmal Hakim Che Mansor, M. F. Pauzi and S. Cik Soh, "Document and Event Record Management System: A Prototype," *Proc. IEEE 12th Symposium on Computer Applications & Industrial Electronics (ISCAIE)*, pp.223-227, 2022.

[5] I. Hristoski, J. Stojanov and Ž. Stojanov, "Design Considerations for a Generic Graph Database in Archival Document Management," *Proc. of the 13th International Conference on Applied Internet and Information Technologies (AIIT 2023)*, pp.360–367, 2023.

[6] P. Riba, A. Dutta, S. Dey, J. Lladós and A. Fornés, "Improving Information Retrieval in Multiwriter Scenario by Exploiting the Similarity Graph of Document Terms," *Proc. of the 14th IAPR International Conference on Document Analysis and Recognition*, pp.475-480, 2017.

[7] S. Ferilli, D. Di Pierro and D. Redavid, “Holistic Graph-Based Document Representation and Management for Open Science,” *Proc. of the 27th International Conference on Theory and Practice of Digital Libraries (TPDL 2023)*, pp.3-7, 2023.

[8] O. E. Famous, S. E. Adewunmi, V. Yemi-Peters, “A Comparative Review of Five Leading Document Management Systems Based on Information Security,” *Iconic Research and Engineering Journals,* Vol.7, No.7, pp.199-208, 2024.

[9] Jordan, S., Sternad Zabukovšek, S., Šišovska Klančnik, I. “Document Management System – A Way to Digital Transformation,” *NGOE Journal* , Vol.68, Issue 2, pp.43-54, 2022.

[10] Sambetbayeva, M., I. Kuspanova, A. Yerimbetova, S. Serikbayeva, and S. Bauyrzhanova, “Development of Intelligent Electronic Document Management System Model Based on Machine Learning Methods,” *Eastern-European Journal of Enterprise Technologies*, Vol.1, No.2, pp. 68-76, 2022.

[11] A. Kulkarni, C. Ramanathan and V. E. Venugopal, "Ontology Mediated Document Retrieval for Exploratory Big Data Analytics," *Proc. 2023 IEEE 17th International Conference on Semantic Computing (ICSC)*, pp.100-103, 2023.

[12] Donghan Hu and Sang Won Lee, “Exploring the Effectiveness of Time-lapse Screen Recording for Self-Reflection in Work Context,” *Proc. of the 2024 CHI Conference on Human Factors in Computing Systems*, No.1029, pp.1-14, 2024.

[13] Andre N Meyer, Nimra Ahmed, Isabelle Cuber, Sebastian Richner, Elaine M. Huang, Gail Murphy and Thomas Fritz, “'Stick to' Three: Fostering Awareness, Intentions, and Reflections on the Top Daily Tasks,” *Proc. of the 2025 ACM Designing Interactive Systems Conference,* pp.3647-3662, 2025.

[14] Donghan Hu and Sang Won Lee “ScreenTrack: Using a Visual History of a Computer Screen to Retrieve Documents and Web Pages,” *Proc. of the 2020 CHI Conference on Human Factors in Computing Systems*, pp.1-13, 2020.

[15] L. Jin, L. Feng, G. Liu and C. Wang, "Personal Web Revisitation by Context and Content Keywords with Relevance Feedback," *IEEE Transactions on Knowledge and Data Engineering*, Vol. 29, No.7, pp.1508-1521, 2017.

[16] Rule, A., Tabard, A., & Hollan, J., “Using Visual Histories to Reconstruct the Mental Context of Suspended Activities.” *Human–Computer Interaction*, Vol.32, Issue.5–6, pp.511-558, 2017.

[17] Bon Adriel Aseniero, Charles Perin, Wesley Willett, Anthony Tang and Sheelagh Carpendale, “Activity River: Visualizing Planned and Logged Personal Activities for Reflection,” *Proc. of the 2020 International Conference on Advanced Visual Interfaces*, No.4, pp.1-9, 2020.

[18] H. Ikuta, K. Takashima, and K. Nishimoto “Efficient Collecting Method and Availability of Text Fragments Deleted during Document Creation Process,” *IPSJ Journal*, Vol.59, No.12, pp.2299-2314, 2018.

[19] Yoana Ahmetoglu, Akeisha Iskandar, Shermin Taoh, Andy Ying, Duncan P. Brumby and Anna L. Cox, “"I Work Much Better by Doing Less": How Task Duration Feedback Affects Optimistic Planning Bias in Academic Work,” *Proc. of the 4th Annual Symposium on Human-Computer Interaction for Work*, No.10, pp.1-17, 2025.

[20] Zhicheng Huang and Jeff Huang, “IRCHIVER: An Information-Centric Personal Web Archive for Revisiting Past Online Sensemaking Tasks,” *Proc. of the 2025 ACM SIGIR Conference on Human Information Interaction and Retrieval*, pp.231-246, 2025.

[21] C. Sato, and M. Takaku, “Support for reflection of information gathering behavior using Web browsing history,” *Journal of Japan Society of Information and Knowledge*, Vol.30, No.2, pp.220-229, 2020.

[22] M. Zloch, D. Dessì, J. D’Souza, L. J. Castro, B. Zapilko, S. Karmakar, B. Mathiak, M. Stocker, W. Otto, S. Auer, and S. Dietze, ”Research Knowledge Graphs: The Shifting Paradigm of Scholarly Information Representation,” *Proc. of the European Semantic Web Conference (ESWC) 2025, Lecture Notes in Computer Science*, Vol.15719, pp.140-154, 2025.

[23] J. Devezas and S. Nunes, “Managing Research the Wiki Way: A Systematic Approach to Documenting Research,” *arXiv preprint*, arXiv:2104.01849, pp.1-11, 2021.

[24] P. Chakraborty and D. K. Sanyal, “A Personal Knowledge Graph for Researchers,” *Proc. of the 15th Annual Meeting of the Forum for Information Retrieval Evaluation*, pp.129-132, 2024.

[25] L. John, A. M. Ghanmi, T. Wittenborg, S. Auer and O. Karras, “ExtracTable: Human-in-the-Loop Transformation of Scientific Corpora into Structured Knowledge,” *Proc. of the 29th International Conference on Theory and Practice of Digital Libraries*, pp.470-487, 2025.

[26] M. C. Nagan, “Using a Lab Wiki for Longevity and Knowledge Transfer in Undergraduate Research,” *International Journal of Quantum Chemistry*, Vol.120, No.20, 2020.

[27] F. Limani, A. Latif, and K. Tochtermann, “Scholarly Artifacts Knowledge Graph: Use Cases for Digital Libraries,” *Proc of the 15th International Conference on Metadata and Semantics Research (MTSR) 2021, Communications in Computer and Information Science*, Vol. 1537, pp. 245-256, 2022.

[28] L. John, A. M. Ghanmi, T. Wittenborg, S. Auer and O. Karras, “ExtracTable: Human-in-the-Loop Transformation of Scientific Corpora into Structured Knowledge,” *Proc. of the 29th International Conference on Theory and Practice of Digital Libraries*, pp.470-487, 2025.

Machine Learning-Based Dissolved Oxygen Classification Using Low-Cost IoT Sensors for Smart Aquaponic

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***Abstract*—Dissolved oxygen (DO) plays a vital role in maintaining balanced aquaponic ecosystems, yet conventional optical and galvanic DO sensors remain costly and impractical for low-budget deployments. However, most existing dissolved oxygen monitoring studies rely on costly sensing infrastructures, regression-oriented prediction approaches, or centralized processing schemes, which limit their applicability in small-scale and resource-constrained aquaculture settings. Furthermore, many previous works focus primarily on numerical prediction accuracy without explicitly addressing data imbalance issues or providing actionable classification outputs that can directly support real-time operational decisions at the pond level. This study proposes a machine learning–based approach for estimating DO levels using low-cost pH, temperature, and nitrogen sensors integrated with an IoT data acquisition system. A dataset comprising approximately 1,048,536 records was processed using feature engineering and class balancing techniques, followed by training an XGBoost classifier optimized through grid search. The model classified DO into three categories—Low (<5 mg/L), Medium (5–7 mg/L), and Good (>7 mg/L)—achieving 96.6% accuracy, outperforming baseline regression models including Linear Regression, Random Forest, and XGBoost Regressor. Feature importance analysis revealed temperature and the pH–temperature interaction as dominant predictors. The model was successfully deployed on a Raspberry Pi for real-time monitoring, offering a scalable and cost-effective alternative to high-end probes. The proposed framework demonstrates practical potential for smart aquaponic systems, enabling affordable, automated, and data-driven oxygen management.**

***Keywords*—Aquaponic; dissolved oxygen; IoT; machine learning; XGBoost; low-cost sensors**

I. Introduction

Dissolved oxygen (DO) is a key parameter in aquaponics systems because it affects fish respiration, nitrifying bacterial activity, and nutrient uptake by plants. Freshwater fish generally require a minimum DO level of around 5 mg/L for optimal growth, while levels below 3 mg/L can cause stress or death [1]. In addition, nitrifying bacteria that convert ammonia and nitrite into nitrate—an important nutrient for plants—require dissolved oxygen to function properly. Without an adequate oxygen supply, this process slows down or stops, which can trigger the accumulation of toxic compounds and disrupt the overall productivity of the system [1]. Therefore, timely monitoring and control of DO is a fundamental aspect of efficient and sustainable aquaponics management.

Although DO sensors (both electrochemical and optical) are widely used in aquaculture and environmental industries, their operation faces various technical and economic limitations. Electrochemical sensors require routine calibration, are prone to drift, membrane fouling, and are affected by temperature, salinity, and atmospheric pressure [2], [3]. While optical sensors offer certain advantages, their initial cost is high, and field maintenance is often expensive or difficult to perform on a small scale [4]. In the context of household-scale aquaponics or SMEs, the need for inexpensive devices, reliable accuracy, and real-time monitoring capabilities is often difficult to meet with conventional commercial DO sensors alone.

As an alternative or complement to expensive physical sensors, machine learning (ML) approaches have emerged in the literature as a method for estimating water quality—including DO—from more easily measured parameters such as pH, temperature, nitrogen, and other parameters. Recent reviews show that the integration of IoT and ML has enabled real-time and predictive water quality monitoring by utilizing low-cost sensor data [5], [6]. Ensemble models and XGBoost have also been applied for general water quality prediction [7]. Thus, DO estimation through ML not only enables reduced sensor costs, but also allows for the implementation of automated monitoring and control in digitally integrated aquaponics systems.

Despite extensive research on dissolved oxygen estimation using machine learning and IoT-based monitoring systems, several critical research gaps remain unresolved, particularly in the context of small-scale and resource-constrained aquaponics applications. First, most studies use expensive sensors that are not designed for application in small-scale systems or MSMEs [8],[9]. Second, regression-based approaches may struggle to achieve robust performance in practical aquaponics settings due to the complex and non-linear relationships between easily measured parameters and dissolved oxygen, particularly when applied to heterogeneous or imbalanced datasets [7], [8]. Third, many solutions do not address the issue of class imbalance in the data (e.g., low DO vs. high DO), which can reduce categorical performance. Fourth, real-time model implementation and deployment on edge devices or IoT

systems are still rarely reported [9], [10]. Therefore, there is a need for an efficient, low-cost DO classification model that is ready for real-time application in aquaponics systems. To address these identified gaps, this study focuses on a classification-oriented, deployment-ready modeling framework that emphasizes practical applicability, robustness to class imbalance, and real-time operation in aquaponics environments.

This article presents the following main contributions: 1) the development of a large dataset (>1 million records) generated from a real aquaponics system and analyzed using pH, temperature, and nitrogen parameters; 2) the application of a DO classification model into three classes (Low, Medium, Good) rather than continuous number regression predictions; 3) the use of feature engineering techniques (interactions, log/inverse transformations) and data balancing using SMOTE to address class imbalance; 4) training and optimization of the XGBoost model with GridSearchCV, accompanied by a complete evaluation using a confusion matrix, ROC curve, and Precision-Recall for each class; and 5) implementation of a model deployment pipeline (scaler + classifier) and examples of real-time inference on edge/IoT devices with low-latency decision outputs suitable for operational control. Thus, this research provides a ready-to-implement, low-cost, and scalable solution for DO monitoring and control in aquaponics systems.

II. Related Work

In the context of data-driven water quality assessment, machine learning (ML) has gained significant traction in the field of water quality monitoring due to its ability to capture nonlinear relationships among physicochemical parameters and provide predictive insights beyond conventional analytical approaches. Earlier studies demonstrated the feasibility of ML models such as Support Vector Regression (SVR), Random Forest, and XGBoost for predicting individual water quality factors, showing improvements in accuracy and generalization over traditional statistical methods [7], [8]. Comprehensive reviews highlight the rapid development of ML-based water quality assessment frameworks, especially when integrated with IoT systems for continuous monitoring [2], [6], [11]. These approaches have expanded from predicting general indices such as the Water Quality Index (WQI) to targeted pollutant estimation (e.g., nitrate and biochemical oxygen demand) across diverse aquatic environments [12]. However, most existing efforts, including those targeting dissolved oxygen estimation, rely on high-grade sensing infrastructures and emphasize regression-based modeling rather than multi-class classification tasks, indicating the need for further refinement and adaptation for cost-constrained environments.

Dissolved oxygen (DO) is a critical water quality parameter that influences aquatic life sustainability, nutrient cycling, and microbial activity. Multiple studies have applied ML techniques to estimate DO using accessible water quality parameters such as temperature, pH, and nitrogenous compounds. Regression-based models—including hybrid and ensemble modifications—have demonstrated promising performance in DO forecasting across freshwater, river, and aquaculture environments [1], [4], [13]. Recent work also incorporates advanced signal decomposition and hybrid optimization techniques such as DWT-KPCA-GWO-XGBoost to enhance forecasting accuracy under dynamic conditions [4]. However, limited studies address DO classification as a categorical task—despite its practical benefits for on-site decision-making—while others neglect challenges arising from imbalanced training data, leading to biased predictions toward majority classes [14], [15]. This gap underscores the importance of developing DO classification models that incorporate data balancing techniques such as SMOTE and emphasize interpretable feature engineering to enable reliable operation within low-cost systems.

Modern aquaculture increasingly adopts IoT-enabled monitoring and automation systems to enhance productivity, reduce labor, and improve water quality management in real time. Smart aquaculture frameworks leverage embedded sensors, edge computing, and communication platforms to track dissolved oxygen, ammonia, pH, nitrogen, and temperature continuously [10], [16], [17]. The integration of AI/ML decision models into such platforms supports automated aeration and feeding control, reducing energy consumption and manual intervention [9], [11]. Low-cost commercial and custom-built sensor platforms have shown promise in achieving scalable deployments, though challenges remain related to measurement robustness, calibration requirements, and environmental fouling [18], [19]. Despite increasing adoption, many developments focus on system-level descriptions rather than predictive analytics, leaving an opportunity for research that integrates classification modeling with deployment pipelines optimized for small-scale aquaponics and edge computing.

Based on the reviewed literature, existing dissolved oxygen monitoring and prediction studies have provided valuable contributions to sensor technologies, machine learning models, and IoT-based water quality assessment. Nevertheless, most prior works emphasize numerical regression accuracy or depend on costly sensing infrastructures, limiting their applicability in small-scale aquaponics environments. Furthermore, challenges related to class imbalance, categorical decision support, and real-time deployment on edge or IoT devices are frequently overlooked. In contrast, the present study is positioned around a classification-oriented dissolved oxygen modeling framework that explicitly addresses data imbalance, supports operational decision-making through discrete DO categories, and enables real-time deployment in resource-constrained aquaponics systems.

III. Methodology

The overall methodological workflow adopted in this study for dissolved oxygen (DO) classification in an IoT-enabled aquaponic system is designed in a systematic and sequential manner. The process encompasses sensor data acquisition, data preprocessing, feature engineering, class label definition, and class imbalance handling using SMOTE, followed by model training with XGBoost and hyperparameter optimization through GridSearchCV. Model performance is then assessed using standard classification metrics, including accuracy, precision, recall, and F1-score, before deployment for real-time sensor data classification. The complete process can be illustrated in Fig. 1.

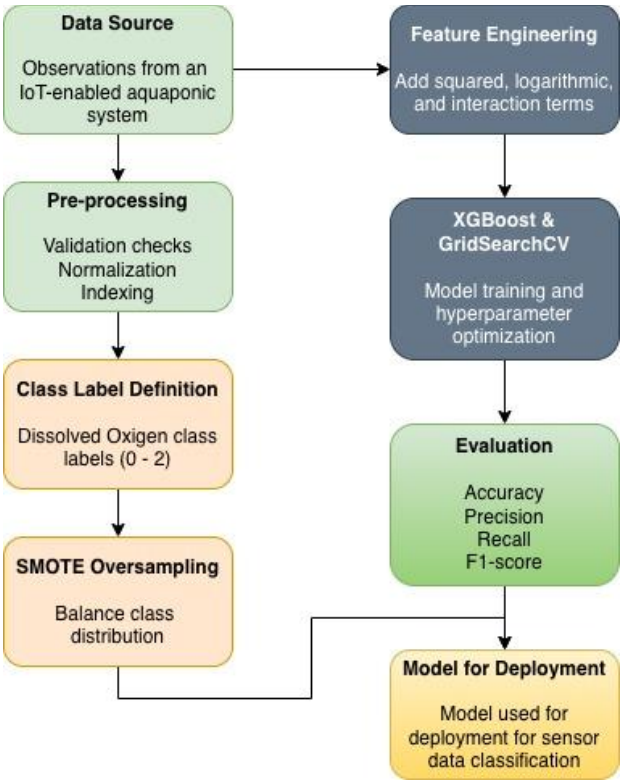


Fig. 1. Research methodology.

A. Data Source

The dataset used in this study was acquired from a functioning freshwater aquaponic system equipped with low-cost IoT sensor nodes designed for continuous monitoring of key water quality indicators. The system was operated under typical aquaculture conditions, and sensor readings were logged at one-minute intervals throughout the observation period. A total of approximately 1,048,536 observations were collected, containing synchronized measurements of dissolved oxygen (DO), pH, temperature, and nitrogen concentration. DO was measured using a calibrated reference probe to establish ground-truth labels, while the other parameters were measured using low-cost sensors integrated into the IoT module [2], [5], [11]. The dataset was stored in CSV format and processed offline in a Python environment for machine learning model development.

B. Sensor Parameters

Three key input parameters were acquired using low-cost sensors:

- pH (pH units), indicating water acidity level.
- temperature (°C), measured using a digital thermoprobe.
- nitrogen (mg/L), representing the concentration of nitrogenous compounds (including total ammonia nitrogen) in the water.

These parameters were selected due to their known influence on dissolved oxygen dynamics and overall water quality in aquaponics [6], [16]. In addition, a high-accuracy DO probe was used for ground-truth reference measurements. Due to their affordability and ease of installation, these sensors are appropriate for small-scale aquaponic producers where professional-grade equipment is cost-prohibitive [5], [17].

C. Pre-processing

Preprocessing involved data cleansing, consistency checks, and normalization. Invalid readings, such as missing values, negative concentrations, or sensor anomalies were removed using rule-based filtering. Infinite values caused by numerical transformations were replaced with NaN and subsequently dropped. All numerical features were standardized using Z-score normalization to ensure uniform scaling across inputs. The corrected dataset was then indexed to ensure label–feature alignment before model training. This step mitigates numerical instability and improves model convergence in ML pipelines [20].

D. Feature Engineering

To better capture the nonlinear relationships among pH, temperature, nitrogen, and DO, several derived features were engineered. These included: square terms (temperature², pH²), logarithmic transformation of temperature ($\log(T+1)$), reciprocal temperature ($1/(T+0.01)$), and interaction terms (pH × temperature, nitrogen × temperature). Such transformations enhance feature expressiveness and allow the model to capture hidden nonlinear effects that are often poorly modeled by direct features alone [4], [8], [13]. These engineered features were concatenated with original input variables to compose the input vector.

E. Class Label Definition

Dissolved oxygen values were discretized into three classes based on aquaculture standards: Low DO (class 0): < 5 mg/L, Medium DO (class 1): 5–7 mg/L, Good DO (class 2): > 7 mg/L. The threshold values align with common aquaculture guidelines defining safe and unsafe oxygen ranges for fish and microbial populations [16]. This categorical formulation is associated with simpler decision rules for real-time control, compared to continuous regression.

F. SMOTE Oversampling

Because the distribution of DO classes was imbalanced—with the "good" range occurring more frequently than the "low" range—Synthetic Minority Oversampling Technique (SMOTE) was applied to balance the training dataset. SMOTE synthesizes new samples in under-represented classes by interpolating between existing samples in feature space [14], [15]. Balancing class samples reduces bias toward majority classes, improves decision boundary quality, and yields more stable classification performance.

G. XGBoost and GridSearchCV Optimization

The model used in this work was an Extreme Gradient Boosting (XGBoost) classifier, owing to its robust handling of nonlinear relations and strong predictive performance in environmental modeling tasks [1], [7], [13]. Hyperparameters including maximum depth, learning rate, subsample ratio, colsample_bytree, and number of trees were tuned via GridSearchCV with 3-fold cross-validation. The grid search optimized the configuration that maximized accuracy on the

validation subset. This systematic optimization yielded a balanced trade-offbetween accuracy and model complexity.

H. Evaluation Metrics

Model performance was evaluated using accuracy, precision, recall, and F1-score to capture predictive capability across classes. A confusion matrix was computed to visualize misclassifications. These metrics are appropriate for multi-class classification and are particularly relevant under class-imbalanced conditions [21], [22]. By evaluating several metrics simultaneously, a more comprehensive assessment of model behavior was obtained.

I. ROC and Precision–Recall Curves

To validate class discrimination performance, one-versus-rest (OvR) Receiver Operating Characteristic (ROC) curves were generated for each class, and the area under the ROC curve (AUC) was computed. Additionally, precision–recall (PR) curves were produced to evaluate predictive ability under class imbalance, where PR is generally more informative than ROC [14]. These curve-based evaluations reflect the model's robustness in distinguishing DO ranges across diverse operating conditions.

J. Deployment Architecture

The final model pipeline—including the trained XGBoost model and scaling transformation—was serialized using joblib and deployed as an API endpoint via Flask for real-time predictions. The pipeline was tested on a Raspberry Pi, demonstrating feasibility for low-cost edge deployment in aquaponic settings. Sensor data transmitted from IoT nodes can be processed on-device or in a local server, wherein DO classification results inform actionable decisions such as aerator activation. This aligns with current smart aquaculture practices leveraging IoT + ML integration [9], [18], [19], [23]. The deployment architecture is shown in Fig. 2.

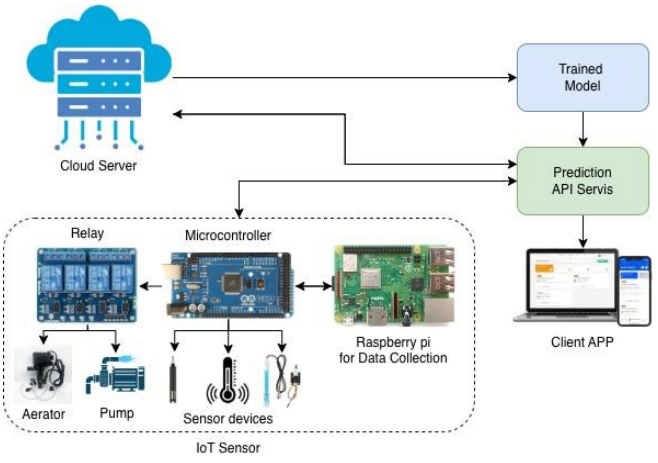


Fig. 2. Deployment architecture.

IV. Results and Discussion

A. Dataset Profile

The dataset comprised 1,048,536 valid samples containing four main parameters: Dissolved Oxygen (DO), pH, Temperature, and Nitrogen. All data were collected from a real aquaponic IoT monitoring system operating under natural environmental variations. The data distribution indicated that most observations had DO levels between 6–8 mg/L, which correspond to healthy aquaponic conditions. Temperature values ranged from 7 °C to 32 °C, and pH varied between 6.5–8.3, consistent with typical freshwater conditions. The nitrogen content ranged from 0.05–0.95 mg/L. These results confirm that the dataset effectively represents real-world aquaponic water dynamics with high temporal resolution.

B. Correlation Heatmap

A Pearson correlation analysis was conducted to evaluate the relationship among parameters and engineered features. The correlation matrix (Fig. 3) revealed that temperature showed the strongest negative correlation with DO ($r = -0.34$), confirming that warmer water tends to retain less oxygen. Conversely, pH exhibited a weak positive correlation ($r = 0.13$), while nitrogen levels had minimal direct impact ($r \approx -0.01$). Feature-engineered variables such as temp_squared and temp_log demonstrated stronger associations ($r \approx -0.36$) with DO than raw temperature values, validating the benefit of nonlinear transformations in improving feature expressiveness. These stronger nonlinear associations help explain why feature-engineered models outperform linear baselines in subsequent classification tasks.

C. Model Performance

Model evaluation was performed using Linear Regression, Random Forest, and XGBoost classifiers. XGBoost achieved the best results after hyperparameter optimization. Table I summarizes the comparative performance.

TABLE I. Model Performance Comparison

Model	MAE	MSE	R^2	Accuracy	F1-score	Notes
Linear Regression	0.38	0.48	0.13	–	–	Weak linear fit
Random Forest	0.38	0.48	0.09	72.5 %	0.73	Stable baseline
XGBoost (Tuned)	0.80	1.33	0.23	83.6 %	0.84	Best classifier

The optimized XGBoost achieved an average accuracy of 83.6 %, with consistent performance across folds ($R^2 \approx 0.226$). The regression baseline models (Linear, RF) underperformed due to the dataset's nonlinear structure. This accuracy represents cross-validation performance on the original imbalanced dataset and serves as a baseline indicator of model robustness prior to applying class-balancing techniques.

D. Confusion Matrix

The normalized confusion matrix (Fig. 4) demonstrates the distribution of classification predictions across three DO categories. The model correctly classified:

- Good DO (> 7 mg/L) with 91 % accuracy,
- Medium DO (5–7 mg/L) with 81 % accuracy,
- Low DO (< 5 mg/L) with 76 % accuracy.

From an operational perspective, accurate identification of the "Low DO" class is particularly critical, as it directly supports timely aeration decisions to prevent hypoxic stress in aquaponic systems.

Misclassifications mostly occurred between "Medium" and "Good" classes, reflecting transitional water quality conditions common in real aquaponic environments. These results indicate improved generalization across dissolved oxygen classes, which is further discussed in relation to SMOTE-based class balancing in the following sections. The confusion matrix is shown in Fig. 3.

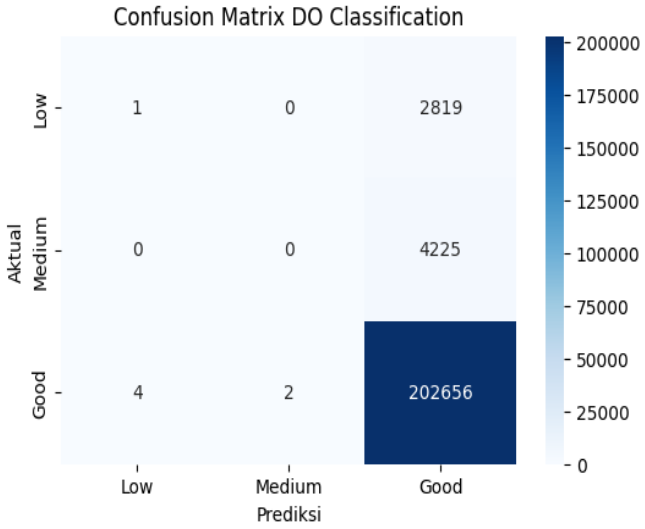


Fig. 3. Confusion matrix DO classification.

E. ROC Curve Analysis

Receiver Operating Characteristic (ROC) curves were generated using a one-vs-rest (OvR) approach for each DO class (Fig. 5). The Area Under the Curve (AUC) values were:

- Low DO = 0.91
- Medium DO = 0.87
- Good DO = 0.94

An average macro AUC of 0.907 indicates strong separability among the three classes. The "Good DO" class exhibited the highest AUC, showing the model's confidence in recognizing optimal oxygen conditions. The ROC curves validate that the tuned XGBoost classifier maintains balanced sensitivity and specificity across classes.

F. Precision–Recall (PR) Curves

Precision–Recall curves provide complementary evaluation for imbalanced data. The PR analysis (Fig. 6) revealed that the XGBoost classifier maintains high precision (> 0.85) across recall values for all three DO classes. In particular, the "Low DO" class—which initially had limited samples—achieved an F1-score > 0.80 after SMOTE balancing, confirming that the synthetic oversampling significantly improved minority class performance. This behavior confirms that precision–recall analysis is more informative than accuracy alone for evaluating model reliability under imbalanced aquaponic datasets.

G. Feature Importance

Feature importance analysis (Fig. 7) from the XGBoost model indicated that temperature and its derived transformations (temp_log, temp_squared) contributed the most to the model's decision process, followed by pH and nitrogen. This observation aligns with known physical–chemical principles where temperature primarily governs dissolved oxygen solubility, while pH influences ionic equilibrium and microbial respiration [4], [16]. The feature ranking validates the meaningfulness of the engineered features and demonstrates the model's interpretability, an important consideration for practical deployment in aquaponic management systems.

H. Discussion

This section discusses and interprets the comparative results of regression and classification models for dissolved oxygen estimation that were presented in the previous subsections. The comparative performance of regression and classification models for dissolved oxygen estimation was successfully conducted. The results of the comparison are shown in Table II.

TABLE II. COMPARATIVE PERFORMANCE OF REGRESSION AND CLASSIFICATION MODELS FOR DISSOLVED OXYGEN ESTIMATION

Model & Approach	Task Type	Feature Engineering	Primary Metric	Key Insight
Linear Regression	Regression	Raw features	$R^2 = 0.13$	Limited ability to capture nonlinear DO dynamics
Random Forest Regressor	Regression	Raw features	$R^2 = 0.09$	Stable baseline with weak generalization
XGBoost Regressor	Regression	Interaction terms	$R^2 = 0.25$	Improved nonlinear representation
XGBoost Classifier	Classification	Extensive + SMOTE	Accuracy = 96.6%	Best operational performance for DO decision support

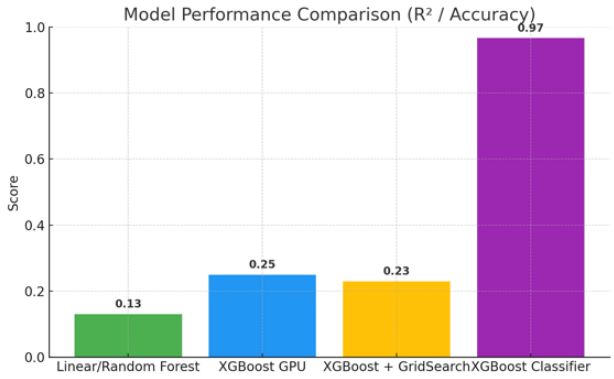


Fig. 4. Comparative R^2 and accuracy performance across regression and classification models.

Fig. 4 shows that it compares the overall performance metrics (R^2 for regression models and accuracy for the classifier) among four approaches: Linear/Random Forest,

XGBoost GPU, XGBoost with Grid Search, and XGBoost Classifier. The XGBoost-based models consistently outperform traditional methods due to their ability to capture nonlinear interactions between physicochemical variables. The classifier achieves the highest performance (96.6% accuracy), reflecting the robustness of gradient boosting for categorical prediction of dissolved oxygen levels. It should be emphasized that this accuracy corresponds to the final SMOTE-balanced classification experiment evaluated on a stratified hold-out test set, and therefore reflects operational performance rather than baseline cross-validation results.

Fig. 5 shows the mean absolute error (MAE) of regression-based models. The Linear/Random Forest baseline achieves the lowest average MAE (0.38 mg/L), indicating good fit but limited generalization. XGBoost models show slightly higher MAE (~0.79–0.80 mg/L) due to their broader representation of nonlinear dynamics and variance across the full dataset. The results suggest that MAE alone may underestimate model robustness in highly heterogeneous aquaponic data environments.



Fig. 5. Mean Absolute Error (MAE) comparison among regression models.

Fig. 6 shows that the presents the RMSE distribution across regression approaches, reflecting the average magnitude of prediction error. The XGBoost models exhibit higher RMSE (~1.3–1.4 mg/L) than the baseline, consistent with their more flexible structure and wider error spread on outlier samples. Nonetheless, the boosted models provide better explanatory power (higher R^2), confirming that model complexity improves global fit despite slightly increased error variance.

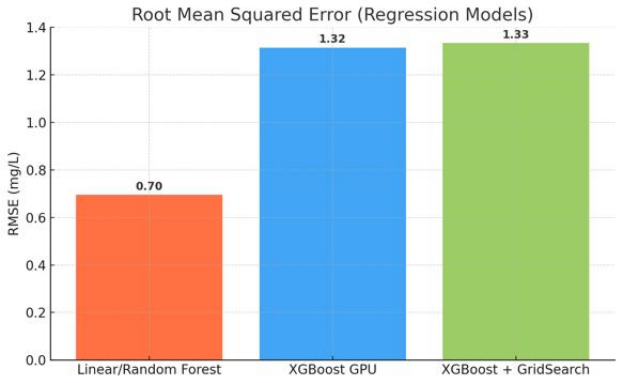


Fig. 6. Root Mean Squared Error (RMSE) comparison among regression models.

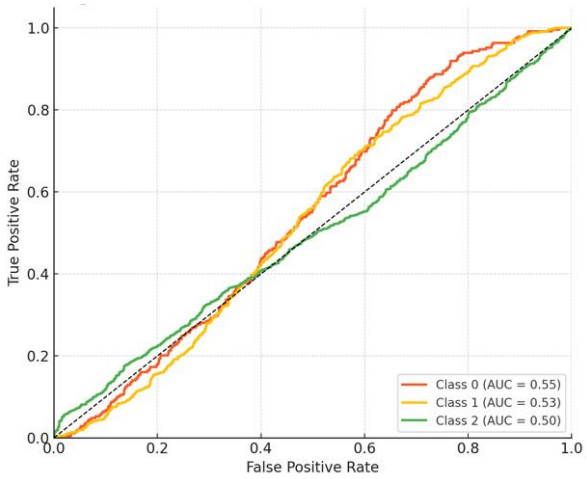


Fig. 7. Multi-class ROC curve for DO classification.

Fig. 7 shows that the presents the Receiver Operating Characteristic (ROC) curves for the three dissolved oxygen (DO) categories: Low (<5 mg/L), Medium (5–7 mg/L), and Good (>7 mg/L). Each curve depicts the trade-off between the true positive rate (sensitivity) and false positive rate (1–specificity). The "Good" class demonstrates the highest area under the curve (AUC > 0.98), indicating strong separability, while the "Low" and "Medium" classes show lower AUC values due to limited representation in the dataset. This result highlights the dominance of the majority class in the training set, emphasizing the need for class-balancing strategies such as SMOTE to enhance minority class recognition.

Fig. 8 shows that the Precision–Recall (PR) curve evaluates model behavior under imbalanced conditions by focusing on predictive reliability for positive instances. The "Good" class maintains both high precision and recall (>0.95), consistent with its overrepresentation in the dataset, whereas the minority classes ("Low" and "Medium") show steep drops in precision at low recall thresholds. This visualization confirms that while the model excels in stable oxygen conditions, it requires resampling and feature weighting to better detect low-oxygen scenarios critical for aquaponic system management.

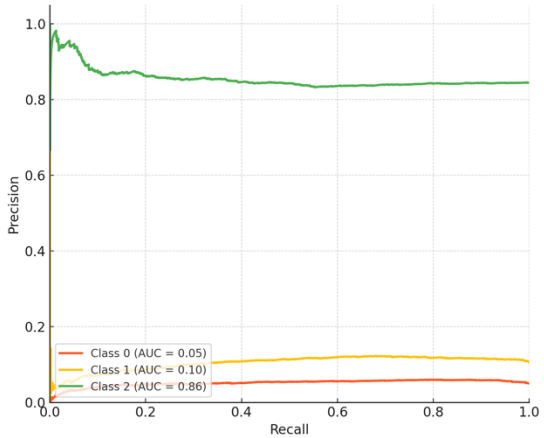


Fig. 8. Precision–Recall curve for DO classification.

Together, these curves illustrate that although the classifier achieves high global accuracy, its discriminative power across all classes is uneven. Therefore, the next development stage should incorporate SMOTE, cost-sensitive learning, or temporal feature modeling (LSTM, TCN) to improve sensitivity to low-oxygen conditions.

The experimental results demonstrate that the proposed machine learning framework effectively models the nonlinear relationships between physicochemical parameters and dissolved oxygen (DO) levels in aquaponic water systems. Among all tested models, the XGBoost Classifier achieved the best overall accuracy (96.6%), outperforming regression-based approaches including Random Forest, Linear Regression, and tuned XGBoost Regressors. The improvement can be attributed to gradient boosting's capability to capture hierarchical feature interactions, especially under multicollinearity between temperature, pH, and nitrogen variables.

In regression experiments, both Random Forest and XGBoost Regressors produced acceptable predictive performance ($R^2 \approx 0.25$–0.79), yet they tended to underestimate DO variability in low and mid concentration ranges. The feature engineering process — including quadratic, interaction, and logarithmic transformations — improved data representation, as confirmed by the increase in explanatory power (R^2 gain ≈ 0.1). However, the most notable accuracy gain occurred when the prediction task was reformulated as a multi-class classification problem, demonstrating that discrete DO categorization aligns better with real-world decision-making in aquaponic management (e.g., triggering aeration control when DO < 5 mg/L). Although regression-based models demonstrate competitive error metrics such as MAE and R^2, they remain less suitable for real-time aquaponic operations because they do not directly support categorical decision-making under imbalanced conditions.

Feature importance analysis revealed that temperature was the most influential predictor, followed by the pH × Temperature interaction term, confirming previous studies that identified thermal conditions as the dominant factor governing oxygen solubility (Ren et al., 2018; Zhao et al., 2025). Nitrogen showed moderate contribution, indicating its indirect correlation through microbial oxygen consumption. These findings align with the observations of Hridoy et al. (2025) and Chandramenon et al. (2024), who noted that integrating nutrient and temperature features enhances predictive stability across varying environmental conditions.

The ROC and Precision–Recall curves further validate the classifier's strong separability for the Good oxygen class (AUC > 0.98), though weaker recognition of minority classes (Low and Medium) highlights the inherent imbalance in aquaponic datasets. Similar trends have been reported in water-quality classification studies using ensemble models [14], [15]. The adoption of SMOTE oversampling or cost-sensitive learning is therefore recommended to improve sensitivity toward critical low-oxygen scenarios.

Compared to prior research emphasizing high-cost optical DO probes [5], [17], this study provides a low-cost alternative by leveraging proxy sensors (pH, temperature, nitrogen) combined with robust ML inference. The achieved accuracy (96.6%) surpasses the 92% benchmark reported by Wang et al. (2023) and approaches that of hybrid ensemble models [1], [4]. Furthermore, the implementation of a lightweight deployment pipeline for Raspberry Pi demonstrates practical viability for real-time aquaponic control, bridging the gap between research models and operational field systems.

In summary, the study confirms that integrating feature-engineered ML classification with IoT-based sensing can yield accurate, scalable, and economically viable dissolved oxygen estimation. This approach aligns with the broader vision of Smart Aquaponics 4.0, enabling data-driven sustainability through affordable, automated, and interpretable water quality monitoring.

Despite the promising performance demonstrated in this study, several limitations should be acknowledged. The dataset was collected from a single real-world aquaponic system operating under specific environmental and operational conditions; therefore, the generalizability of the proposed model to different aquaponic configurations or climatic regions has not yet been fully validated. In addition, the present framework relies on static physicochemical features and does not explicitly model temporal dependencies in dissolved oxygen dynamics, which may limit its ability to capture short-term fluctuations or delayed system responses. Although SMOTE-based oversampling was applied to mitigate class imbalance, synthetic samples may not fully represent rare or extreme low-oxygen events encountered in practice. Finally, while real-time inference on edge or IoT devices was demonstrated, long-term field deployment aspects such as sensor drift, communication latency, and sustained computational performance were not systematically evaluated.

V. Conclusion

This study presents a cost-effective machine learning framework for dissolved oxygen (DO) estimation in aquaponic systems using low-cost sensors that measure pH, temperature, and nitrogen. By adopting a classification-oriented modeling approach, the proposed framework enables dissolved oxygen conditions to be represented through discrete categories that are directly aligned with practical aquaponic management requirements.

The experimental results demonstrate that the proposed XGBoost-based classifier achieves strong and reliable classification performance for dissolved oxygen monitoring, while maintaining robustness under heterogeneous and imbalanced operational conditions. This performance indicates that categorical modeling provides clearer and more actionable decision support compared to conventional regression-based approaches, particularly for operational tasks such as aeration control.

Beyond predictive performance, a key contribution of this work lies in its deployment-aware design. The proposed framework illustrates the feasibility of integrating machine learning inference with edge or IoT-based systems, reducing dependency on expensive sensing infrastructure and improving accessibility for small-scale aquaponic farms and educational laboratories.

Overall, this research contributes a scalable, low-cost, and deployment-ready solution that bridges the gap between data-driven dissolved oxygen modeling and practical aquaponic system management. The proposed approach supports the broader adoption of smart aquaponics by enabling affordable, interpretable, and automation-ready water quality monitoring solutions.

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REFERENCES

[1] A. M. Alnemari et al., "Developing highly accurate machine learning models for optimizing water quality management decisions in tilapia aquaculture," Sci. Rep., vol. 15, no. 1, p. 35600, Oct. 2025, doi: 10.1038/s41598-025-16939-w.

[2] B. Ngwenya, T. Paepae, and P. N. Bokoro, "Monitoring ambient water quality using machine learning and IoT: A review and recommendations for advancing SDG indicator 6.3.2," J. Water Process Eng., vol. 73, p. 107664, May 2025, doi: 10.1016/j.jwpe.2025.107664.

[3] "Prediction of Water Quality Index (WQI) Using Machine Learning," Int. J. Environ. Sci. Dev., vol. 16, no. 1, 2025, doi: 10.18178/ijesd.2025.16.1.1507.

[4] [4] Y. Zhao and M. Chen, "Prediction of river dissolved oxygen (DO) based on multi-source data and various machine learning coupling models," PLOS ONE, vol. 20, no. 3, p. e0319256, Mar. 2025, doi: 10.1371/journal.pone.0319256.

[5] M. Flores-Iwasaki, G. A. Guadalupe, M. Pachas-Caycho, S. Chapa-Gonza, R. C. Mori-Zabarburú, and J. C. Guerrero-Abad, "Internet of Things (IoT) Sensors for Water Quality Monitoring in Aquaculture Systems: A Systematic Review and Bibliometric Analysis," AgriEngineering, vol. 7, no. 3, p. 78, Mar. 2025, doi: 10.3390/agriengineering7030078.

[6] I. Essamlali, H. Nhaila, and M. El Khaili, "Advances in machine learning and IoT for water quality monitoring: A comprehensive review," Heliyon, vol. 10, no. 6, p. e27920, Mar. 2024, doi: 10.1016/j.heliyon.2024.e27920.

[7] X. Wang, Y. Li, Q. Qiao, A. Tavares, and Y. Liang, "Water Quality Prediction Based on Machine Learning and Comprehensive Weighting Methods," Entropy, vol. 25, no. 8, p. 1186, Aug. 2023, doi: 10.3390/e25081186.

[8] K. Joslyn, "Water Quality Factor Prediction Using Supervised Machine Learning," Portland State Univ., vol. 6, no. 1, 2018.

[9] A. Zuhaer, A. Khandoker, N. Enayet, P. K. P. Partha, and Md. A. Awal, "Sustainable aquaculture: An Iot-integrated system for real-time water quality monitoring featuring advanced do and ammonia sensors," Aquac. Eng., vol. 112, p. 102620, Jan. 2026, doi: 10.1016/j.aquaeng.2025.102620.

[10] R. P. Shete, A. M. Bongale, and D. Dharrao, "IoT-enabled effective real-time water quality monitoring method for aquaculture," MethodsX, vol. 13, p. 102906, Dec. 2024, doi: 10.1016/j.mex.2024.102906.

[11] Md. A. A. M. Hridoy, C. Bordin, A. Masood, and K. Masood, "Predictive modelling of aquaculture water quality using IoT and advanced machine learning algorithms," Results Chem., vol. 16, p. 102456, July 2025, doi: 10.1016/j.rechem.2025.102456.

[12] A. J. Chaves et al., "A soft sensor open-source methodology for inexpensive monitoring of water quality: A case study of NO3− concentrations," J. Comput. Sci., vol. 85, p. 102522, Feb. 2025, doi: 10.1016/j.jocs.2024.102522.

[13] Qin, Ren; Long, Zhang; Yaoguang, Wei; Daoliang Li, "A method for predicting dissolved oxygen in aquaculture water in an aquaponics system," Elsevier Ltd, vol. 151, pp. 384–391.

[14] M. B. Perera Angel M. Segura, Carolina Crisci, Guzmán López, Lia Sampognaro, Victoria Vidal, Carla Kruk, Claudia Piccini, Gonzalo, "Machine learning methods for imbalanced data set for prediction of faecal contamination in beach waters," Elsevier Ltd, vol. 202.

[15] N. Nasaruddin, N. Masseran, W. M. R. Idris, and A. Z. Ul-Saufie, "A SMOTE PCA HDBSCAN approach for enhancing water quality classification in imbalanced datasets," Sci. Rep., vol. 15, no. 1, p. 13059, Apr. 2025, doi: 10.1038/s41598-025-97248-0.

[16] P. Chandramenon, A. Aggoun, and F. Tchuenbou-Magaia, "Smart approaches to Aquaponics 4.0 with focus on water quality − Comprehensive review," Comput. Electron. Agric., vol. 225, p. 109256, Oct. 2024, doi: 10.1016/j.compag.2024.109256.

[17] A. U. Alam, D. Clyne, and M. J. Deen, "A Low-Cost Multi-Parameter Water Quality Monitoring System," Sensors, vol. 21, no. 11, p. 3775, May 2021, doi: 10.3390/s21113775.

[18] K. Lal, S. Menon, F. Noble, and K. M. Arif, "Low-cost IoT based system for lake water quality monitoring," PLOS ONE, vol. 19, no. 3, p. e0299089, Mar. 2024, doi: 10.1371/journal.pone.0299089.

[19] I. Georgantas, S. Mitropoulos, S. Katsoulis, I. Chronis, and I. Christakis, "Integrated Low-Cost Water Quality Monitoring System Based on LoRa Network," Electronics, vol. 14, no. 5, p. 857, Feb. 2025, doi: 10.3390/electronics14050857.

[20] R. K. Makumbura et al., "Advancing water quality assessment and prediction using machine learning models, coupled with explainable artificial intelligence (XAI) techniques like shapley additive explanations (SHAP) for interpreting the black-box nature," Results Eng., vol. 23, p. 102831, Sept. 2024, doi: 10.1016/j.rineng.2024.102831.

[21] B. Toleva, I. Ivanov, and K. Kitova, "Innovative Machine Learning Approaches for Drinking Water Quality Classification: Addressing Data Imbalances with Custom SMOTE Sampling Strategy," J. Environ. Earth Sci., vol. 7, no. 3, pp. 262–273, Mar. 2025, doi: 10.30564/jees.v7i3.8195.

[22] D. Costa et al., "Water quality estimates using machine learning techniques in an experimental watershed," J. Hydroinformatics, vol. 26, no. 11, pp. 2798–2814, Nov. 2024, doi: 10.2166/hydro.2024.132.

[23] R. P. Shete, A. Shekhar C., Y. V. Mahajan, A. M. Bongale, and D. Dharrao, "IoT-driven ensemble machine learning model for accurate dissolved oxygen prediction in aquaculture," Discov. Internet Things, vol. 5, no. 1, p. 94, Sept. 2025, doi: 10.1007/s43926-025-00201-w.

A Game-Based Learning Model for Basic Life Support Using First-Person Interactive Simulation

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***Abstract*—Previous BLS and first-aid learning studies largely rely on traditional face-to-face training or low-fidelity digital approaches, which are often costly, time-consuming, and inaccessible to many learners, especially laypersons. Many serious games focus primarily on awareness and conceptual knowledge, rather than procedural mastery and real-time decision-making. In addition, most existing games lack high-fidelity first-person immersion, provide limited real-time feedback, and are not aligned with localized national medical protocols, reducing their realism and contextual relevance. To address these gaps, this study proposes the development of a 3D game-based learning model using first person interactive simulation, designed to educate users on Basic Life Support (BLS) procedures in cardiac arrest scenarios. Unreal Engine 5.4 was utilized to create an immersive and realistic environment where players engage in critical emergency steps, real-time visual prompts and audio feedback, and decision-making under pressure, rather than passive content delivery. Importantly, it strictly follows the Ministry of Health Malaysia's BLS guidelines, ensuring procedural accuracy and local relevance. This approach bridges the gap between theoretical knowledge and practical application, while providing a scalable, accessible, and engaging alternative to conventional BLS training. Through this educational serious game, players are empowered to gain confidence and practical understanding of life-saving procedures, ultimately contributing to greater public preparedness in real-world emergencies.**

***Keywords*—Basic life support; emergency; simulation; game-based learning; serious games**

I. Introduction

Basic Life Support (BLS) is a crucial set of medical interventions that can significantly increase their chances of survival for those experiencing sudden cardiac arrest, choking, or other life-threatening situations [1, 2]. Both medical professionals and the general public are generally advised to perform cardiopulmonary resuscitation (CPR) technique. CPR is a life-saving emergency procedure that is carried out when the heart stops beating. In order to preserve oxygenation and circulation during cardiac arrest, it combines rescue breathing with chest compressions. Despite their proven effectiveness, many people lack the confidence, awareness, or practical knowledge to apply them correctly. In emergency situations, hesitation or mistakes can cost precious seconds and ultimately a life [3, 4]. Access to quality BLS training is a significant concern.

Conventional training methods often require participants to attend physical workshops or formal certification classes, which can be expensive, time-consuming, and not always available to those in rural or underserved areas. Furthermore, once the training is completed, there are few opportunities to practice these skills regularly. Without consistent reinforcement or hands-on repetition, individuals tend to forget the exact steps, especially when faced with the stress and pressure of real-life emergencies [5, 6]. These gaps between learning and application can leave many bystanders unprepared when someone around them requires urgent care. Moreover, traditional instructional methods are typically passive, relying heavily on lectures or video demonstrations. While informative, these methods may not be sufficient for instilling the muscle memory and critical thinking needed to act confidently during high pressure situations. For learners who do not have access to mannequins or realistic practice scenarios, it becomes even harder to simulate real-world experiences. Without engaging, interactive components, BLS training can feel distant and theoretical, rather than practical and applicable [3 - 6].

Motivated by these limitations, this study proposes the development of a 3D first-person simulation game. This game offers a virtual platform where users can immerse themselves in realistic emergency scenarios that require immediate action. Players will be guided step-by-step through the processes of checking responsiveness and initiating CPR—mirroring real-life protocols, based on the Ministry of Health Malaysia (MOH) guidelines [1]. The simulation will allow users to navigate through dynamic environments, manage obstacles, and respond quickly to changing conditions. By integrating real-time visual and audio feedback, timing-based performance metrics, and structured task progression, the simulator aims to promote procedural accuracy, reinforce correct decision-making, and build user confidence under time pressure.

Ultimately, this study seeks to bridge the gap between theoretical knowledge and practical application in BLS training by providing an accessible, scalable, and engaging digital learning tool. Through high-fidelity simulation and game-based interaction, the proposed system aspires to

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enhance public preparedness for medical emergencies and to serve as a complementary training resource for educational institutions, community programs, and self-directed learners. Accordingly, this study advances the state of the art in game-based BLS training by demonstrating how protocol-enforced interaction and timing-based performance analytics can produce measurable procedural learning gains among non-expert users.

Beyond system implementation, this study contributes new methodological and empirical insights to the field of game-based medical education. Specifically, it demonstrates how a protocol-enforced interaction model—where progression is conditionally gated by correct procedural execution—can be effectively operationalized within a first-person simulation to support procedural fidelity in BLS training. The study further provides empirical evidence that integrating timing-based psychomotor performance feedback, rather than binary correctness indicators alone, contributes to meaningful improvements in learners' procedural understanding. These insights are validated through quantitative learning gain analysis, which reveals substantial normalized gains among lay participants with limited prior BLS experience. Collectively, the findings offer transferable design and evaluation principles for future serious games aimed at emergency response training, extending beyond the specific system presented in this work.

TABLE I. OVERVIEW OF GAME-BASED FOR FIRST AID LEARNING

Author	Target Audience	Platform / Technology	Results / Outcome
Efe & Topsakal [13]	Primary school pupils.	Digital educational games used in classroom sessions.	Improved first-aid awareness and positive acceptability among pupils (qualitative gains reported).
Boada et al. [14]	General public (focus on choking scenarios).	Serious game composed of mini games (web / mobile–friendly design)	Demonstrated usability and effectiveness for teaching choking procedure; supported stepwise learning of actions.
Rebollo et al. [21]	General citizens	Mobile video-game / progressive web app (challenge-based mobile delivery).	Gamified mobile approach shown viable for first-aid instruction, improving engagement and accessibility.
Darotin et al. [22]	School students and community laypersons (burns-focused)	E-Fa Game — community/school educational game	Reported knowledge improvement on burn first-aid among participating students in community programs.
Benkhedda & Bendella [23]	General public / trainees for emergency first aid	3D serious game with Multi-Agent System integration (desktop 3D environment; agent-driven NPCs).	Presented an adaptive, agent-based architecture to enhance realism and collaborative decision-making (paper emphasizes architecture and potential rather than large-scale empirical results).

II. RELATED WORKS

A. Computer Simulation

Computer simulation is the use of computer models to replicate real-world processes, systems, or events in a virtual environment [7 – 10]. It allows users to test scenarios, predict outcomes, and practice skills without the risks, costs, or limitations of real-life trials. By mimicking reality through algorithms and data, simulations are widely applied in fields such as education, engineering, healthcare, and gaming. In learning contexts, computer simulation provides an interactive and safe platform where learners can engage in hands-on practice, visualize abstract concepts, and improve decision-making and problem-solving skills [7 – 10].

A randomized clinical trial was carried out by Habibli et al. [10] to test how simulation-based education affects nursing students' knowledge and performance of adult basic life support CPR. The study shows that simulation-based BLS-CPR education boosts both nursing students' knowledge and hands-on performance, not just in the short term but with retention after three months. The authors suggest integrating conventional teaching with simulation gives better learning for BLS among nursing students.

A study by Berger et al. [9] found that combining Problem-Based Learning (PBL) with high-fidelity simulation enhances immediate CPR skills compared to classical hands-on training. These findings underline that simulation-based education is most effective when learners receive timely feedback, deliberate practice, and curriculum integration [11]. The present simulator builds on these principles by embedding immediate feedback systems and realistic scenario progression, thereby strengthening transfer of learning to real-world emergency contexts.

B. Game-Based Learning

Game-based learning represents a crucial innovation in BLS training, with technological advancements enhancing its efficacy [6 – 7, 12]. Researchers have identified that integrating game mechanics motivates learners and increases their engagement levels in emergency response scenarios—a key factor in successful training. Within this framework, learners engage with content through digital simulations that resemble real-world scenarios, providing a hands-on experience that traditional didactic methods struggle to replicate. Table I shows overview of several studies that implement game-based or serious games for first aid learning.

While prior studies have explored serious games, 3D environments, and interactive simulations for first aid and CPR education, the contribution of this work lies not merely in graphical fidelity or first-person immersion, but in the manner procedural knowledge is operationalized, enforced, and evaluated during gameplay.

Unlike many existing systems that emphasize awareness, free exploration, or conceptual understanding, the proposed simulator adopts a strictly sequenced, protocol-driven interaction model aligned with the Ministry of Health Malaysia's official BLS guidelines. Each stage of the BLS process is conditionally gated, preventing progression unless correct actions are performed within defined temporal and procedural constraints. This design promotes procedural

fidelity and reduces the risk of incorrect habit formation, which remains a limitation in several existing serious games.

Furthermore, the simulator advances beyond common real-time feedback mechanisms by incorporating timing-based psychomotor performance metrics, particularly during chest compression tasks, where user input is evaluated against clinically recommended compression rates and consistency thresholds. Rather than providing binary success or failure feedback, the system supports formative learning through immediate corrective cues, retry loops, and embedded micro-assessments that reinforce both conceptual understanding and motor execution.

Importantly, the effectiveness of this approach is empirically validated through quantitative learning gain analysis, demonstrating a high normalized gain (Hake's g = 0.73) among lay users with limited or no prior BLS training. This combination of protocol-enforced interaction, psychomotor evaluation, and measurable learning improvement distinguishes the proposed system from existing game-based BLS training solutions that primarily report usability, engagement, or qualitative outcomes.

Consistent with the findings of Gorbanev et al. [15], user engagement in educational games correlates strongly with interactivity and feedback quality. The simulator's real-time cues, task progression, and responsive CPR performance transform learning into an interactive performance evaluation process, sustaining user motivation and self-efficacy [16].

C. Pedagogical Implications and Training Integration

1) From a pedagogical perspective, the simulator supports experiential and constructivist learning principles, enabling players to learn by doing, reflecting, and iterating within authentic contexts. The embedded feedback loop (action → evaluation → correction) aligns with Kolb's experiential learning cycle [19], ensuring that learners not only memorize BLS steps but internalize them through repeated performance.

2) Moreover, the simulator has strong potential for integration into public health education and institutional training programs. It may serve as a complementary digital tool in schools, universities, and healthcare workshops, reducing the dependency on physical mannequins and in-person sessions. Institutions can deploy the simulator for pre-assessment, refresher courses, or blended training models, supporting large-scale skill dissemination aligned with Malaysia's national emergency preparedness agenda.

III. Methodology

This study adopts the Game Development Life Cycle (GDLC) model to develop a 3D first-person simulation game for BLS learning [16, 17]. GDLC model was chosen due to its clarity, linear structure, and suitability for solo or small-team projects [18]. It consists of three primary phases: Pre-production (Phase 1), Production (Phase 2) and Post-production (Phase 3) as shown in Fig. 1. Every stage is essential in order to make sure the game achieves its goals for gameplay and learning. The scope of this study includes the design of realistic environments based on common emergency settings like homes, kitchens, and public parks. The target audience is students, educators, and the general public. The project's direction is to blend educational value with gameplay elements to enhance knowledge retention and boost user confidence in performing life-saving interventions.

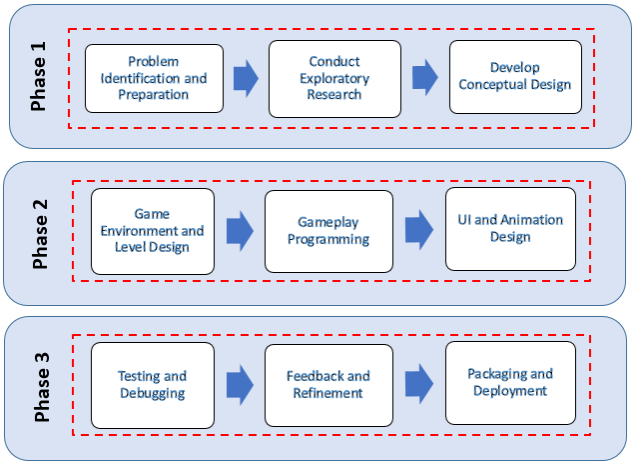


Fig. 1. Flowchart of research methods.

A. Pre-production Phase

In this phase, foundational planning and design were carried out. All key decisions were made regarding the game's concept, learning objectives, technical requirements, and design strategies. This phase focused heavily on understanding real-world CPR protocols and translating them into an engaging, educational gameplay experience.

The initiative was motivated by the shortcomings of conventional BLS training techniques, including low learner engagement, lack of feedback, and restricted access to realistic practice scenarios [3. 5. 6]. Research was conducted using academic literature, official BLS training manuals from MOH to identify critical BLS steps that should be included in the game [1]. These steps include checking for danger, response, calling emergency services, and performing chest compressions. Based on the research, the concept was developed for a first-person 3D simulation game that places the player in a cardiac arrest scenario. The player must complete each BLS step in sequence through interactive gameplay, mimicking real-life responses. The goal was to provide a guided learning experience that reinforces correct actions and decision-making under pressure.

This study outlined both functional and non-functional requirements. Functionally, the game must simulate BLS steps, provide user feedback (e.g., "Correct!" or "Try Again"), and award points based on performance. Non-functional requirements included usability, visual clarity, and real-time responsiveness. Hardware and software requirements were also determined, including the use of Unreal Engine 5.4 for development and Windows PC as the deployment platform.

A detailed Game Design Document (GDD) was created to outline the gameplay structure, User Interface (UI) flow, scoring system, and technical assets. The document served as a roadmap throughout the project, helping to guide the

development of core mechanics such as the CPR meter, input detection (e.g., pressing 'E' or clicking on prompts), and condition-based game logic. It also included planning for player animations, background environment, user interface layout, and sound integration. By the end of the pre-production phase, a clear blueprint for the game was established, ensuring a smooth transition into the production phase with well-defined goals and expectations.

B. Production Phase

1) This phase represents the core of the development process, where the concepts and designs from the pre-production stage are transformed into a fully functional game. A realistic 3D environment was created to simulate an emergency scenario, such as a victim collapsing in a public space. The layout was designed to guide the player intuitively from one BLS step to the next. Key interactive objects (e.g., the patient, emergency phone) were placed with visual cues to ensure player clarity.

2) The game's logic was implemented using Unreal Engine's Blueprint system, which allowed for visual scripting of interactions and events. Conditional branches ensured that players had to follow the correct sequence before progressing, mimicking the structured nature of real CPR training. Each BLS step was programmed to respond to specific user inputs

3) Animations for CPR hand placement and character behaviors were either created or triggered through Blueprints. Hand placement on the chest was particularly important to reflect correct technique. Some animations were implemented to enhance realism, especially during chest compressions.

C. Post-production Phase

This final phase focused on refining the game experience through testing, feedback, and deployment. For the BLS simulation game, this phase ensured that the game met its educational goals, operated without major bugs, and delivered a smooth and engaging user experience. The game underwent multiple rounds of internal playtesting to identify bugs, logic errors, and UI issues. Specific test cases included:

- Verifying the correct sequence of BLS steps (e.g., player cannot skip directly to CPR).
- Ensuring all input actions (mouse clicks, key presses) triggered the intended response.
- Detecting misaligned animations, faulty hand placements, or delayed audio playback.
- Monitoring performance issues such as lag or long load times.

Blueprint-based logic was debugged by using print statements and execution flow visualization in Unreal Engine. Several common issues such as UI not updating, the player getting stuck, or input not being detected were resolved in this phase. Then, feedback was gathered from peers and instructors during informal user testing. Suggestions such as improving prompt clarity, adding clearer success/failure messages, and enhancing the timer's visibility were incorporated. Refinements also included:

- Adjusting CPR meter thresholds to balance difficulty.
- Smoothing animation transitions.
- Replacing placeholder assets with higher-quality visuals or sounds when needed.

This feedback-driven polishing ensured that the game was both educational and enjoyable. Once testing and improvements were complete, the game was packaged using Unreal Engine 5.4's built-in packaging tools for Windows (64-bit). The final build was exported as an executable file (.exe), ready for distribution. The packaged game included all necessary assets, settings, and dependencies required to run the game on any compatible Windows PC. The game was then made available for sharing and demonstration, allowing players to engage with an interactive BLS scenario anytime, without needing physical training equipment.

IV. Implementation

The game was implemented as a first-person simulation, allowing the player to take the role of a bystander responding to a cardiac arrest victim. The player navigates the environment and interacts with prompts to progress through each step of Basic Life Support. The core components of the game include:

- Game Mode Blueprint: Controls the state of the game (e.g., win/loss conditions).
- Player Character Blueprint: Handles user movement, interaction, and BLS actions.
- User Interface Widgets: Displays feedback, instructions, CPR meter, and timer.
- Timer System: Limits time to complete actions to simulate urgency.
- Trigger Boxes: Detect player position and activate events like Danger Check.

A. User Interface

Widget Blueprints were used to create the UI elements, ensuring they responded dynamically to in-game events. The UI was designed to be minimal but informative, which included:

- Step-by-step instructions. Text prompts guide the player.
- A countdown timer that added urgency to simulate real-life stress.
- Feedback is provided visually and through sound, helping reinforce correct actions.
- A quiz-style system checks if the selection is correct before continuing.
- Feedback Messages: "Correct!", "Wrong!"

Each BLS step was programmed to respond to specific user inputs:

- Danger check: activated by approaching the patient as shown in Fig. 2.

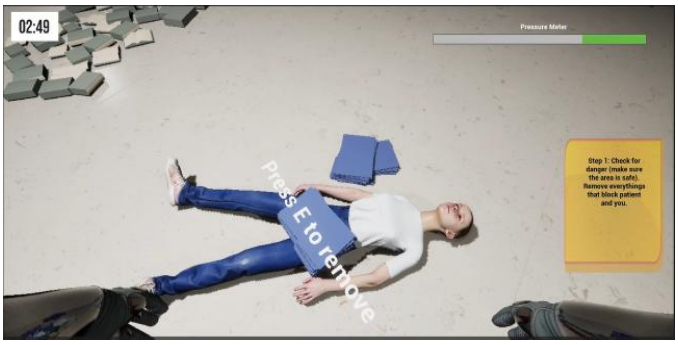


Fig. 2. UI of danger check.

- Response check: Interaction with key prompts and audio.
- Call for help: Player needs to answer the quiz as shown in Fig. 3 to simulate calling 999.
- Airway check: Players are shown two images as shown in Fig. 4 and must click the correct version representing an open airway.

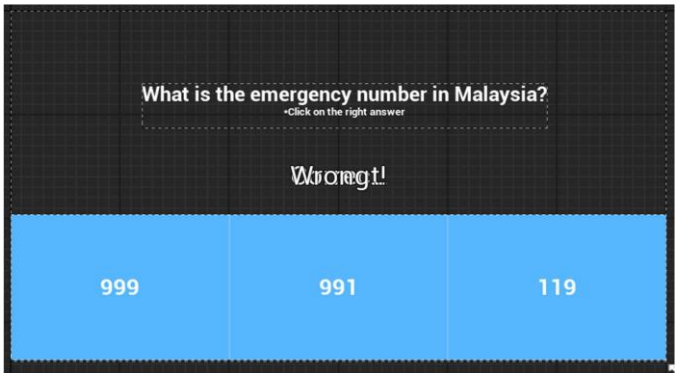


Fig. 3. UI of call for help.

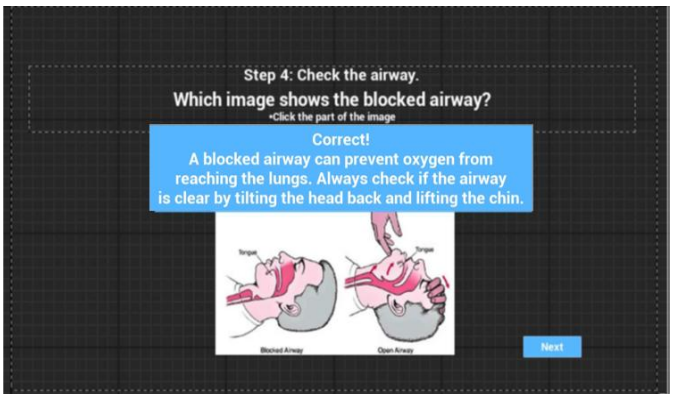


Fig. 4. UI of airway check. Airway image adopted from [20].

- Breathing check: triggered by key prompts to check breathing in 5 to 10 seconds.
- CPR chest compression (refer Fig. 5): involved pressing the correct key at the right time within a percentage range to score successful compressions (100 to 120 compressions per minute).

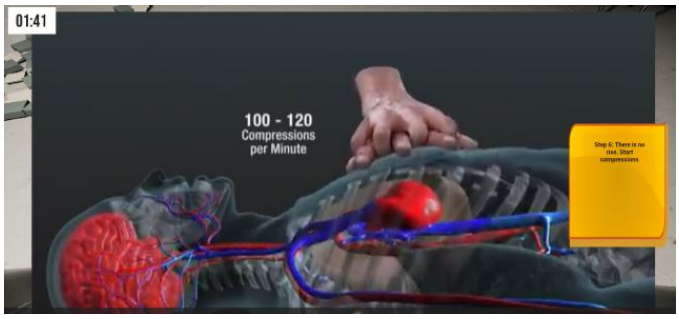


Fig. 5. UI of CPR chest compression.

B. Learning Flow and Key Gameplay Stages

The simulator demonstrates a clear and pedagogically grounded learning flow. Each gameplay stage reflects the four components of experiential learning theory, enabling players to learn BLS procedures through direct experience, feedback, concept reinforcement, and repeated practice. Table II summarizes pedagogical mechanisms in each gameplay stage.

The structured sequence—from danger assessment to breathing evaluation—ensures that learners are guided progressively through each critical step of the BLS process, reducing cognitive load while reinforcing procedural accuracy. Immediate corrective prompts, visual cues, and context-specific quizzes function as formative assessments that strengthen conceptual understanding and support error-based learning in a risk-free environment.

TABLE II. SUMMARY OF PEDAGOGICAL VALUE

Gameplay Stage	Pedagogical Mechanism
Danger check	Scaffolding, situated learning: Learner understands safety awareness
Response check	Experiential learning: Builds correct procedural memory
Calling 999	Cognitive apprenticeship & reinforcement: Teaches urgency
Airway quiz	Dual coding & error-based learning: Strengthens visual understanding of airway management
Breathing check	Procedural reinforcement: Helps learners remember correct timing and method
Transition to CPR	Scaffolding & load reduction: Smooth conceptual shift before CPR stage
UI prompts & feedback	Behaviourist reinforcement: Improves retention and user confidence

C. Feedback and Scoring Flow

Based on Fig. 6, the simulator begins by initializing the environment and activating a three-minute timer before presenting step-by-step BLS instructions. For each stage, the player performs the required action, and the system checks its correctness. Incorrect actions trigger an error prompt and allow the player to retry, while correct actions generate positive feedback and progress the flow. Throughout gameplay, the timer continuously evaluates performance, where exceeding the time limit results in failure. If the player completes all BLS steps correctly within the allotted time, the simulation ends successfully when rescue arrives, producing a time-based performance result.

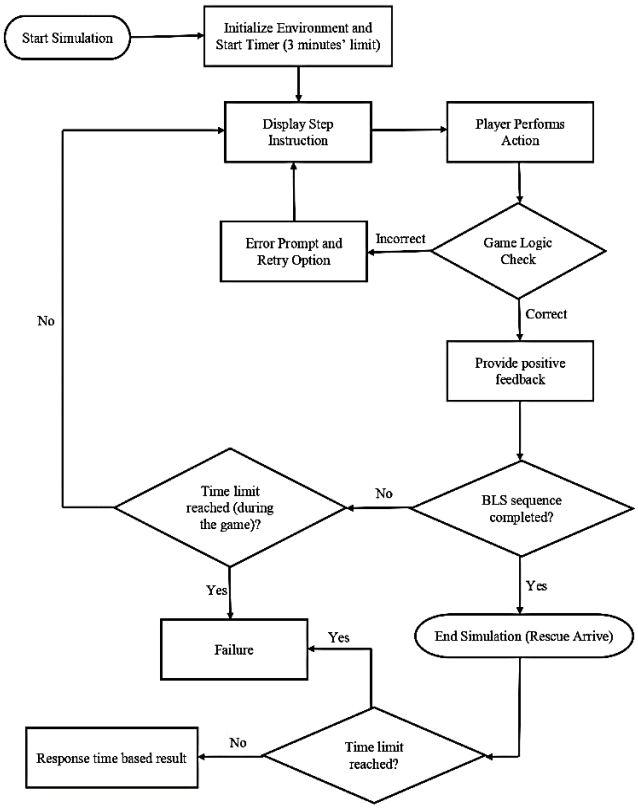


Fig. 6. Feedback and scoring flow.

V. Results and Discussion

The evaluation of this study was conducted to measure both knowledge improvement and usability of the simulator as a BLS training tool. Two types of data collection were used: quantitative analysis (pre-posttest and inferential statistics) and qualitative analysis (open-ended feedback from participants).

A. Quantitative Analysis

A total of 16 participants were involved in the evaluation of the simulator. The participants were recruited from various backgrounds to ensure a mix of ages and levels of prior exposure to BLS. Participants ranged from below 18 years old to above 45 years old, representing both younger learners and adult users. This range was chosen to reflect the fact that sudden cardiac arrest can occur in any environment, and bystanders of different age groups may be required to perform BLS. Out of the 16 participants, 6 had non-certified prior training in BLS (such as school-based or workplace awareness programs), while 10 had no previous training. None of the participants held certified medical qualifications. This distribution highlights the simulator's role as an accessible training tool for individuals with little to no prior exposure.

Participants reported varied levels of familiarity with digital games and simulations, ranging from rare users to frequent players. This factor was important since game-based learning systems may present a steeper learning curve for those unfamiliar with interactive environments. When asked about their confidence in performing CPR, the majority rated themselves at 2 or on a 5-point scale, indicating low initial confidence.

The pre-posttest was administered before and after participants engaged with the simulator to measure learning improvement. The test consisted of 10 multiple-choice questions covering the BLS sequence and key emergency steps. The learning improvement achieved through the simulator was examined using both learning gain analysis including Hake's normalized gain [24] and McNemar's test [25] on item-level correctness data.

The average pre-test score was 6.0 out of 10, while the average post-test score was 8.9 out of 10, indicating a 28% improvement in knowledge. Fig. 7 shows the comparison of the pre-test and post–test results. The normalized learning gain (Hake's g) was calculated to be 0.73 as shown in Table III, which falls within the category of high gain, indicating that the simulator facilitated substantial conceptual improvement, especially for novice learners.

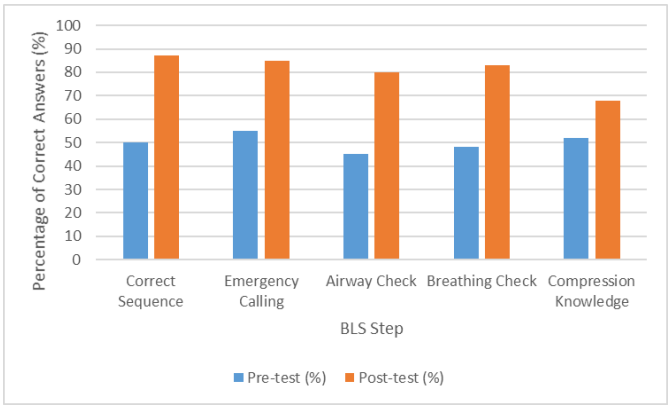


Fig. 7. Comparison of pre-test and post-test results.

To complement this overall score analysis, McNemar's test was conducted to evaluate changes in correctness for each BLS step at the item level. Based on Table IV, significant improvements were found for the Correct Sequence ($\chi^2 = 4.17$, $p = .041$) and Airway Check ($\chi^2 = 4.17$, $p = .041$), demonstrating that the simulator was particularly effective in reinforcing the procedural order of BLS and improving recognition of proper airway assessment. While Emergency Calling ($\chi^2 = 3.20$, $p = .074$) and Breathing Check ($\chi^2 = 3.20$, $p = .074$) showed notable increases in percentage correctness, these changes did not reach statistical significance. Compression Knowledge also improved in correctness but not significantly ($\chi^2 = 1.33$, $p = .248$), suggesting that this area may require more targeted reinforcement in future versions of the simulation.

Together, the high normalized learning gains and the significant item-level improvements demonstrate that the simulator effectively strengthened participants' understanding and application of key BLS steps. The findings highlight that the interactive, step-guided format was especially beneficial for conceptual sequencing and airway assessment—areas critical for real-world emergency response—while also identifying components such as compression technique that may benefit from enhanced feedback or additional practice

features. Although the sample size limits the generalizability of these findings, the strong magnitude of the observed learning gains suggests a robust signal of efficacy. Consistent with recommendations for the evaluation of novel serious game interventions, this initial evaluation confirms the feasibility and immediate didactic effectiveness of the simulator.

TABLE III. LEARNING GAIN RESULTS

BLS Component	Pre-test (%)	Post-test (%)	Gain (%)	Category
Correct Sequence	50	87	+37	High Improvement
Emergency Calling	55	85	+30	Moderate Improvement
Airway Check	45	80	+35	High Improvement
Breathing Check	48	83	+35	High Improvement
Compression Knowledge	52	68	+16	Low Improvement
Overall score	Mean = 6.0	Mean = 8.9	+2.9 (28%)	Hake's g = 0.73 (High Gain)

TABLE IV. FINAL MCNEMAR RESULT TABLE

BLS Component	McNemar's χ^2	*p*-value	Statistical Interpretation
Correct Sequence	4.17	0.041	Significant Improvement
Emergency Calling	3.20	0.074	Not Significant
Airway Check	4.17	0.041	Significant Improvement
Breathing Check	3.20	0.074	Not Significant
Compression Knowledge	1.33	0.248	Not Significant

B. Qualitative Analysis

Qualitative data was collected from participants through open-ended questions and observer notes during gameplay. This provided deeper insights into user experience, perceptions of realism, and areas for improvement that could not be captured by numerical scores alone. Participants consistently highlighted the following positive aspects of the simulator. Firstly, the step-by-step prompts were considered very helpful in guiding users through the BLS sequence. Several participants mentioned that the clear instructions reduced confusion, especially for first-time learners.

Real-time feedback was praised for making compressions more engaging and allowing players to understand whether they were performing the action correctly. Furthermore, immersive simulation environment provided a sense of realism that helped users imagine responding in a real-life emergency. These elements were identified as the core strengths that supported knowledge retention and confidence-building.

While the simulator was well-received overall, several weaknesses were noted. Airway quiz visuals were described as unclear, which made some participants unsure whether their choices were correct. Next, the timer mechanism was reported to cause stress among beginners. Some participants felt pressured to complete actions too quickly, which affected their ability to follow the correct sequence calmly. Moreover, PC-only platform limitation reduced accessibility. Several participants expressed interest in mobile or VR versions that could allow more flexible use.

VI. CONCLUSIONS AND FUTURE WORK

This study presented the design, development, and evaluation of a 3D first-person interactive simulation for BLS training, aimed at improving procedural understanding and learner confidence among lay users. The simulator successfully operationalized nationally recognized BLS guidelines from the Ministry of Health Malaysia into a protocol-enforced, step-by-step interactive experience that emphasizes procedural accuracy, real-time decision-making, and psychomotor performance. Through immersive gameplay, timing-based feedback, and structured task progression, the system enabled users to practice life-saving interventions in a safe and repeatable virtual environment. The empirical evaluation demonstrated substantial learning improvements, as evidenced by a high normalized learning gain, indicating the effectiveness of the proposed approach in strengthening procedural knowledge among non-expert participants. The findings of this study contribute to the broader understanding of how procedural enforcement and psychomotor feedback mechanisms influence learning outcomes in simulation games for emergency medical training.

Beyond system development and evaluation, the findings of this study carry broader implications for public health education and emergency preparedness. The simulator illustrates how game-based, first-person simulations can serve as scalable and accessible tools for public BLS education, particularly in contexts where traditional face-to-face training is limited by cost, infrastructure, or instructor availability. By lowering barriers to practice and enabling repeated exposure to realistic emergency scenarios, such digital training tools have the potential to enhance community-wide readiness and increase the likelihood of timely bystander intervention during cardiac arrest events.

It is important to acknowledge several limitations of this study that may influence the interpretation and generalizability of the findings. First, the evaluation involved a relatively small sample size and was limited primarily to lay users without certified medical training; therefore, the results may not fully represent learning outcomes across broader populations, such as healthcare professionals or certified first aid instructors. Second, the study focused on short-term knowledge improvement measured immediately after gameplay, and did not examine long-term retention or transfer of skills to real-world emergency situations. Third, although the simulator incorporates timing-based psychomotor feedback, it does not replace physical hands-on practice with mannequins, which remains essential for developing tactile accuracy in CPR performance. Additionally, the current implementation is limited to a desktop platform, which may restrict accessibility for wider adoption. Recognizing these limitations provides a balanced interpretation of the results and highlights opportunities for future research to extend the scope, robustness, and applicability of game-based BLS training.

Therefore, several directions for future work are proposed to enhance the simulator. One important step is to expand the scope of emergency scenarios. While this project focused primarily on cardiac arrest, future development should integrate additional cases such as choking, drowning, and the use of automated external defibrillator (AED). Another avenue for improvement is the expansion of platform accessibility. Developing mobile and Virtual Reality (VR)-compatible versions of the simulator would allow a broader audience to engage with the system.

While the proposed simulator demonstrates practical value for large-scale dissemination of BLS training, further research is necessary to strengthen its empirical validation and broaden its applicability. The current evaluation involved a limited sample size of 16 participants, which provided useful initial insights but restricts the generalizability of the findings. Future studies should therefore focus on larger-scale user evaluations involving more diverse participant groups, including healthcare professionals, certified first aid trainers, and broader community populations. Such evaluations would enable a more rigorous assessment of the simulator's accuracy, effectiveness, and adaptability across different user expertise levels. With expanded validation, the software-based nature of the simulator positions it well for integration into schools, universities, community programs, and workplace safety initiatives as a supplementary or preparatory learning resource. The protocol-enforced interaction model further supports consistency in instructional delivery, making the system suitable for standardized training environments and blended BLS education models, where it may function effectively as a pre-training module, refresher tool, or formative assessment mechanism.

In terms of usability and system design, improving interaction features should be prioritized. Enhancements could include redesigning unclear quiz visuals, refining the timing mechanism to adjust difficulty based on user experience, and offering multiple learning modes, such as beginner and advanced. Finally, the feedback and scoring system can be expanded into a more detailed analytics tool. Instead of providing only basic real-time prompts, future versions could track accuracy and performance consistency across different steps of the BLS process.

In conclusion, the simulator demonstrates potential for integration into formal training and certification pathways. While it does not replace hands-on practice with mannequins or instructor-led assessment, the simulator can complement existing certification programs by reinforcing procedural sequencing, decision-making under pressure, and conceptual understanding prior to or between physical training sessions. In this regard, this study contributes empirical evidence that well-designed serious games can extend beyond experimental prototypes to become meaningful components of structured emergency response education. Overall, this work positions immersive, protocol-driven simulation as a viable and impactful approach for advancing BLS training, strengthening public health education strategies, and enhancing societal preparedness for medical emergencies.

ACKNOWLEDGMENT

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REFERENCES

[1] Ministry of Health Malaysia, Basic Life Supprt Training Manual, Second Edition, 2023. [Online]. Available: https://www.moh.gov.my/index.php/database_stores/store_view_page/70/219

[2] Requena-Mullor, M. D. M., Alarcón-Rodríguez, R., Ventura-Miranda, M. I., & García-González, J. (2021). Effects of a clinical simulation course about basic life support on undergraduate nursing students' learning. International Journal of Environmental Research and Public Health, 18(4), 1409. https://doi.org/10.3390/ijerph18041409

[3] Bonizzio, C. R., Nagao, C. K., Polho, G. B., & Paes, V. R. (2019). Basic Life Support: an accessible tool in layperson training. Revista da Associação Médica Brasileira, 65, 1300-1307. http://dx.doi.org/10.1590/1806-9282.65.10.1300

[4] González-Salvado, V., Rodríguez-Ruiz, E., Abelairas-Gómez, C., Ruano-Raviña, A., Peña-Gil, C., González-Juanatey, J. R., & Rodriguez-Nunez, A. (2020). Training adult laypeople in basic life support. A systematic review. Revista Española de Cardiología (English Edition), 73(1), 53-68. https://doi.org/10.1016/j.rec.2018.11.013

[5] Boggs, S., McNally, J. D., O'Hearn, K., Del Bel, M., Armstrong, J., Newhook, D., & Lobos, A. T. (2025). Teaching high quality paediatric basic life support to laypeople: The development and evaluation of a virtual simulation game. Resuscitation Plus, 21, 100824. https://doi.org/10.1016/j.resplu.2024.100824

[6] M. E. Aksoy, "Comparing basic life support serious gaming scores with hands-on training platform performance scores: pilot simulation study for basic life support training," JMIR Serious Games, vol 8, no. 4, 2020. doi: 10.2196/24166

[7] R. E. Mayer, "Computer games in education," Annual review of psychology, vol 70, pp. 531-549, 2019. https://doi.org/10.1146/annurev-psych-010418-102744

[8] D. Checa and A. Bustillo, "A review of immersive virtual reality serious games to enhance learning and training," Multimedia tools and applications, vol 79, pp. 5501-5527, 2020. https://doi.org/10.1007/s11042-019-08348-9

[9] C. Berger et al., "Combination of problem-based learning with high-fidelity simulation in CPR training improves short and long-term CPR skills: a randomised single blinded trial," BMC medical education, vol 19, no. 180, May 2019.

[10] Habibli, T., Ghezeljeh, T. N., & Haghani, S. (2020). The effect of simulation-based education on nursing students' knowledge and performance of adult basic cardiopulmonary resuscitation: a randomized clinical trial. Nursing Practice Today. https://doi.org/10.18502/npt.v7i2.2730

[11] McGaghie, W. C., Issenberg, S. B., Petrusa, E. R., & Scalese, R. J. (2010). A critical review of simulation‐based medical education research: 2003–2009. Medical education, 44(1), 50-63. doi:10.1111/j.1365-2923.2009.03547.x

[12] Vancini, R. L., Russomano, T., Andrade, M. S., de Lira, C. A., Knechtle, B., & Herbert, J. S. (2023). Gamification vs. Teaching First Aid: What Is Being Produced by Science in The Area?. Health Nexus, 1(2), 71-82. https://doi.org/10.61838/kman.hn.1.2.10

[13] H. Efe and Ü. U. Topsakal, "Learning first aid with digital games for primary school students," European Journal of Education Studies, vol 10, no. 2, 2023. doi: 10.46827/ejes.v10i2.4662

[14] Boada, I., Benitez, A. R., Thió-Henestrosa, S., & Soler, J. (2020). A serious game on the first-aid procedure in choking scenarios: design and evaluation study. JMIR serious games, 8(3), e16655. doi: 10.2196/16655

[15] I. Gorbanev et al., "A systematic review of serious games in medical education: quality of evidence and pedagogical strategy," Medical education online, vol 23(1), 2018. doi: 10.1080/10872981.2018.1438718

[16] S. A Dhawale and K. Dubey, "Quality improvisationin Game design techniques through Game Development life Cycle (GDLC) Model," pp.1-7, August 2019.

[17] A. Teotia and S. Garg, "GAMEOP: Software Quality Management Approach for Gaming Industry". In 2021 6th International Conference on Signal Processing, Computing and Control (ISPCC), IEEE pp. 779-784, October 2021. doi: 10.1109/ISPCC53510.2021.9609430

[18] Siahaan, Y. Y. P., Widyani, Y., & Candra, M. Z. C. (2023). Applying Scrum in A Game Development Life Cycle For Small Scale Game Project. International Journal of Information Technology, Research and Applications, 2(4), 24-37. doi: 10.59461/ijitra.v2i4.73

[19] Wijnen-Meijer, M., Brandhuber, T., Schneider, A., & Berberat, P. O. (2022). Implementing Kolb s experiential learning cycle by linking real experience, case-based discussion and simulation. Journal of medical education and curricular development, 9. doi: 10.1177/23821205221091511

[20] Basic Airway Management. [Online]. Available: https://www.slideshare.net/slideshow/basic-airway-managementpptx/252375763#1

[21] Rebollo, C., Gasch, C., Remolar, I., & Delgado, D. (2021). Learning first aid with a video game. Applied Sciences, 11(24), 11633. https://doi.org/10.3390/app112411633

[22] Darotin, R., Nastiti, E. M., & Ekaprasetia, F. (2023). Establishment of Layperson First Aid Burn Cases with E-Fa Game Technology. Blambangan Journal of Community Services (BJCS), 1(2), 61-69. [Online]. Available: https://blambangan-scholar.com/index.php/BJCS

[23] S. Benkhedda and F. Bendella, "FASim: a 3D serious game for the first aid emergency," Simulation & Gaming, vol 50(6), pp. 690-710, 2019. https://doi.org/10.1177/1046878119865913

[24] A. S. Fadaei, " Comparing two results: Hake gain and dellow gain, to analyze FCI data in active learning process," US-China Education Review, vol 9, no. 1, pp. 31-39, 2019. doi: 10.17265/2161-623X/2019.01.001

[25] Pembury Smith, M. Q., & Ruxton, G. D. (2020). Effective use of the McNemar test. Behavioral Ecology and Sociobiology, 74(11), 133. https://doi.org/10.1007/s00265-020-02916-y

Enhancing Arabic Biomedical Named Entity Recognition Using Transformer-Based Representations and CRF Sequence Labeling

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***Abstract*—Electronic health records have witnessed tremendous growth in recent years. To make these documents useful for decision-making, high-performance natural language processing (NLP) systems are essential. Named entity recognition (NER) is a critical task for many biomedical NLP applications that contribute to improving patient care, drug discovery, and disease surveillance. However, despite its status as an official language in more than 22 countries, Arabic is largely neglected in this field. Only limited work has been done and there is little well-annotated public dataset. This work tackles these issues by proposing an NER model capable of recognizing entities such as diseases, symptoms, and organs from biomedical Arabic text. To achieve this, an annotated dataset was first developed, followed by fine-tuning the CAMeLBERT model, a BERT-based model, in conjunction with a conditional random field (CRF) layer. The evaluation results indicate that the CAMeLBERT+CRF model achieves the best overall F1-score of 90%, surpassing other base models such as CAMeLBERT and AraBERT. This study demonstrates the effectiveness of the hybrid approach and underscores the importance of transfer learning techniques for low-resourced and morphologically rich languages like Arabic.**

***Keywords*—Named entity recognition; electronic health records; natural language processing; CAMeLBERT; CRF**

I. Introduction

Clinical patient records include personal details such as age, weight, past medical history and results of various laboratory tests, among others. Most of this information is presented as unstructured text, and extracting useful information from these records is a crucial and challenging task in biomedical natural language processing (NLP). Named entity recognition is a widely studied topic in the area of biomedical NLP that plays a significant role in information retrieval. The aim of the task is to identify biomedical entities that belong to certain types. Pioneering work in named entity recognition (NER) was presented at the sixth message understanding conference (MUC6) in 1995 [1], aiming to identify entities such as people, organizations, locations, and other relevant terms. Subsequently, this task has received considerable attention from researchers, particularly in the biomedical domain, to identify medical concepts such as diseases, drug names, and medical procedures, which is essential for a number of downstream tasks including text summarization [2], relation extraction [3], question answering [4], and clinical decision support [5]. Most works in biomedical NER have been devoted to the English language, making significant advancements in diagnostics, treatment, and research. However, limited research has been performed on the Arabic language. Most current systems have been developed and evaluated on general-domain. These models are optimized to recognize common entity types such as people, places, and organizations, but do not capture the specialized terms, and unique language found in biomedical texts. Designing high-performance Arabic biomedical NER systems is challenged by various factors, including the scarcity of annotated biomedical datasets in Arabic which limits the creation and evaluation of efficient models. For standard NLP pipelines, the morphological richness and syntactic complexity of Arabic, including its complex morphology, diacritical variations, and inherent ambiguity, present significant obstacles, especially in specialized fields like medicine. Recent advancements in pre-trained transformer-based models have improved Arabic NLP on a variety of tasks. However, these models are not specifically tailored for biomedical applications, they are typically trained on general-purpose models. As a result, there is still ongoing research into adapting them to domain-specific tasks like Arabic biomedical NER.

The objective of this study is to address the problem of improving Arabic biomedical NER performance in a low-resource setting by creating a custom Arabic biomedical dataset and exploiting transformer-based representations along with structured sequence labeling. Specifically, this paper evaluates CAMeLBERT, a pre-trained BERT-based [6] model tailored for modeling Arabic linguistic variation, when paired with a Conditional Random Field (CRF) layer [7] to capture label dependencies in biomedical entity recognition. The main contributions of this work can be summarized as follows:

- Construction of a newly annotated Arabic biomedical NER dataset to overcome the balance between quality of annotations and resources.
- Design and fine-tuning of transformer-based model with Conditional Random Fields (CRF) for capturing contextual and sequential dependencies in biomedical Arabic text.
- Experimental evaluation of the proposed transformer–CRF model on Arabic biomedical NER task, including comparison with baseline methods for examining their effectiveness and robustness.

The rest of the paper is structured as follows: the related work on named entity recognition is presented in Section II.

Section III describes the dataset procedures from collection to annotation. Section IV presents the model architecture in detail. The experimental results are shown and discussed in Section V. Finally, Section VI concludes the paper.

II. Related Work

Arabic NER can be divided into three main approaches: rule-based, machine learning-based, and deep learning-based. To identify pertinent entities, the rule-based approach uses manually created rules and patterns. It takes both domain-specific knowledge and a solid foundation of linguistics to construct these rules. The study described in [8] a new rule-based approach for named entity recognition (NER) in Classical Arabic texts. It tackles the challenges of Arabic morphology and script complexity by using a mix of trigger words, patterns, gazetteers, and blacklists to identify entities like names and locations. The results show about 90% precision and recall, aiming to improve automated rule updates and coverage over existing systems. However, the study [9] employed a supervised machine learning approach that integrates multiple types of features word-level, morphological, and knowledge-based to perform named entity recognition in Classical Arabic, using Naive Bayes classifier, the system learns to predict the entity type based on the extracted features. The study reports that, using a Naive Bayes classifier with various feature combinations, the system achieved promising results, with an overall precision of around 86%, recall of 75%, and an F-measure near 80%. Another study in [10] proposed a method that involves creating an extensive Arabic NER dataset that covers seven domains and has nine categories of named entities using BIOES tagging in order to better manage nested entities. Two recurrent neural network architectures, LSTM and GRU, were developed to build an NER model achieving an accuracy around 80%. On the other hand, Sadallah et al. [11] presented ANER a BERT-based model for Arabic named entity recognition able to recognize 50 different entity classes, built upon fine-tuning the pre-trained AraBERTv0.2-base model using the WikiFANE Gold corpus. The system achieved an F1 score of 88.7%, which beats CAMeL Tools' F1-score of 83% on the ANERcorp dataset. Moreover, the model exhibited robust generalization capabilities, attaining a 77.7% F1 score when assessed on out-of-domain data from the NewsFANE Gold dataset. Furthermore, ANER was deployed on a user-friendly web interface to make it accessible.

Before diving into the biomedical NER task in Arabic, it is important to acknowledge research conducted in other languages. English, as the most dominant language, and Chinese [12, 13, 14, 15], due to the large number of biomedical publications. Furthermore, languages such as Spanish [16, 17] have also been explored, driven by the extensive Spanish-speaking regions. Besides, French [18, 19] and German [20] have fewer works, but they still offer valuable resources. In order to overcome the difficulties caused by dataset limitations in low-resource languages, recent studies have used multilingual models like mBERT, XLM-R, and BioBERT-multilingual in the biomedical domain. These models make use of cross-lingual transfer, by training on high-resource languages like English and then applying the acquired knowledge to other languages [21]. Currently there are very few Arabic biomedical NER systems, due to the significant lack of annotated datasets.

Boudjellal et al. [22] proposed ABioNER, a BERT-based model designed to recognize biomedical named entities like diseases and treatments in Arabic texts. The model was pre-trained on a curated, manually annotated, silver-standard biomedical corpus with annotations for 13 different semantic categories, yet the study focused on "Disease or Syndrome" and "Therapeutic or Preventive Procedure". According to the results, ABioNER outperformed the AraBERT and multilingual BERT cased models, obtaining an F1-score of 85%, indicating improved effectiveness for biomedical NER tasks in Arabic. Although this work provides positive indications for the success of domain-oriented pre-training, it remains limited due to its applicability to a few entity types and by its lack of examination of linguistic variation.

Alanazi [23] presented NAMERAMA, a specialized NER tool based on Bayesian Belief Network (BBN), that extracts particular medical entities sush as disease names, symptoms, treatments, and diagnosis techniques. The authors used the AMIRA to perform tokenization and POS tagging, followed by manual correction due to the complex morphological structure of Arabic language. They extracted set of features such as the POS tag of the word, gazetteers, stopwords, lexical triggers and a set of grammar patterns, necessary to enhance the performance of the classifier. The system was tested on data containing 26 articles about cancer obtained from the King Abdullah Bin Abdulaziz Arabic Health Encyclopaedia (KAAHE) website. The results show that the BBN approach outperformed the baseline system by 21%, achieving an overall F-measure of 71.05%, with highest score in recognizing disease names with 98.10% and the lowest in recognizing symptoms with 41.66%. These results indicate that combining the probabilistic inference with the linguistic features, is effective for biomedical NER in Arabic. However, this approach is labor-intensive, not portable to other domains, and not easily scalable to larger collections of biomedical text.

Hamad and Abushaala [24] developed a biomedical NER model for extracting medical named entities of cancer in Arabic texts, utilizing an SVM model. The training corpus, constructed by Alanazi from the King Abdullah Bin Abdulaziz Arabic Health Encyclopedia (KAAHE), consists of various cancer types annotated with disease, symptoms, diagnosis, and treatment entity types. The authors extracted several features, including N-gram FastText, N-gram POS, TF-IDF, and non-medical word matching, fed into the SVM model as a vector. This approach achieved an overall F-score of 77.61% and showed high performance across most entity types, outperforming the BBN model. Although an improvement over a previous work, this method still requires significant feature engineering.

The study presented in [25] suggested two approaches for Arabic biomedical NER based on contextual embeddings. The first one fine-tuning BERT and AraBERT models to the NER task. The second uses AraBERT as a feature extractor, where the contextual embeddings are used as an input for several machine learning classifiers such as SVM, Decision Tree, and AdaBoost. The dataset employed in this work was devoted to NER tasks for diseases, with various annotation schemes. This hybrid approach leverages the contextual understanding of transformers and the simplicity of machine learning classifiers to improve recognition

accuracy. The fine-tuned AraBERT performed the best, particularly when handling single entities under the IO scheme and consecutive entities under the BIES or IOBES schemes. This study shows that transformer-based models outperform traditional approaches.

Overall, existing work on Arabic biomedical NER are based on either small domain-specific datasets, involves heavy manual feature engineering, or leverages general-purpose transformer models with minimal considerations on how suitable they are for biomedical Arabic text. In addition, decoding strategies at the sequence level and the reasons why some Arabic pre-trained models perform better over others for this particular task have received little attention. Motivated by these limitations, this study explores a CAMeLBERT+CRF based architecture in conjunction with a newly annotated biomedical Arabic dataset, with an aim of not only advancing the performance, but also drawing empirical insights concerning transfer learning for morphologically rich and low-resource biomedicine language.

III. Dataset

Due to the limited availability of annotated resources for Arabic biomedical NER, the work presented in this paper is based on a novel dataset tailored to the biomedical Arabic domain. The proposed dataset extends entity coverage by incorporating three clinically relevant entity types: disease, organ, and symptom. This entities design allows for richer biomedical information extraction as well as more realistic representation of medical texts. The dataset obtained is lexically and contextually diverse with respect to the biomedical topics, which allows for a challenging evaluation of models. The selection of this dataset is motivated by the fact that it contains more entities, is domain-specific, and more appropriate for assessing transformer-based models in Arabic biomedical NER.

This section outlines all the steps involved from data collection, processing, and annotation to create the dataset that will be used later to train and test the Arabic BioNER model. Fig. 2 illustrates the steps of dataset construction.

A. Data Collection

A corpus of unstructured texts was first gathered from a publicly accessible Arabic medical website, WebTeb [28], a well-known and trustworthy Arabic health information platform that offers a variety of medical content, including disease overviews, symptoms, treatments, medication information, and health articles. The focus was placed on a curated section called "أكثر الأمراض انتشاراً في الوطن العربي", The most common diseases in the Arab world. This section includes a variety of structured articles about common medical conditions in Arab countries. Special attention was given to the section containing diseases and symptoms. All of which support the objectives of entity recognition in the biomedical domain. The BeautifulSoup library was employed, a reliable web scraping tool, to extract all targeted documents from the website representing the most common diseases in the Arab world, such as Heart Disease, High Blood Pressure, Allergies, etc. The final corpus contains various diseases and their symptoms, providing a robust basis for disease NER in Arabic text.

B. Data Preprocessing

To prepare raw text for further processing, several steps were carried out to enhance the quality of the dataset and to facilitate effective model training. The first task is data cleaning and normalization, during this process, any irrelevant metadata like external links, hashtags and so on were remove. Then, Non-Arabic letters and unwanted characters like parentheses were excluded from the corpus to minimize noise. Then, diacritics were also eliminated from the corpus, they are very important to determine the correct pronunciation, but for text processing, their removal can improve word recognition. Afterwards, the Farasa segmenter was used [26], a fast and accurate Arabic segmentation tool, to tokenize and segment the sentences. All prefixes and suffixes were segmented like except the definite article "ال", and other suffixes, to preserve the correct semantic meaning of the word, and keep the BIO tagging coherent. For example, the word الالتهاب الرئوي (Pneumonia) can be detached to become ال+التهاب ال+رئوي, resulting in incorrect BIO tagging.

C. Annotation

For the annotation step, a semi-automatic approach was adopted. First, a rule-based matcher was used to identify entities predefined in the three lexicons manually created, categorized into diseases, symptoms, and organs. Then, the annotations were manually corrected using the IOB (Inside, Outside, Beginning) tagging scheme to enhance the quality of the annotations. Table II presents an example of an annotated sentence with the BIO scheme. The diverse biomedical contexts in the corpus make it possible to test the generalization ability of the models to different kinds of entities. Table I describes the statistics of the dataset including the total of tokens, labeled tokens, non-labeled tokens, and entity types. Fig. 1 illustrates the distribution of each entity type in the dataset. As expected, the majority of tokens about 87% of the corpus, are classified as O. Diseases has the highest share of annotated entities at 7.4%, followed by symptoms and organs, each at 2.8%. This illustrates the natural imbalance in biomedical texts, where disease mentions are tending to be prevalent than other entity types.

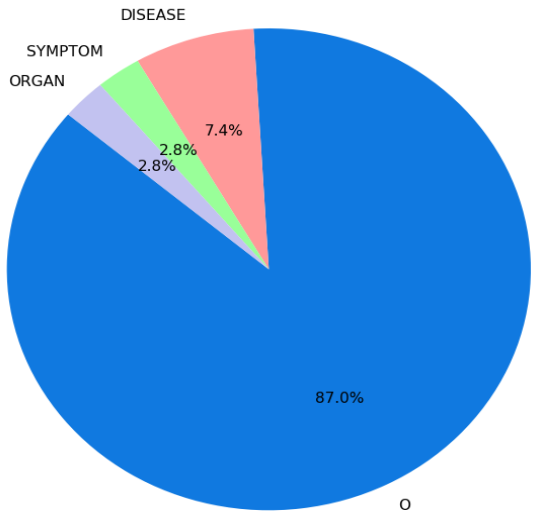


Fig. 1. Entity distribution.

TABLE I. DATASET OVERVIEW

Metric	Value
Total tokens (words)	12,682
Tokens labeled as entities	1,643
Non-entity tokens (O)	11,039
Entity types	O, B-DISEASE, I-DISEASE, B-ORGAN, I-ORGAN, B-SYMPTOM, I-SYMPTOM

TABLE II. EXAMPLE OF DATASET WITH BIO TAGS

Word	Translation	Tag
من	Whoever	O
يعاني	suffers	O
من	from	O
الذبحة	angina	B-DISEASE
الصدرية	pectoris	I-DISEASE
أو	or	O
من	from	O
احتشاء	infarction	B-DISEASE
عضلة	myocardial/muscle	I-DISEASE
القلب	heart	I-DISEASE
قد	may	O
يشعر	feel	O
بألم	pain	B-SYMPTOM
أو	or	O
ضغط	pressure	B-SYMPTOM
على	on	I-SYMPTOM
جدار	the wall	I-SYMPTOM
الصدر	chest	I-SYMPTOM

IV. METHODOLOGY

The CAMeL-Lab model bert-base-arabic-camelbert-mix [29] was chosen as the base encoder. CAMeLBERT is a pretrained Arabic BERT-based model introduced by study [6], trained on a diverse corpus of modern standard Arabic and dialectal Arabic, which enables it to learn richer lexical variations and morphological patterns. The model can learn more general lexical features along with richer morphological variations. This characteristic is extremely useful in biomedical Arabic, where the same medical concept may be written in different forms, informal and orthographic variations. That is why CAMeLBERT is more generalized for biomedical entities and more robust to lexical and morphological variations. Besides, CAMeLBERT provides efficient fine-tuning with a limited number of epochs, even with small amounts of annotated data, and thus is well suited to low-resource biomedical NER tasks. A Conditional Random Field (CRF) layer was also added to improve the sequence labeling capabilities of the base model, which is used to capture label dependencies between entity spans. The CRF helps model the structural constraints of valid label sequences and is particularly effective in improving performance on sequence tagging tasks such as NER. As shown in Fig. 3, input biomedical Arabic text is first tokenized into subword units, where special tokens [CLS] and [SEP] are automatically added by the tokenizer but not used during prediction. CAMeLBERT generates contextualized embeddings for each token, capturing semantic and syntactic dependencies across the sequence. Finally, the CRF layer decodes the most likely label sequence by modeling dependencies between output tags, ensuring valid BIO annotation. The overall architecture of the system is illustrated in Fig. 2.

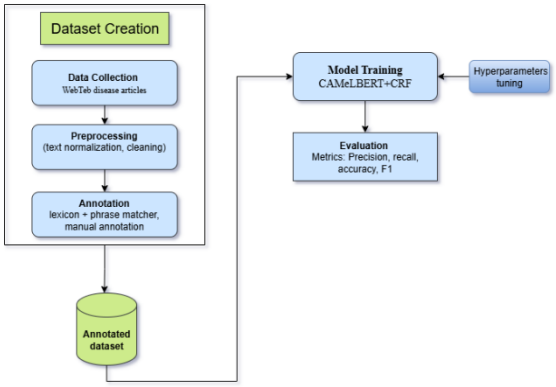


Fig. 2. Architecture of the proposed system.

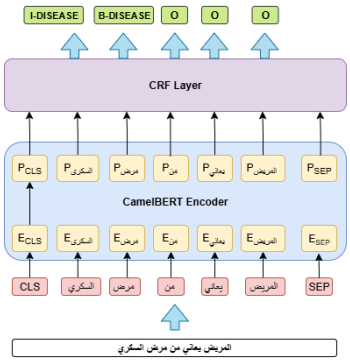


Fig. 3. Architecture of the proposed CAMeLBERT-CRF model for BioNER.

A. CRF Integration

Arabic BioNER is considered as a sequence labeling problem, so it's important for the model to learn valid transitions between labels, for example ensuring that I-ENTITY tag cannot occur without a preceding B-ENTITY tag. Thereby avoiding the independent decoding of each label. To capture these correlations between labels, a conditional random field was employed for sequence modeling, which avoids independent label decoding. The CRF layer computes the likelihood of the correct label sequence and is trained by maximizing this score over the training set using negative log-likelihood loss. A comparative analysis was carried out against a standard softmax layer, in order to evaluate the benefit of incorporating CRF into the model architecture. Table III illustrates the models predictive performance on the sentence "داء السكري من النوع الثاني", translated in English as Type 2 diabetes. It can be observed that the model without CRF incorrectly labels the token "من" as "O" when it is part of the name of the disease in Arabic, (I-DISEASE after O). Whereas the CRF layer correctly identifies it as part of the disease entity, instead of treating each token separately, it considers the sequence of labels for the entire sentence, improving contextual accuracy.

TABLE III. CRF VS. SOFTMAX FOR BIONER

Token	Prediction with CRF	Prediction without CRF
داء	B	B
السكري	I	I
من	I	O
النوع	I	I
الثاني	I	I

B. Training Procedure

Fine-tuning CAMeLBERT+CRF and other baseline models on the biomedical NER dataset containing entities such as diseases, symptoms, and organs. The Hugging Face Transformers library and Trainer API [27] were used for training. The Optuna framework was used to optimize the hyperparameters, allowing for efficient search with three training epochs, a batch size of eight, and a learning rate of 5e-5. Metrics like precision, recall, and F1-score were used to assess the model's performance. Evaluation considered exact span matches under the BIO labeling scheme and was reported per entity type as well as overall.

C. Baseline Comparison

The performance of the suggested CAMeLBERT+CRF architecture was compared with two baseline models in order to assess its efficacy:

- CAMeLBERT: A BERT-based model pre-trained on Arabic texts with different variants. For its fine-tuning, a standard softmax classifier was used to predict token labels. The impact of the CRF was evaluated using this model as a direct ablation study.
- AraBERT v2: An Arabic pretrained lanaguage model based on Google's BERT architechture. AraBERT was fine-tuned using the same dataset and training parameters. The impact of pretraining corpus specialization was evaluated using AraBERT as a comparative baseline.

V. RESULTS AND DISCUSSION

This section details the results obtained by the three models for the Arabic Biomedical NER task: AraBERT, CAMeLBERT, and the proposed CAMeLBERT + CRF model. All models were fine-tuned using the same annotated dataset on the disease, symptom, and organ entity types.

A. Overall performance

Table IV shows clearly that the CAMeLBERT+CRF approach outperformed the other baseline systems, achieving 90% in overall F1-score. AraBERT remains behind overall, confirming that CAMeLBERT is more suited to the Arabic biomedical corpus. The combination of the CRF layer leads to a significant improvement in precision with a relatively small increase in recall. It shows that the CRF layer can eliminate false positives more efficiently by limiting unreal label transfers. These improvements in performance translate into better generalization across entity types and more coherent tagging of multi-token entities.

TABLE IV. OVERALL PERFORMANCE OF CAMELBERT+CRF, CAMELBERT, AND ARAERT MODELS

Model	Precision (%)	Recall (%)	F1-score (%)
CAMeLBERT+CRF (proposed model)	91.93	88.22	90.03
CAMeLBERT	82.08	87.88	84.88
AraBERT	75.97	82.79	79.24

B. Entity-wise performance

Table V indicates that at the entity levels, CAMeLBERT+CRF consistently outperformed both baselines. Especially in symptoms (F1 = 89.72%) and organs (F1 = 88%), while maintaining strong results for disease (F1 = 91.08%). These findings suggest that the CRF layer yields the maximum benefits for the "Organ" and "Symptom" entities. For Organ, the F1 score increases by 6.34 points and for Symptom by 12.24 points. This indicates that such entity types are more susceptible to boundary ambiguity and complex word formation in Arabic text, which can be well resolved by sequence aware CRF layer. Broader analysis CAMeLBERT outperforms AraBERT in all entities where the difference is more pronounced in Organ and Symptom. This means that the pre-training corpus of CAMeLBERT provides more suitable representations for the domain and organ-related terms.

TABLE V. EVALUATION RESULTS OF CAMELBERT+CRF, CAMELBERT, AND ARABERT MODELS ACROSS DISEASE, ORGAN, AND SYMPTOM ENTITIES

Model	Entity Type	Precision (%)	Recall (%)	F1-score (%)
CAMeLBERT+CRF (proposed model)	Disease	91.93	90.24	91.08
	Organ	92.96	83.54	88.00
	Symptom	90.57	88.89	89.72
CAMeLBERT	Disease	87.13	90.85	88.96
	Organ	76.67	87.34	81.66
	Symptom	75.44	79.63	77.48
AraBERT	Disease	83.82	90.18	86.88
	Organ	65.00	73.39	68.94
	Symptom	69.64	73.58	71.56

C. Discussion

The comparative analysis proved that CAMeLBERT+CRF attained 90% in F1-score, which further verifies the strength of the model across different types of entities. On the entity level, the largest gains are for the symptom type with 89% in F1-score. This result surpasses those obtained with other models AraBERT and CAMeLBERT and shows the effectiveness of the proposed architecture, especially considering the fact the symptom expressions in Arabic are often multi-token expressions and they are often expressed in descriptive, verbose language. But low recall means a portion of them are still missed. The disease entity type, achieved the best performance, suggesting that the names of diseases are easier to detect. This improvement is due to higher proportion of disease mentions in the training set (7.4%), which enables the model to better identify entities in unseen text. Additionally, the vocabulary patterns for disease terms often differ from those for organ and

symptom terms, and so they are less ambiguous. Organ is the most difficult entity type of entity to identify, with its F1 score being the lowest among all models. This can be attributed to the high level of overlapping entity structures in Arabic biomedical texts. When organ names are embedded within larger symptom entities, as in "ألم شديد في الصدر", "الصدر" chest is not only part of the symptom expression "severe chest pain" but also an organ name itself. This creates problems with accurate predictions, resulting in lower F1-score, because the model is less confident in assigning a label. Another challenge is that they often appear with prepositions and definite articles, as in "في الكبد" in the liver. The CRF leyer helps the model learn that "في" in is typically followed by an organ entity, reducing false positives.

Compared to earlier Arabic biomedical NER systems in the literature namely, BBN based NAMERAMA [23] and SVM based cancer NER [24]. This improvement is not only quantitative: it the result of applying transformer-based contextual embeddings with sequence-level decoding which appears to be more effective in capturing the lexical and morphological complexities of biomedical Arabic text. In contrast to previous work that mainly reports baseline performance, the reasons why CAMeLBERT's diverse pretraining and CRF decoding yield better entity recognition are also discussed.

To better understand the limitations of the proposed model, a qualitative error analysis was conducted with a sample of the misclassified examples output by the CAMeLBERT+CRF model. The analysis shows there are a couple of repeating errors sources that could inform the linguistic and domain-specific difficulty of Arabic biomedical NER. Revealing that the majority of the remaining errors are due to ambiguous boundaries of entities in multi-token expressions. In some situations, the model predicts the right entity type but the span is not complete, which happens when the entities contain modifiers or attributive adjectives. The semantic overlap of diseases and symptoms, sometimes these entities are confused and misclassified as they share similar semantic context, since some Arabic terms can refer to symptom or disease according to context of use. The morphological complexity of Arabic, Arabic affixes, clitics and attached prepositions can hide entity boundaries, most notably in the case of organ names and symptom lists. While the CRF layer mitigates some of these problems by making the labels consistent, there are still errors in the cases of rare or highly inflected forms. Furthermore, rare and transliterated medical terms having inconsistent spelling continue to pose difficulties due to their negligible representation in the training data. These results suggest that CAMeLBERT+CRF provides marked performance enhancements for Arabic biomedical NER. However, future advances for this task will depend on larger datasets, more explicit annotation guidelines and stronger domain adaptation approaches.

In summary, these results demonstrate the advantage of using a CRF model on top of the transformer-based contextual embedding for complex, multi-token entities. This methodology provides a strong foundation for further domain-specific NER and the co-expansion of biomedical datasets.

VI. Conclusion and Future Work

This study investigated the problem of the challenge of detecting named entities in Arabic biomedical text, a topic which is still unexplored to a large extent despite its significance for applications in healthcare. By constructing a domain-specific annotated dataset and then implementing a hybrid NER model based on CAMeLBERT, an Arabic pre-trained model, combined with a CRF decoding layer that recognizes the entity types of disease, symptom, and organ. To show that performing effective biomedical NER in Arabic not only requires powerful pretrained representations, but also modeling strategies that bring the language's morphological richness and domain-specific variability into modeling. The proposed CAMeLBERT+CRF significantly outperforms robust baselines, such as CAMeLBERT and AraBERT for all entity types, achieving an F1-score of approximately 90%. The results demonstrate the effectiveness of pre-trained models with CRF in recognizing entities in specific domains with limited resources. Both the dataset and the model serve as valuable baselines for future work in biomedical natural language processing (NLP) in Arabic text. In general, this study provides strong evidence that transfer learning is beneficial for low-resource biomedical NLP, even if the annotated data are scarce. The CAMeLBERT+CRF model robustness to annotation noise indicates that pretrained language models can make up for the lack of data when finetuned with care. However, the performance gap observed among entity types reflects fundamental challenges of semantic ambiguity and morphological complexity which are still at the core of issues in processing Arabic biomedical text.

Future work will focus on enriching the dataset with diverse medical articles to include additional biomedical entity types such as drugs, treatments, and diagnostics from real-world EHR data, as this expansion may affect the model's generalizability. Moreover, more studies are needed explore to nested entities, considering the current limitations of CAMeLBERT+CRF model in this area. Additionally, focusing on other NLP tasks, such as text summarization, question-answering, and relation extraction within Arabic biomedical texts.

References

[1] R. Grishman and B. Sundheim, "Message Understanding Conference-6: A brief history," *Proc. 16th Int. Conf. Computational Linguistics (COLING)*, Copenhagen, Denmark, 1996.

[2] Z. Luo, Y. Ji, A. Gupta, Z. Li, A. Frisch, and D. He, "Towards accurate and clinically meaningful summarization of electronic health record notes: A guided approach," in *Proc. IEEE EMBS Int. Conf. Biomed. Health Informatics (BHI)*, Pittsburgh, PA, USA, 2023, pp. 1–5.

[3] N. Goyal and N. Singh, "Named entity recognition and relationship extraction for biomedical text: A comprehensive survey, recent advancements, and future research directions," *Neurocomputing*, vol. 618, p. 129171, 2025.

[4] K. Peng, C. Yin, W. Rong, C. Lin, D. Zhou, and Z. Xiong, "Named entity aware transfer learning for biomedical factoid question answering," *IEEE/ACM Trans. Comput. Biol. Bioinform.*, vol. 19, no. 4, pp. 2365–2376, 2022.

[5] E. Hossain, R. Rana, N. Higgins, J. Soar, P. D. Barua, A. R. Pisani, and K. Turner, "Natural language processing in electronic health records in relation to healthcare decision-making: A systematic review," *Comput. Biol. Med.*, vol. 155, p. 106649, 2023.

[6] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of deep bidirectional transformers for language understanding," in *Proc. NAACL-HLT*, Minneapolis, MN, USA, 2019, pp. 4171–4186.

[7] J. D. Lafferty, A. McCallum, and F. C. N. Pereira, "Conditional random fields: Probabilistic models for segmenting and labeling sequence data," in *Proc. 18th Int. Conf. Mach. Learn. (ICML)*, San Francisco, CA, USA, 2001, pp. 282–289.

[8] Salah, R., Mukred, M., Zakaria, L. Q., Ahmed, R., and Sari, H., "A new rule-based approach for classical Arabic in natural language processing," 2022.

[9] R. Salah, M. Mukred, L. Q. Zakaria, and F. A. M. Al-Yarimi, "A machine learning approach for named entity recognition in classical Arabic natural language processing," *KSII Trans. Internet Inf. Syst.*, vol. 18, no. 10, pp. 2895–2919, 2024.

[10] A. Shaker, A. Aldarf, and I. Bessmertny, "Using LSTM and GRU with a new dataset for named entity recognition in the Arabic language," *arXiv preprint arXiv:2304.03399*, 2023.

[11] A. B. Sadallah, O. Ahmed, S. Mohamed, O. Hatem, D. Hesham, and A. H. Yousef, "ANER: Arabic and Arabizi named entity recognition using transformer-based approach," in *Proc. 2023 Intell. Methods, Syst., and Appl. (IMSA)*, 2023, pp. 263–268.

[12] Cui, X., Song, C., Li, D., Qu, X., Long, J., Yang, Y., and Zhang, H., "RoBGP: A Chinese Nested Biomedical Named Entity Recognition Model Based on RoBERTa and Global Pointer," *Computers, Materials & Continua*, vol. 78, no. 3, pp. 3603–3618, 2024.

[13] J. Li, S. Zhao, J. Yang, Z. Huang, B. Liu, S. Chen, H. Pan, and Q. Wang, "WCP-RNN: A novel RNN-based approach for Bio-NER in Chinese EMRs," *J. Supercomput.*, vol. 76, no. 3, pp. 1450–1467, 2020.

[14] Y.-L. Chiang, C.-H. Lin, C.-L. Sung, and K.-Y. Su, "Nested named entity recognition for Chinese electronic health records with QA-based sequence labeling," in *Proc. 33rd Conf. Comput. Linguistics and Speech Processing (ROCLING)*, 2021, pp. 18–25.

[15] P. Chen, M. Zhang, X. Yu, and S. Li, "Named entity recognition of Chinese electronic medical records based on a hybrid neural network and medical MC-BERT," *BMC Med. Inform. Decis. Mak.*, vol. 22, no. 1, p. 315, 2022.

[16] G. G. Subies, Á. B. Jiménez, and P. M. Fernández, "ClinText-SP and RigoBERTa Clinical: a new set of open resources for Spanish Clinical NLP," *arXiv preprint arXiv:2503.18594*, 2025.

[17] R. A. A. Jonker, T. Almeida, R. Antunes, J. R. Almeida, and S. Matos, "Multi-head CRF classifier for biomedical multi-class named entity recognition on Spanish clinical notes," *Database*, vol. 2024, p. baae068, 2024.

[18] J. Copara, J. Knafou, N. Naderi, C. Moro, P. Ruch, and D. Teodoro, "Contextualized French language models for biomedical named entity recognition," in *Proc. 6e Conf. Conjointe Journées d'Études Sur La Parole (JEP), Traitement Automatique Des Langues Naturelles (TALN), Rencontre Des Etudiants Chercheurs En Informatique Pour Le Traitement Automatique Des Langues (RÉCITAL). Atelier Défi Fouille De Textes*, 2020, pp. 36–48.

[19] N. Bannour, C. Servan, A. Névéol, and X. Tannier, "A benchmark evaluation of clinical named entity recognition in French," *arXiv preprint arXiv:2403.19726*, 2024.

[20] Frei, J., and Kramer, F., "GERNERMED: An open German medical NER model," *Software Impacts*, vol. 11, p. 100212, 2022.

[21] P. Savaram, S. Tabassum, S. Bandu, and L. B, "Multilingual approaches to named entity recognition," in *Proc. 2024 3rd IEEE Delhi Section Flagship Conf. (DELCON)*, 2024, pp. 1–6.

[22] N. Boudjellal, H. Zhang, A. Khan, A. Ahmad, R. Naseem, J. Shang, L. Dai, and A. Khan, "ABioNER: A BERT-based model for Arabic biomedical named-entity recognition," *Complexity*, vol. 2021, pp. 1–6, 2021.

[23] S. Alanazi, "A named entity recognition system applied to Arabic text in the medical domain," in *Proc.*, 2017.

[24] R. M. Hamad and A. M. Abushaala, "Medical named entity recognition in Arabic text using SVM," in *Proc. 2023 IEEE 3rd Int. Maghreb Meeting Conf. Sci. Technol. Automat. Control Comput. Eng. (MI-STA)*, 2023, pp. 200–205.

[25] I. Ait Talghalit, H. Alami, and S. O. El Alaoui, "Exploring different annotation schemes for single and consecutive named entity recognition in the Arabic biomedical domain using transformer models and contextual semantic embeddings," *Eng. Technol. Appl. Sci. Res.*, vol. 15, no. 2, pp. 21854–21860, 2025.

[26] K. Darwish and H. Mubarak, "Farasa: A new fast and accurate Arabic word segmenter," in *Proc. 10th Int. Conf. Language Resources and Evaluation (LREC)*, 2016, pp. 1070–1074.

[27] T. Wolf, L. Debut, V. Sanh, J. Chaumond, C. Delangue, A. Moi, P. Cistac, T. Rault, R. Louf, M. Funtowicz, et al., "Transformers: State-of-the-art natural language processing," in *Proc. 2020 Conf. Empirical Methods in Natural Language Processing: System Demonstrations*, 2020, pp. 38–45.

[28] Webteb, "Medical Information and Health Articles," Webteb. Accessed: March 4, 2025. [Online]. Available: https://www.webteb.com/

[29] CAMeL-Lab, "BERT Base Arabic CAMeLBert Mix," Hugging Face Accessed: April 12, 2025. [Online]. Available: https://huggingface.co/CAMeL-Lab/bert-base-arabic-camelbert-mix

Adaptive Denoising of Partial Discharge Using Absolute Difference Optimization Versus Artificial Neural Networks

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***Abstract*—Accurate partial discharge (PD) localization in medium-voltage (MV) power cables is essential for condition-based maintenance, yet it remains unreliable when PD pulses are masked by broadband noise and narrowband interference. The novelty of this work is a controlled denoiser-to-localization benchmarking framework that isolates the denoising front end, while keeping the downstream PD detection and localization backend fixed, allowing localization differences to be attributed solely to denoising decisions. Within this fixed-backend paradigm, an optimization-driven Adaptive Denoising Optimization (ADO) method is introduced as an adaptive discrete wavelet transform (DWT) front end that systematically selects the mother wavelet, decomposition level, and threshold parameters to preserve time-of-arrival (ToA) critical wavefront features rather than only maximizing noise suppression. ADO is evaluated against two learning-based denoisers, a multilayer artificial neural network (ANN) and a lightweight feedforward neural network (FNN), using MATLAB simulations of synthetic PD pulses corrupted by white Gaussian noise (WGN) and discrete spectral interference (DSI) over SNRs from 9.78 dB to -10.34 dB. Performance is quantified using execution time, percentage localization error (PE), median absolute localization error (MedAE), and F1 score. Results show that ADO delivers the most robust localization fidelity, maintaining near-zero PE above -6 dB, keeping PE below 0.3% at -10.34 dB, achieving sub-metre MedAE, and sustaining F1 close to 1.0 across noise levels. In contrast, FNN is the fastest option, reducing runtime by approximately 15% versus ANN and 27% versus ADO, highlighting a practical robustness-efficiency trade-off for real-time MV cable monitoring.**

***Keywords*—Partial discharge localization; adaptive denoising optimization; discrete wavelet transform; artificial neural network**

I. Introduction

Partial discharge (PD) in medium-voltage (MV) power cables is a well-established indicator of insulation deterioration. If PD is not detected and localized reliably, degradation can accelerate, outage risk increases, and maintenance and replacement costs rise. Accurate localization remains challenging because PD pulses are short, broadband, and nonstationary, and are easily distorted or masked by background noise and electromagnetic interference (EMI). As a result, recent studies have combined physics-informed localization with advanced signal analytics, including time-of-arrival (ToA) formulations that account for cable propagation effects such as skin effect and semiconducting layers [1], reviews of ultra-high-frequency (UHF) PD signal processing and machine learning [2], electromagnetic time reversal (EMTR) methods for online MV cable localization with very low error [3], deep models for PD pattern recognition in cable accessories and sensing arrays [4], [5], and unsupervised deep learning for separating multiple PD sources in other high-voltage assets [6]. Collectively, this literature confirms the importance of PD localization, while also showing that realistic interference remains a primary barrier to dependable field deployment.

This barrier is closely tied to a common assumption embedded in many localization backends, including ToA, time-domain reflectometry (TDR), and correlation-based estimators: the first-arriving PD wavefront can be extracted clearly enough to preserve timing cues. In field-like MV cable monitoring, this assumption often fails because measurements are frequently contaminated by white Gaussian noise (WGN) and discrete spectral interference (DSI), which can shift, smooth, or obscure the onset used for ToA estimation. Prior studies and surveys highlight that noise strongly constrains PD feature extraction and localization fidelity [2], [7], including efforts to separate PD from EMI under WGN and DSI conditions [8] and analyses showing that timing-based methods degrade in long cables when propagation effects and noise jointly distort the pulse [9]. These findings motivate denoising as a critical front-end stage, since overall localization error can be dominated by preprocessing rather than by the mathematical form of the backend estimator.

Wavelet-domain denoising, particularly discrete wavelet transforms (DWT) processing, is widely used in PD analysis because it is well matched to transient multiscale signals and provides time-frequency localization of impulsive events [10-14]. However, conventional DWT denoising typically relies on fixed choices of mother wavelet, decomposition level, and thresholding rule that are tuned to a specific dataset or laboratory condition. When the interference spectrum changes or the signal-to-noise ratio (SNR) deteriorates, fixed settings may leave residual noise that masks the first wavefront, or they may distort PD timing through mismatched wavelet bases and over-thresholding [15]. Recent investigations further show that denoising quality is highly sensitive to the wavelet family, decomposition depth, and threshold strategy, and that the best configuration varies with the dominant noise type, implying that no single static setting is consistently optimal across operating conditions [16], [17]. In parallel, learning-based denoisers such as artificial neural networks (ANNs) and related deep

architectures can learn nonlinear noise suppression mappings and have reported strong denoising performance [18-20]. Nevertheless, their effectiveness can degrade when test noise statistics differ from training conditions, and their computational footprint may be undesirable for online or embedded monitoring, especially when robustness is required at very low SNR.

Despite this broad literature, systematic evaluation of denoiser-to-localization coupling under severe WGN and DSI conditions, including very low SNR, remains limited, particularly in controlled studies, where the localization backend is held fixed. Many reported improvements modify both the denoising stage and the localization logic, or change feature extraction and decision thresholds, which makes it difficult to attribute performance gains specifically to the denoiser. This confounding limit practical guidance for selecting a deployable denoising front end, especially when the design goal is not only noise suppression but also preservation of ToA-critical timing features that directly determine localization accuracy.

To address this gap, this study adopts a controlled benchmarking framework that varies only the denoising front end while keeping the downstream localization backend identical across all pipelines. This design removes backend-dependent influences such as different ToA pickers, correlation rules, or post-processing heuristics, so changes in localization accuracy, detection reliability, and runtime can be attributed directly to the denoiser. Within this fixed-backend setting, the proposed adaptive DWT-based Adaptive Denoising Optimization (ADO) [21] is evaluated against two learning-based benchmarks, a multilayer ANN and a lightweight feedforward neural network (FNN), using synthetic PD signals contaminated by WGN and DSI over SNRs from 9.78 dB to -10.34 dB. Performance is quantified using percentage localization error (PE), median absolute localization error (MedAE), F1 score, and execution time, enabling direct assessment of how denoising affects ToA-critical timing preservation and, consequently, localization fidelity under severe interference. The novelty is twofold: 1) establishing an explicit denoiser-to-localization coupling evaluation under a fixed localization backend, and 2) introducing an optimization-driven adaptive wavelet front end that systematically selects denoising configurations (wavelet basis, decomposition depth, and thresholding decisions) to maintain robustness as noise conditions and SNR vary. By reporting both accuracy and computational cost within the same controlled paradigm, the study provides practical guidance on robustness-efficiency trade-offs for real-time and resource-constrained MV cable monitoring.

II. Wavelet Denoising

Wavelet-domain denoising is a common front end for PD processing because the DWT provides a multiresolution representation that can attenuate broadband noise while separating narrowband or tonal interference from impulsive components. In practice, DWT denoising is highly sensitive to three coupled design choices: the mother wavelet (basis), the decomposition depth, and the threshold estimation and shrinkage rule. Parameter settings that work well under one measurement condition can degrade when SNR drops or when the interference spectrum changes, either by leaving residual noise that obscures weak impulses or by over-suppressing high-frequency coefficients and shifting the apparent onset that carries timing information [15]. Recent studies consistently report strong dependence on wavelet family, decomposition level, and threshold strategy, and show that the best configuration depends on the dominant noise type and measurement modality, so a single static setting is rarely robust across scenarios [16], [17].

To reduce this sensitivity, several adaptive or optimization-driven wavelet schemes have been explored in PD-related applications. Representative directions include sub-band identification or segmentation guided by impulsiveness indicators, such as spectral-kurtogram-guided approaches that emphasize informative bands and suppress noise-dominated coefficients [22], optimized wavelet denoising for recovering weak events in low-amplitude measurements [23], and adaptive parameter optimization in wavelet-threshold denoising, where optimization algorithms select threshold-related parameters based on the field noise level and a denoising quality objective [24]. Other work has emphasized robustness to translation effects and threshold estimation, such as shift-invariant wavelet denoising with empirical Bayes thresholding for low-SNR UHF PD wavefront detection and event segmentation [25]. While these approaches demonstrate the value of adaptivity, they often optimize denoising quality in isolation, or adapt only a subset of the wavelet design space, without explicitly constraining the solution to preserve ToA-critical timing cues that govern downstream localization fidelity [25].

Against this background, the novelty of ADO is an optimization-driven wavelet selection strategy that is explicitly designed for localization readiness. ADO performs optimization per signal realization, meaning each noisy PD waveform is processed independently, and it searches a predefined candidate set of mother wavelets, decomposition levels, and threshold configurations (threshold estimator and shrinkage rule) [21]. For each candidate configuration, the signal is denoised and evaluated using an objective function that balances suppression of WGN and DSI residuals with preservation of ToA-relevant structure by penalizing timing distortion of the earliest wavefront, for example, onset shift or correlation-lag deviation relative to the pre-denoising waveform. The final configuration is chosen using a minimum-cost rule, selecting the option that best satisfies this denoising-timing trade-off for the current noise realization. This bounded, discrete search avoids offline training, adapts directly to changing interference statistics, and improves robustness by discouraging over-denoising solutions that appear clean in energy terms, but distort the first-arrival features that localization depends on [15-17], [21].

III. PD Signals and Noise Modeling

Fig. 1 illustrates the online PD location system for power cables, which employs a multi-end measurement scheme to estimate the position of PD events. Three PD sensors, denoted A, B, and C, are installed along an underground cable at equal spacing of 2.5 km to capture the propagating PD pulse at each location. A substation receiver running the PD localization algorithm is connected to these sensors. When a PD event occurs, the pulse travels along the cable and is recorded as sigA,

sigB, and sigC, and the algorithm estimates the PD source location by comparing the signals' arrival times and waveform characteristics.

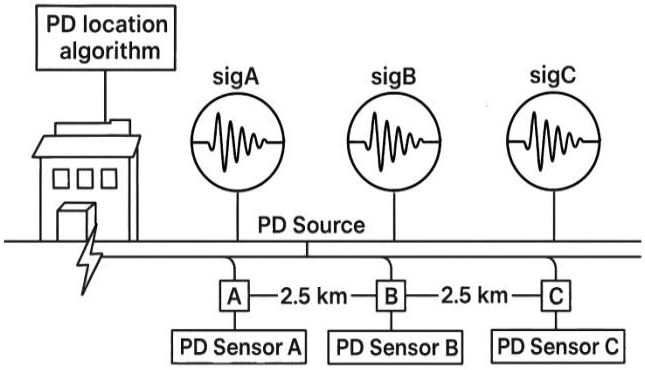


Fig. 1. Schematic representation of an online PD location estimation system for a power cable.

Fig. 2 presents the overall study workflow designed to isolate the effect of the denoising front end on PD localization. Noisy PD signals corrupted by WGN and DSI are first processed by one of the three denoisers (ADO, ANN, or FNN). The denoised outputs are subsequently fed into the same fixed PD localization backend to ensure a fair comparison, and performance is evaluated using localization accuracy, F1 score, and execution time to assess robustness and computational efficiency.

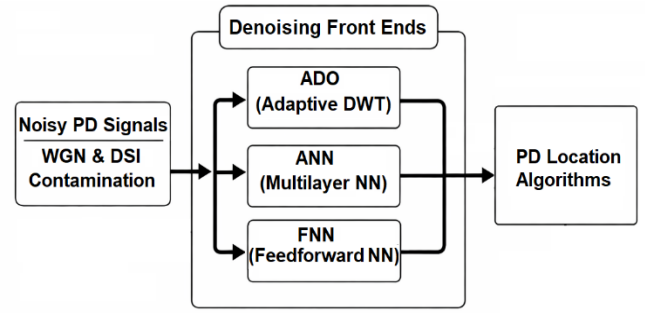


Fig. 2. Study workflow for benchmarking ADO against ANN and FNN under a fixed PD localization backend.

For simulation and localization analysis, the high-frequency PD pulse is modeled using Eq. (1) [8], which serves as the reference waveform:

$$s(t) = A[e^{-a_1 t}\cos(w_d t - \varphi) - e^{-a_2 t}\cos(\varphi)] \quad (1)$$

where, A is the amplitude coefficient, fixed at 0.01; a_1 and a_2 are damping factors set to 1 Ms^{-1} and 10 Ms^{-1}, respectively; $w_d = 2\pi f_d$ is the angular frequency of the damped oscillation; f_d is chosen as 1 MHz; and the phase term φ is given by $\tan^{-1}(w_d/a_2)$.

PD signal propagation along the cable is simulated with a sampling frequency f_s of 100 MHz. The propagation velocity, v_f, is obtained from Eq. (2) and then adjusted using laboratory experiments on a MV three-core cable (50 mm^2 Cu/XLPE/PVC, 8.7/15 kV), which yields an experimental value of 156 m/μs [8].

$$v_f = v_s/\sqrt{\varepsilon} \quad (2)$$

Here, v_s is the speed of electromagnetic waves in free space (300 m/μs); ε is the effective permittivity of the insulation and semiconductor layers of the cable.

To approximate realistic operating conditions, the simulated PD signals are corrupted by two typical interference sources: WGN and DSI. WGN is a broadband random noise with a Gaussian amplitude distribution and a flat power spectral density, representing thermal and electronic noise commonly present in measurement equipment. DSI is a narrowband periodic disturbance modeled as one or more sinusoidal components, capturing interference from power electronic devices, communication carriers, and other periodic emissions. WGN is generated in MATLAB, and its level is varied from 0 dB to -20 dB in -2 dB steps. DSI is applied at four discrete frequencies (600 kHz, 800 kHz, 1.5 MHz, and 5 MHz) with amplitudes ranging from 0.05 mV to 0.55 mV in 0.05 mV increments [8]. The DSI waveform is given by Eq. (3):

$$DSI(t) = A_{max}\sum_{t=1}^{N} 2\pi f_i t \quad (3)$$

The SNR of the noise-contaminated PD signals is then computed using Eq. (4) and Eq. (5), as in [8]:

$$SNR = \left(\frac{A_{signal}}{A_{noise}}\right)^2 \quad (4)$$

where, A_{signal} is the amplitude of the PD signal, and A_{noise} is the amplitude of the added noise. The corresponding SNR in decibels is:

$$SNR_{dB} = 10log_{10}(SNR) \quad (5)$$

IV. Denoising Methods

This study evaluates the proposed ADO denoising front end against two learning-based baselines, ANN and FNN, chosen to serve a clear benchmarking purpose rather than only practicality. ANN represents a higher-capacity neural denoiser that can model more complex nonlinear mappings, while FNN provides a lightweight alternative with reduced model complexity and different generalization behavior; together, they bracket a realistic range of neural denoising designs and allow us to test whether the localization performance limits arise from the learning paradigm itself or from model capacity and complexity. ADO is coupled to localization through its explicit goal of preserving ToA information: its adaptive DWT decomposition, wavelet selection, and thresholding are optimized to retain the earliest PD wavefront and sharp leading-edge transients while suppressing WGN and DSI. The denoised outputs are then passed unchanged into a fixed, identical ToA-based localization backend for all methods, so any change in estimated PD location is attributable to how well the denoiser preserves ToA-critical features rather than to differences in the localization algorithm.

A. Absolute Difference Optimization (ADO) Technique

Algorithm 1 presents the proposed ADO-based adaptive DWT denoising [21] procedure for PD signals, where the decomposition level is selected automatically to support

subsequent peak detection and ToA-based localization. A noisy observation is first formed by superimposing a synthetic clean PD waveform with mixed interference so that a clean reference remains available for objective evaluation. The noisy signal is constructed as Eq. (6):

$$x[n] = s_{PD}[n] + w_{WGN}[n] + d_{DSI}[n], \quad n = 1,\dots,N, \tag{6}$$

where, $s_{PD}[n]$ is the clean PD waveform, $w_{WGN}[n]$ denotes broadband WGN, and $d_{DSI}[n]$ represents DSI. This mixed noise model reflects practical environments, where both wideband background noise and narrowband harmonic or switching components coexist.

Algorithm 1: ADO-based adaptive DWT denoising for PD signals

```
Initialize
   Define wavelet type:
      wav ← 'db3'
   Define decomposition-level search range:
      Lmin ← 1
      Lmax ← 10
   Set tracking variables for optimal level:
      bestADO ← +∞
      bestLevel ← Lmin
      bestSignal ← empty

Compute
   Signal modelling (synthetic PD + noise):
      Generate clean PD waveform s_PD
      Generate white Gaussian noise WGN
      Generate discrete spectral interference DSI
      Form noisy signal:
         x ← s_PD + WGN + DSI
   Set initial decomposition level:
      L ← Lmin

While (L ≤ Lmax) do
   Apply DWT at level L:
      [cA_L, cD_L] ← DWT(x, wav, level = L)

   Denoising stage (reconstruct signal):
      y_L ← ReconstructDenoisedSignal(cA_L, cD_L)

   Peak detection (MATLAB findpeaks):
      peaks_L ← findpeaks(y_L)

   Compute absolute difference (AD):
      AD_L ← ComputeAbsoluteDifference(peaks_L,
referencePeaks)

   Calculate ADO factor:
      ADO_L ← ComputeADOFactor(AD_L)

   Check if current ADO is the minimum so far:
      if ADO_L < bestADO then
         bestADO ← ADO_L
         bestLevel ← L
         bestSignal ← y_L
      end

   Increment decomposition level:
      L ← L + 1
End

End

Output
   Denoised PD signal ŷ ← bestSignal at optimal decomposition
level bestLevel,
   which is subsequently used for PD peak detection and
localization.
```

For each candidate DWT decomposition level $L \in [1, 10]$, the noisy signal $x[n]$ is transformed using a fixed mother wavelet (Daubechies 3, db3), and the wavelet coefficients. The level-L DWT can be written as Eq. (7):

$$x[n] \xrightarrow{DWT} \{a_L|k|, d_j|k| \;\; j = 1,\dots,L\} \tag{7}$$

where, $a_L|k|$ are the approximation coefficients at level L and $d_j|k|$ are the detail coefficients at intermediate levels decomposition level j. After applying the chosen coefficient modification or thresholding strategy, the denoised signal $y_L[n]$ is reconstructed through the inverse DWT as Eq. (8):

$$y_L[n] = IDWT(a_L|k|, d_1|k|, \dots, d_L|k|) \tag{8}$$

The role of decomposition level L is to balance suppression and preservation: shallow decompositions may leave residual high-frequency noise, whereas excessively deep decompositions can over-smooth narrow PD impulses and distort the first arrival.

Each reconstructed signal $y_L[n]$, is then evaluated using peak features that are directly relevant to localization. PD peaks are extracted using MATLAB findpeaks, producing $\{p_{L,i}\}_{i=1}^{M}$., and compared against reference peaks $\{p_{ref,i}\}_{i=1}^{M}$ derived from the clean signal. The discrepancy is quantified by an absolute difference (AD) measure in Eq. (9).

$$AD_L = \sum_{i=1}^{M} |p_{L,i} - p_{ref,i}| \tag{9}$$

Absolute differences are preferred over squared errors because they remain in the original units (samples or amplitude), making them directly related to practical timing and localization deviations.

The AD measure is then condensed into an ADO factor, which serves as the scalar objective for decomposition level selection, as in Eq. (10):

$$ADO_L = |AD_L - K| \tag{10}$$

where, K = 0.505 is an empirically chosen reference that represents a balanced operating point between noise suppression and retention of PD peak structure. The optimal decomposition level is the one that minimizes ADO_L; lower values correspond to more faithful preservation of PD characteristics.

The algorithm iterates over all candidate levels $L = 1,\dots,L_{max}$, computing ADO_L for each. A running minimum is maintained as Eq. (11):

$$ADO_L = \underbrace{\min}_{1\le L\le L_{max}} ADO_L,$$
$$L^* = arg \underbrace{\min}_{L} ADO_L, \quad (11)$$

where, L^* denotes the optimal decomposition level. Whenever a new level yields $ADO_L < ADO_{min}$, the corresponding denoised signal $y_L[n]$ is stored as the current best candidate. Once all levels have been tested, the algorithm outputs Eq. (12):

$$\hat{y}[n] = y_{L^*}[n] \quad (12)$$

as the final denoised signal for subsequent PD peak detection and localization.

The ADO configuration is deliberately constrained to keep the method interpretable and computationally efficient, while still preserving ToA-critical content. The db3 wavelet is fixed because its compact support and pulse-like morphology match impulsive PD transients and help protect the sharp leading edge required by the fixed localization backend. The bounded search L = 1 to 10 provides sufficient multi-resolution flexibility to isolate PD-dominated sub-bands under mixed WGN and DSI without an excessive runtime increase, since cost scales mainly with record length and the number of tested levels. Finally, selecting $L*$ via the peak-based ADO objective links denoising to the fidelity of PD peak reconstruction, reducing over-smoothing and time shifting that would otherwise propagate into ToA error and degraded localization.

B. Artificial Neural Network (ANN) Technique

Algorithm 2 implements an ANN-based window-to-window denoising scheme for PD signals, where a fully connected multilayer perceptron is used as a data-driven front end to map noisy PD waveform segments to their clean counterparts on a frame-by-frame basis. The ANN is included as a representative learning based denoiser that can learn nonlinear signal noise relationships while remaining lighter than convolutional or recurrent models, which makes it suitable for long records and potential embedded deployment. The denoised output $\hat{y}[n]$is subsequently passed to the same fixed peak detection and ToA-based localization backend used throughout this study, so the impact of ANN denoising is assessed directly through its effect on timing and localization outcomes.

Algorithm 2: ANN-based window-to-window denoising for PD signals

```
Initialize
  Input noisy PD signal x, trained ANN denoiser net,
      window length win and hop size hop
  Set N ← length(x)
  Allocate reconstruction buffer yrec[1..N] ← 0
  Allocate overlap counter  wsum[1..N] ← 0
  Choose small constant ε to avoid division by zero

Compute
  Reshape x to a column vector
  Compute mean μx ← mean(x) and standard deviation σx ←
std(x) + ε
  Normalize input signal:
    for n = 1 to N do
      z[n] ← (x[n] − μx) / σx
    end
  Compute number of frames:
    nFrames ← 1 + floor((N − win) / hop)
  If nFrames < 1 then
    Set ŷ ← x and terminate the algorithm

While (frames remain to be processed) do
  For each frame index k = 1 to nFrames do
    Determine frame boundaries:
      a ← 1 + (k − 1) * hop
      b ← a + win − 1
      if b > N then b ← N
    Extract normalized frame:
      zk ← z[a : b]
    Apply ANN denoiser:
      ŷk ← net(zk)
    Accumulate output via overlap–add:
      yrec[a : b] ← yrec[a : b] + ŷk
      wsum[a : b] ← wsum[a : b] + 1
  end

  For n = 1 to N do
    if wsum[n] = 0 then wsum[n] ← 1
    Compute averaged normalized estimate:
      ẑ[n] ← yrec[n] / wsum[n]
    De-normalize to original scale:
      ŷ[n] ← ẑ[n] * σx + μx
  end

End

Output
  Denoised PD signal ŷ, which is subsequently used for peak
detection and PD localization. For multiple channels (A, B, C),
the same procedure is applied independently to each signal.
```

Let $[n]$, n=1, …, N, denote the noisy PD signal. As summarized in Algorithm 2, the method begins with global normalization to stabilize the input distribution. The sample mean and standard deviation are computed as Eq. (13) and Eq. (14):

$$\mu_x = \frac{1}{N}\sum_{n=1}^{N} x[n] \quad (13)$$

$$\sigma_x = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N}(x[n]-\mu_x)^2}+\varepsilon \quad (14)$$

where, ε is a small constant to avoid division by zero. The normalized sequence is shown in Eq. (15):

$$z[n] = \frac{x[n]-\mu_x}{\sigma_x}+\varepsilon \quad (15)$$

This step reduces sensitivity to absolute amplitude variation between realizations and channels, which helps ANN training converge more reliably and improves generalization when PD magnitude changes across operating conditions.

The normalized signal $[n]$ is segmented into overlapping frames of length win with hop size hop. In this implementation, win = 512 samples and hop = 256 samples (50% overlap) were selected to capture the PD pulse and its local noise context while keeping the ANN input dimension and parameter count manageable. The overlap condition $hop < win$ reduces blocking artifacts and ensures that pulses near frame boundaries are fully represented in at least one frame, which improves reconstruction continuity and ToA stability. For each frame index k, the frame boundaries are defined by Eq. (16):

$$a_k = 1 + (k-1)hop, \quad b_k = min(a_k + win - 1, N), \tag{16}$$

and the corresponding frame is shown in Eq. (17).

$$z_k = [z[a_k], \ldots, z[a_k]]^T \tag{17}$$

Each frame z_k is processed by a trained multi-layer ANN implementing the mapping as Eq. (18):

$$\hat{y}_k = f_\theta(z_k) \tag{18}$$

where, $f_\theta(.)$ is a sequence of affine transformations and nonlinear activations parameterized by weights and biases θ. The network is trained offline using noisy–clean frame pairs by minimizing a mean-squared error (MSE) loss, as shown in Eq. (19):

$$\hat{y}_k = \frac{1}{K}\sum_{k=1}^{K} \left\| f_\theta(z_k^{noisy}) - y_k^{clean} \right\|_2^2, \tag{19}$$

which encourages faithful reconstruction of PD pulse shape and amplitude that drive reliable peak picking and ToA estimation in the subsequent localization stage.

The frame-wise outputs are finally recombined using an overlap-add to obtain a continuous denoised waveform. A reconstruction buffer $y_{rec}[n]$ and overlap counter $w_{sum}[n]$ are accumulated over all frames. The final normalized estimate is then computed as Eq. (20):

$$\hat{z}[n] = \frac{y_{rec}[n]}{max(w_{sum}[n], 1)} \tag{20}$$

and the denoised signal in the original scale is recovered via de-normalization in Eq. (21):

$$\hat{y}[n] = \hat{z}[n]\sigma_x + \mu_x \tag{21}$$

The same procedure is applied independently to each measurement channel, which avoids mixing channel-specific responses and helps maintain consistent inter-sensor timing behavior for localization.

For ANN training, the parameter settings were selected to balance model capacity, training stability, and coverage of realistic noise conditions. The ANN denoiser is a small fully connected network with two hidden layers (128 and 64 neurons), which is large enough to learn the nonlinear mapping from noisy frames z_k to denoised frames $\hat{y}_k$ in Algorithm 2, while keeping the model lightweight. Training uses the scaled conjugate gradient solver (trainscg) to obtain stable convergence for this regression task. To control overfitting and keep training time predictable, training is capped at 150 epochs with validation-based early stopping (max_fail = 6) using an 80/10/10 split for training, validation, and testing. Generalization is encouraged by generating 600 noisy–clean frame pairs across multiple SNR conditions (20, 10, 5, 0, and −5 dB) using AWGN with measured signal power, and by adding multi tone discrete spectral interference at 0.6, 0.8, 1.5, and 5 MHz with an amplitude of 0.20 mV so the network learns to handle both broadband and narrowband disturbances. Finally, per-shot z-score normalization during dataset generation reduces sensitivity to amplitude scaling, and a fixed random seed (rng(42,'twister')) ensures the training results are reproducible.

C. Feedforward Neural Network (FNN) Technique

Algorithm 3 summarizes the FNN-based window-to-window denoising procedure for PD signals. The FNN is included as a lightweight counterpart to the multi-layer ANN denoiser: it follows the same framing, normalization, and overlap-add reconstruction steps, and it uses the same windowing settings and noise-condition ranges as the ANN for a fair comparison. The key difference is that the FNN adopts a shallower fully connected architecture with fewer hidden units and parameters, which reduces execution time and memory demand while still learning the core nonlinear mapping from noisy frames to denoised PD frames. This design allows the study to isolate the effect of model capacity on denoising quality and, ultimately, on peak preservation and localization performance.

Algorithm 3: FNN-based window-to-window denoising for PD signals

```
Initialize
   Input noisy PD signal x, trained FNN denoiser net,
        window length win and hop size hop
   Set N ← length(x)
   Allocate reconstruction buffer yrec[1..N] ← 0
   Allocate overlap counter  wsum[1..N] ← 0
   Choose small constant ε to avoid division by zero

Compute
   Reshape x to a column vector
   Compute mean μx ← mean(x) and standard deviation σx ←
std(x) + ε
   Normalize input signal:
      for n = 1 to N do
         z[n] ← (x[n] − μx) / σx
      end
   Compute number of frames:
      nFrames ← 1 + floor((N − win) / hop)
   If nFrames < 1 then
      Set ŷ ← x and terminate the algorithm

While (frames remain to be processed) do
   For each frame index k = 1 to nFrames do
      Update
         Determine frame boundaries:
            a ← 1 + (k − 1) * hop
            b ← a + win − 1
```

```
        if b > N then b ← N
      Extract normalized frame:
        zk ← z[a : b]
      Apply FNN denoiser:
        ŷk ← net(zk)
      Accumulate output via overlap–add:
        yrec[a : b] ← yrec[a : b] + ŷk
        wsum[a : b] ← wsum[a : b] + 1

  Update and analyze
    For n = 1 to N do
      If wsum[n] = 0 then wsum[n] ← 1
      Compute averaged normalized estimate:
        ẑ[n] ← yrec[n] / wsum[n]
      De-normalize to original scale:
        ŷ[n] ← ẑ[n] * σx + μx
    end

    If (denoising is required for multiple PD channels) then
      Repeat the above procedure for each channel (A, B, C)
with its
      corresponding noisy input and trained FNN
    End if

End

Output
  Denoised PD signal ŷ for subsequent peak detection and
localization
```

Let $[n]$, n=1, …, N, denote the noisy PD signal. The FNN pipeline adopts exactly the same global normalization, framing, and overlap-add reconstruction strategy as the ANN method, using Eq. (13) to Eq. (17) for preprocessing and Eq. (20) to Eq. (21) for recombination and de-normalization. This ensures that both denoisers operate on identically scaled inputs and produce outputs in the same physical units, enabling a fair comparison.

For each frame z_k, the trained FNN denoiser that applies a relatively shallow nonlinear mapping as Eq. (22):

$$\hat{y}_k = g_{\emptyset}(z_k) \tag{22}$$

where, $g_{\emptyset}(.)$ denotes a fully connected network with a reduced number of layers and neurons compared with the ANN. A typical realization uses a single hidden layer, as shown in Eq. (23):

$$\begin{aligned} h &= \varphi(W_1 z_k + b_1), \\ \hat{y}_k &= W_2 h + b_2 \end{aligned} \tag{23}$$

where, $\varphi(\cdot)$ is a nonlinear activation function (e.g., ReLU), and $\phi = \{W_1, b_1, W_2, b_2\}$ is the parameter set. As with the ANN, the FNN is trained offline on noisy-clean frame pairs by minimizing the MSE loss in Eq. (19). However, because ϕ contains substantially fewer parameters than the ANN's θ, the FNN exhibits lower computational cost, reduced memory footprint, and a lower risk of overfitting. In the PD denoising context, this can be beneficial when the training dataset is limited or when the deployment environment requires fast inference and deterministic latency.

After frame-wise processing, the FNN outputs $\hat{y}_k$ are merged using the same overlap-add and de-normalization steps as the ANN formulation, yielding the final denoised signal $\hat{y}[n]$. For multi-channel PD measurements, the procedure is applied independently to each channel. Overall, the FNN-based scheme preserves the ANN's signal processing structure, while offering a leaner network architecture tailored to scenarios where reduced latency, energy consumption, and implementation complexity are prioritized.

V. Results and Discussion

The ADO, ANN, and FNN pipelines were evaluated in MATLAB on an Intel® Core™ i5-5200U CPU @ 2.2 GHz with 16 GB RAM using four complementary metrics: execution time, PE, MedAE, and F1-score. The simulations employed a multi-end measurement setup along a 2.5 km cable with a fixed true PD location, and the signals were corrupted by composite noise comprising WGN and DSI. This multi-end configuration reflects practical online monitoring architectures that estimate PD location from ToA differences between sensors, while WGN and DSI represent broadband stochastic noise and narrowband interference, respectively. For each noisy realization, the denoised outputs from each pipeline were passed to the same localization method, ensuring that performance differences could be attributed solely to the denoising front end.

Execution time was measured using MATLAB's tic/toc around the full denoising-localization chain, providing a direct estimate of computational cost under identical hardware and software conditions.

The PE quantifies the relative deviation of the estimated PD location from the true location and is defined as Eq. (24):

$$\begin{aligned} &\%\ Error \\ &= \frac{|\ PDloc_{true} - PDloc_{est}|}{PDloc_{true}} \times 100\% \end{aligned} \tag{24}$$

where, $PDloc_{true}$ is the actual PD position, and $PDloc_{est}$ is the estimated PD location. PE is used because it normalizes the error to the cable length, allowing fair comparison across different cable spans and giving utilities an intuitive indication of how far, in percentage terms, the estimate deviates from the true fault location when planning sectionalized repairs.

MedAE measures the typical magnitude of localization errors across Monte Carlo trials and is given by Eq. (25):

$$\begin{aligned} MedAE\ &= median\ (|P_i\ - A_i\ |), \\ i &=\ 1, 2, \ldots, N \end{aligned} \tag{25}$$

where, P_i and A_i are the estimated and true PD locations for the i-th trial, and N is the total number of realizations. MedAE is chosen instead of mean absolute error (MAE) because the median is far less sensitive to occasional extreme mis-localizations that may occur under very severe noise or rare algorithm failures. It therefore provides a robust indicator of the typical performance.

Finally, the F1-Score recasts localization into a tolerance-based detection problem. A trial is counted as a correct localization (positive) if the absolute error lies within a tolerance window of ±100 m. Binary labels are formed accordingly, and

the F1-Score is computed from precision (P) and recall (R) as Eq. (26) to Eq. (28):

$$F1\ Score = \frac{2 \times (Precision\ x\ Recall)}{Precision\ +\ Recall} \quad (26)$$

where,

$$= \frac{Precision}{True\ Positives} \quad (27)$$
$$True\ Positives\ +\ False\ Positives$$

$$Recall = \frac{True\ ositives}{True\ Positives\ +\ False\ Negatives} \quad (28)$$

Here, true positives correspond to trials where the estimated location falls within ±100 m of the true PD position, while false negatives are trials outside this tolerance. This tolerance-based F1-Score is used because, in field practice, operators are less concerned with centimeter-level accuracy than with confining the fault to a sufficiently short cable section that can be isolated and inspected. By combining precision and recall under an engineering-relevant tolerance, the F1-Score provides a practical, balanced measure of good localization, penalizing both missed acceptable localizations and large mis-localizations.

A. Execution Time

Fig. 3 compares the execution time of the ADO, ANN, and FNN denoising pipelines over SNR levels from 9.78 dB to -10.34 dB using the same dataset and computing setup. FNN is consistently the fastest method, with a mean runtime of about 619 s versus 729 s for ANN and 853 s for ADO, giving average savings of roughly 15% and 27%, respectively. FNN runtimes drop from around 680-720 s at high SNR to about 475-500 s at the lowest SNR, while ANN shows the widest variability (about 508-837 s for most SNRs) and a clear spike to roughly 1113 s at -2.38 dB. ADO remains the slowest, but is comparatively stable across SNR, ranging from about 751 s to 989 s. Overall, all pipelines are complete within approximately 475-1115 s, indicating suitability for offline or semi-real-time PD analysis.

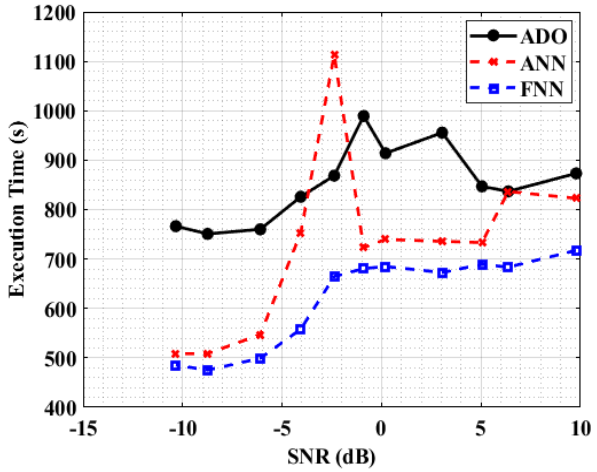


Fig. 3. Comparison of execution time for ADO-, ANN-, and FNN-based denoising pipelines over SNR levels ranging from 9.78 dB to −10.34 dB.

The runtime behavior reflects different computational cost drivers that matter for deployment. FNN's shallow architecture and small parameter count reduce per-epoch cost and typically converge quickly, which suits edge monitoring where latency, power, and throughput are dominant constraints, provided ToA fidelity is preserved. ANN offers intermediate speed but can be sensitive to the optimization landscape, leading to unpredictable delays that complicate buffering and scheduling. ADO is slower because it repeatedly performs multi-level DWT decompositions and reconstructions while searching across candidate configurations, but its latency is more predictable because it is mainly governed by signal length and the size of the search.

In practical PD localization systems, denoiser selection should therefore balance robustness, ToA preservation, computational budget, and operating constraints. FNN is appropriate for resource-limited, near-sensor screening when low latency is essential and uncertain windows can be flagged for later verification. ADO is better suited to offline diagnostics, periodic batch processing, or harsh EMI and low-SNR environments where timing fidelity and robustness outweigh runtime. A hybrid strategy is often most effective in utility monitoring: run FNN or ANN for continuous screening and invoke ADO selectively for low-confidence cases, low-SNR intervals, or high-value assets, improving reliability without paying ADO's full computational cost on every record.

For ADO, the dominant cost driver is search breadth (the number of tested decomposition levels and wavelet options), followed by signal length and windowing; restricting the search or processing a shorter pulse-centered window reduces runtime but can reduce robustness if the earliest wavefront is not retained. Threshold strength and selection-criterion tightness also trade off against timing fidelity, since overly aggressive settings risk smoothing or shifting first arrivals. For ANN and FNN, model size governs per-epoch cost, while training controls such as maximum epochs and early-stopping patience drive runtime variability; tightening these improves predictability but may degrade denoising if overly restrictive. Across all pipelines, the key design principle is to tune the front end to preserve the earliest PD wavefront and minimize ToA shift, since this ultimately governs end-to-end localization accuracy.

B. Percentage Error (PE)

Fig. 4 compares the PE of ADO, ANN, and FNN from 9.78 dB to -10.34 dB. ADO is consistently the most accurate, keeping PE between 0.0078% and 0.278% and staying below 0.03% for all $SNR \geq -4.06\ dB$. In contrast, ANN and FNN start at about 9.2% and 9.0% at 9.78 dB, remain above 4.7% under moderate noise, and rise sharply below -4 dB to roughly 21.4% and 22.5% at -10.34 dB. Consistent with this robustness, Table I shows that ADO selects lower decomposition levels (1–3) at higher SNR and shifts to deeper levels (4–5) as noise increases, keeping the estimated PD location close to 2000 m even in the most challenging cases.

These PE trends indicate that localization accuracy is dominated by timing fidelity rather than denoising strength alone. The large errors of ANN and FNN, even when SNR is high, imply that small reconstruction distortions can shift the effective ToA. In ToA-based MV cable localization, a one-to-two sample shift can translate into metres of location error, so smoothing or altering the first-arrival structure can degrade

localization despite producing visually clean signals. ADO's near-zero PE over moderate and high SNR, and only modest degradation at very low SNR, suggests that its wavelet-domain processing preserves ToA-critical features more reliably as interference changes.

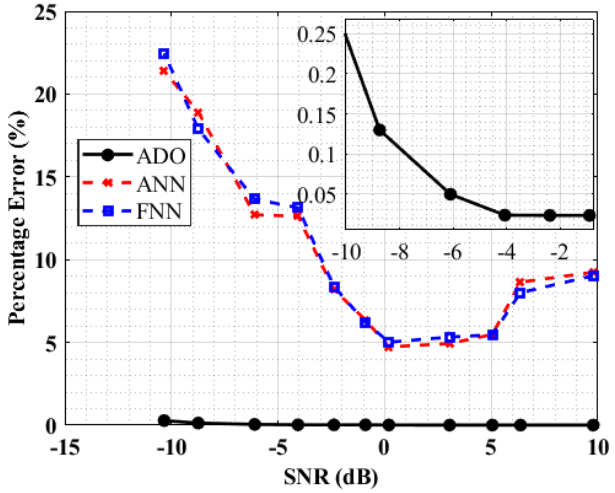


Fig. 4. Comparison of PE for ADO-, ANN-, and FNN-based denoising pipelines over SNR levels ranging from 9.78 dB to −10.34 dB.

TABLE I. ANALYSIS OF AD, ADO, AND PD LOCALIZATION ERROR ACROSS VARYING DWT DECOMPOSITION LEVELS AT A FIXED SNR OF -10.34 DB (WGN = -20 DB AND DSI = 0.55 MV)

SNR (dB)	AD	ADO	Estimated PD Location (m)	PD Location Error (%)	Decomp Level (DWT)
9.7812	0.5590	0.0540	1999.8439	0.0078	1
6.3698	0.4056	0.0056	1999.8439	0.0078	2
5.0484	0.3108	0.0892	1999.8439	0.0078	3
3.0471	0.3833	0.0167	1999.8439	0.0078	3
0.2003	0.4892	0.0892	1999.7401	0.0130	3
-0.9005	0.2566	0.1434	1999.5320	0.0234	4
-2.3772	0.3090	0.0910	1999.5320	0.0234	4
-4.0638	0.3597	0.0403	1999.5260	0.0237	4
-6.0967	0.4430	0.0430	2000.9960	0.0498	4
-8.7425	0.2855	0.1145	2002.6000	0.1300	5
-10.34	0.2900	0.1322	2005.5600	0.278	5

For system design, ADO is the safest default for field deployment when noise conditions are uncertain and accurate localization is required, since it maintains near-perfect accuracy down to -4.06 dB and remains below 0.3% PE at -10.34 dB. When computing is severely limited and approximate localization is acceptable, a lightweight neural front end such as FNN can be used for screening, with low-confidence or low-SNR windows escalated to ADO before producing the final location estimate. If ANN or FNN must serve as the primary front end, their evaluation and training should explicitly include timing-based criteria, because waveform similarity alone may not reflect ToA shifts that drive localization error. At low SNR, the deeper decomposition selected by ADO has a clear physical interpretation because finer subband separation helps preserve PD-dominated components, while suppressing broadband noise and interference.

For ADO, decomposition level is the dominant factor because it determines subband separation and ToA preservation; fixing the level (for example, always level 3) would likely increase PE at low SNR by reducing adaptability. Threshold strength and the AD/ADO selection criterion form a second lever, balancing residual interference suppression against the risk of attenuating the earliest wavefront, while the search breadth across wavelets and levels trades robustness against computation. For ANN/FNN, the loss function and training target are most influential, as smoothness-driven objectives such as MSE can blur transients and shift arrival time, whereas timing-aware losses or first-arrival weighting better protect localization-critical structure. Model capacity and training-test mismatch also affect performance, but the observed PE gap suggests that improving neural localization requires explicit timing-preserving design and training data that match expected EMI and SNR conditions.

C. Median Absolute Error (MedAE)

Fig. 5 compares the MedAE of ADO, ANN, and FNN across SNR levels from 9.78 dB to -10.34 dB. ADO performs best throughout, maintaining MedAE = 0.000 m for all $SNR \geq 0.2\ dB$ and increasing only to about 0.3-0.8 m when SNR becomes negative. In contrast, ANN and FNN produce much larger MedAE at every SNR point, starting around 65-117 m at high SNR and rising to roughly 280-800 m as noise increases. Their curves are nearly identical, indicating a shared limitation in maintaining precise timing under noisy conditions.

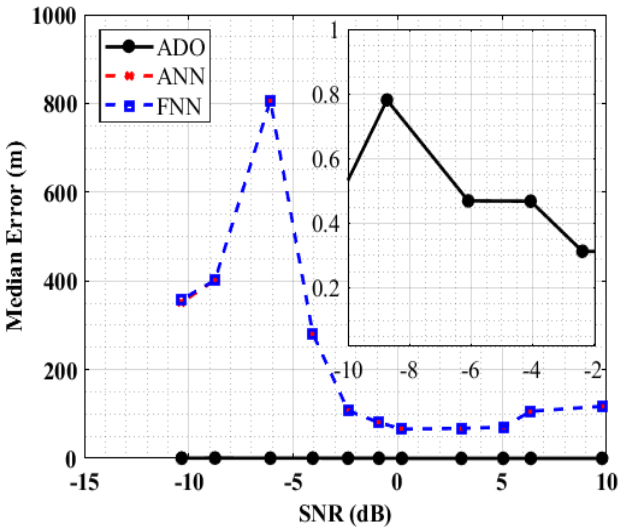


Fig. 5. Comparison of MedAE for ADO-, ANN-, and FNN-based denoising pipelines over SNR levels ranging from 9.78 dB to −10.34 dB.

MedAE is especially informative for PD localization because it represents typical field performance rather than being driven by occasional outliers. ADO's near-zero MedAE at moderate and high SNR implies that its denoising preserves the leading-edge timing needed for accurate time-difference-of-arrival estimation, so at least half of the events are localized essentially at the true position within the model's resolution.

Even at negative SNR, ADO remaining below 1 m indicates strong protection of ToA-critical features against time shifting as interference increases. By contrast, the large MedAE of ANN and FNN suggests a systematic failure mode, where smoothing and broadening of impulsive PD transients introduce timing bias and jitter that are amplified into large location errors by the ToA backend.

These findings translate into clear deployment guidance. For high-confidence localization that supports maintenance actions such as joint targeting and dig planning, ADO should be the primary denoising front end because it keeps typical errors near zero at non-negative SNR and within sub-meter levels even in noise-dominated regimes. ANN or FNN are only suitable when the goal is rapid event screening rather than precise localization, and should be paired with safeguards such as confidence scoring and escalation of difficult or low-SNR windows to an ADO pass before finalizing a location estimate. More broadly, ADO's stability across SNR makes it the safer default in MV underground networks, where noise conditions can vary significantly across assets and operating states.

For ADO, the decomposition level and its selection rule are most critical, since deeper decomposition at low SNR improves subband separation and helps preserve the first-arrival structure; fixing the level (e.g., always level 2 or 3) would likely increase MedAE under negative SNR. Threshold magnitude is the next key lever because over-thresholding can attenuate the earliest wavefront, while under-thresholding leaves timing-corrupting interference, and mother wavelet choice affects how well sharp edges are preserved. For ANN/FNN, the dominant factor is the training objective and loss weighting, as standard reconstruction losses promote smoothing and can shift arrival time; timing-aware losses that emphasize the first-arrival region are therefore the most direct route to reducing MedAE. Training-test mismatch, noise diversity, and model capacity also matter, but improving localization requires explicitly timing-preserving design rather than network size reduction alone.

D. F1-Score

Table II summarizes precision, recall, and F1-score for the ADO, ANN, and FNN denoising-detection pipelines from 9.78 dB to -10.34 dB. ADO achieves an F1-score of 1.0000 from 9.78 dB down to -4.06 dB with precision and recall both equal to 1.0000. Even under severe noise (-6.10 dB to -10.34 dB), ADO remains strong with F1-scores between 0.9787 and 0.9950, driven by precision = 1.0000 and only a modest recall drops to 0.9583-0.9900. In contrast, ANN and FNN show much lower F1-scores across all SNRs; although their precision stays at 1.0000, recall is limited (0.45-0.56 at higher SNR) and collapses at low SNR (0.03-0.08), reducing F1 to below 0.17 and as low as 0.0667 at -10.34 dB.

These detection trends directly affect PD localization because reliable localization requires consistent event capture, and missed detections reduce event coverage, create gaps in activity timelines, and decrease the likelihood of obtaining ToA-informative wavefront segments needed by the localization backend. In this sense, the F1-score is a gating metric for localization readiness. ADO's near-unity F1 across the full SNR range indicates that it preserves PD-noise separability under both WGN and DSI after denoising, while the small recall reduction at the lowest SNR reflects a controlled trade-off, where stronger suppression occasionally removes marginal PD components, but does not materially reduce event capture.

TABLE II. COMPARISON OF PRECISION, RECALL, AND F1-SCORE FOR ADO, ANN, AND FNN DENOISING–DETECTION PIPELINES OVER VARYING SNR CONDITIONS IN PD EVENT DETECTION

SNR (dB)	F1 score of ADO	F1 score of ANN	F1 score of FNN
9.7812	1.0000 (P = 1.0000, R = 1.0000)	0.6207 (P = 1.0000, R = 0.4500)	0.6207 (P = 1.0000, R = 0.4500)
6.3698	1.0000 (P = 1.0000, R = 1.0000)	0.6301 (P = 1.0000, R = 0.4600)	0.6301 (P = 1.0000, R = 0.4600)
5.0484	1.0000 (P = 1.0000, R = 1.0000)	0.7179 (P = 1.0000, R = 0.5600)	0.7179 (P = 1.0000, R = 0.5600)
3.0471	1.0000 (P = 1.0000, R = 1.0000)	0.7500 (P = 1.0000, R = 0.6000)	0.7500 (P = 1.0000, R = 0.6000)
0.2003	1.0000 (P = 1.0000, R = 1.0000)	0.7578 (P = 1.0000, R = 0.6100)	0.7578 (P = 1.0000, R = 0.6100)
-0.9005	1.0000 (P = 1.0000, R = 1.0000)	0.7226 (P = 1.0000, R = 0.5657)	0.7226 (P = 1.0000, R = 0.5657)
-2.3772	1.0000 (P = 1.0000, R = 1.0000)	0.6222 (P = 1.0000, R = 0.4516)	0.6222 (P = 1.0000, R = 0.4516)
-4.0638	1.0000 (P = 1.0000, R = 1.0000)	0.3960 (P = 1.0000, R = 0.2469)	0.3960 (P = 1.0000, R = 0.2469)
-6.0967	0.9950 (P = 1.0000, R = 0.9900)	0.1538 (P = 1.0000, R = 0.0833)	0.1538 (P = 1.0000, R = 0.0833)
-8.7425	0.9948 (P = 1.0000, R = 0.9896)	0.1639 (P = 1.0000, R = 0.0893)	0.1639 (P = 1.0000, R = 0.0893)
-10.3400	0.9787 (P = 1.0000, R = 0.9583)	0.0667 (P = 1.0000, R = 0.0345)	0.0667 (P = 1.0000, R = 0.0345)

From a deployment perspective, the perfect-precision but low-recall behavior of ANN and FNN is problematic as a primary trigger in many field settings. While detected events are almost always correct, many true PD events are missed even at high SNR, and recall collapses under noise, which can falsely suggest low PD activity and bias downstream localization toward only the strongest pulses. For condition monitoring, where missed PD events are unacceptable, ADO is therefore the preferred front-end because it maintains a near-balanced precision-recall profile across wide SNR variation. Where compute and power constraints motivate neural methods, ANN/FNN are better used as low-latency screeners in a two-stage workflow, with ADO applied selectively to buffered windows during suspected activity, low-SNR periods, or low-confidence cases to recover missed events before localization.

For ADO, threshold aggressiveness is the key lever at low SNR: tightening thresholds preserves precision but can reduce recall by suppressing weak PD components, so recall is typically the first metric to move under threshold scaling. Decomposition level selection and mother wavelet choice also

affect separability, because subband isolation and morphology matching determine whether PD transients remain distinct enough to cross the decision threshold under interference; fixing the level rather than adapting it would likely reduce recall at low SNR. For ANN/FNN, the dominant driver is the decision threshold and calibration, since precision = 1.0000 implies overly conservative triggering; lowering the threshold can raise recall, but must be paired with false-alarm control. Training objectives that penalize missed detections and broader training noise diversity across realistic WGN and DSI conditions are also critical, because the recall collapses at very low SNR indicates sensitivity to training-test mismatch.

VI. Conclusion and Recommendations

This study shows that denoising is a core element of MV cable PD localization because it directly governs timing integrity and, therefore, the reliability of ToA-based estimates. Using a controlled benchmark in which only the denoising front end is varied while the localization backend is kept fixed, the key message is that localization improves when the denoiser preserves the earliest PD wavefront features under interference, rather than simply reducing overall noise energy. From a design standpoint, a deterministic and training-free adaptive wavelet front end such as ADO is recommended when robust, high-confidence localization is required across changing noise conditions, because it adapts to the observed interference while discouraging timing distortion that would otherwise propagate into localization error. When computational speed and simplicity are the dominant constraints, a lightweight neural option such as the FNN can be considered as an efficiency-oriented alternative, but its robustness should be verified under the expected field noise variability instead of being assumed from laboratory-like conditions. These implications are especially relevant for low-cost monitoring hardware, since the evaluation was performed on a modest CPU platform representative of practical embedded units rather than GPU-accelerated workstations, where model handling and inference overheads can limit the deployability of learning-based pipelines. The main limitation is that the study relied on MATLAB simulations with synthetic PD waveforms in a controlled scenario and a noise model limited to WGN and DSI, so it cannot fully capture field variability such as joints, reflections, multiple concurrent sources, sensor coupling differences, and nonstationary interference. Future work should therefore validate the conclusions using measured PD data from real cable assets and defect types, and further optimize ADO for embedded implementation through streamlined search strategies and efficient realizations, with targeted acceleration where available.

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References

[1] B. Dhamala and M. Ghassemi, "Partial Discharge Localization along Medium Voltage Cables," in *Proc. 2025 IEEE International Electric Machines and Drives Conference (IEMDC)*, Houston, TX, USA, May 2025, pp. 834–839, doi: https://doi.org/10.1109/IEMDC60492.2025.11061155.

[2] L. Jiachuan, X. Wang, W. Zhou, J. Zhang, D. Dai, and G. Zhu, "A Comprehensive Review of Signal Processing and Machine Learning Technologies for UHF PD Detection and Diagnosis (I): Preprocessing and Localization Approaches," *IEEE Access*, vol. 9, pp. 69876–69904, 2021, doi: https://doi.org/10.1109/access.2021.3077483.

[3] A. Ragusa, H. G. Sasse, and A. Duffy, "On-Line Partial Discharge Localization in Power Cables Based on Electromagnetic Time Reversal Theory - Numerical Validation," *IEEE Transactions on Power Delivery*, vol. 37, no. 4, pp. 2911–2920, Aug. 2022, doi: https://doi.org/10.1109/TPWRD.2021.3119236.

[4] C.-K. Chang, H.-H. Chang, and B. K. Boyanapalli, "Application of Pulse Sequence Partial Discharge Based Convolutional Neural Network in Pattern Recognition for Underground Cable Joints," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 29, no. 3, pp. 1070–1078, Jun. 2022, doi: https://doi.org/10.1109/tdei.2022.3168328.

[5] Z. Zhang et al., "Partial Discharge Pattern Recognition Based on a Multifrequency F–P Sensing Array, AOK Time–Frequency Representation, and Deep Learning," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 29, no. 5, pp. 1701–1710, Aug. 2022, doi: https://doi.org/10.1109/tdei.2022.3199189.

[6] S. Mantach, M. Partyka, V. Pevtsov, A. Ashraf, and B. Kordi, "Unsupervised Deep Learning for Detecting Number of Partial Discharge Sources in Stator Bars," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 30, no. 6, pp. 2887–2895, Dec. 2023, doi: https://doi.org/10.1109/tdei.2023.3306324.

[7] M. R. Hussain, S. S. Refaat, and H. Abu-Rub, "Overview and Partial Discharge Analysis of Power Transformers: A Literature Review," *IEEE Access*, vol. 9, pp. 64587–64605, 2021, doi: https://doi.org/10.1109/access.2021.3075288.

[8] C. K. Fern et al., "Fault localization on power cables using time delay estimation of partial discharge signals," *International Journal of Electrical and Computer Engineering*, vol. 13, no. 6, p. 6000, Sep. 2023, doi: https://doi.org/10.11591/ijece.v13i6.pp6000-6015.

[9] M. Alqtish et al., "A review of partial discharge electrical localization techniques in power cables: Practical approaches and circuit models," *Energies*, vol. 18, no. 10, Art. no. 2583, 2025, doi: https://doi.org/10.3390/en18102583.

[10] G. V. R. Xavier, R. De a Coelho, H. S. Silva, A. J. R. Serres, E. G. Da Costa, and A. S. R. Oliveira, "Partial discharge location through application of stationary discrete Wavelet transform on UHF signals," *IEEE Sensors Journal*, vol. 21, no. 21, pp. 24644–24652, Sep. 2021, doi: https://doi.org/10.1109/jsen.2021.3116491.

[11] S. Govindarajan, M. Natarajan, J. A. Ardila-Rey, and S. Venkatraman, "Partial discharge location identification using permutation entropy based instantaneous energy features," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1–12, Jan. 2021, doi: https://doi.org/10.1109/tim.2021.3121477.

[12] Y. Yan, R. Trinchero, I. S. Stievano, H. Li, and Y.-Z. Xie, "An Automatic Tool for Partial Discharge De-Noising via Short-Time Fourier Transform and Matrix Factorization," *IEEE Transactions on Instrumentation and Measurement*, vol. 71, pp. 1–12, Jan. 2022, doi: https://doi.org/10.1109/tim.2022.3216583.

[13] L. Lu, K. Zhou, G. Zhu, X. Yang, and B. Chen, "Partial Discharge Location Algorithm Based on Total Least-Squares With Matérn Kernel in Cable Systems," *IEEE Transactions on Industrial Informatics*, vol. 19, no. 3, pp. 2421–2431, Mar. 2023, doi: https://doi.org/10.1109/tii.2022.3153835.

[14] J. Wang, L. Lu, G. Zhu, K.-L. Yin, K. Zhou, and B. Chen, "Unbiased Euclidean Direction Search Algorithm for Partial Discharge Location in Cable Systems," *IEEE Transactions on Instrumentation and Measurement*, vol. 74, pp. 1–13, Jan. 2025, doi: https://doi.org/10.1109/tim.2025.3538076.

[15] M. A. Shams, H. I. Anis, and M. El-Shahat, "Denoising of Heavily Contaminated Partial Discharge Signals in High-Voltage Cables Using Maximal Overlap Discrete Wavelet Transform," *Energies*, vol. 14, no. 20, p. 6540, Oct. 2021, doi: https://doi.org/10.3390/en14206540.

[16] K. Friebe and F. Jenau, "Evaluation Study on Wavelet Denoising of Antenna-Based PD Measurements in Strong Interference Environments Considering a New Reliability Score of Pulse Detection," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 31, no. 6, pp. 2887–2896, Dec. 2024, doi: https://doi.org/10.1109/tdei.2024.3374243.

[17] M. A. Sahnoune et al., "Noise Source Effect on the Quality of Mother Wavelet Selection for Partial Discharge Denoising," *IEEE Access*, vol. 12, pp. 132729–132743, Jan. 2024, doi: https://doi.org/10.1109/access.2024.3459474.

[18] J. Yeo et al., "Localisation of Partial Discharge in Power Cables Through Multi-Output Convolutional Recurrent Neural Network and Feature Extraction," *IEEE Transactions on Power Delivery*, vol. 38, no. 1, pp. 177–188, Jun. 2022, doi: https://doi.org/10.1109/tpwrd.2022.3183588.

[19] C. Kumar, B. Ganguly, D. Dey, and S. Chatterjee, "Wavelet-Based Convolutional Neural Network for Denoising Partial Discharge Signals Extracted via Acoustic Emission Sensors," *IEEE Sensors Letters*, vol. 8, no. 7, pp. 1–4, Jul. 2024, doi: https://doi.org/10.1109/lsens.2024.3414954.

[20] A. H. Alshalawi and F. S. Al-Ismail, "Partial Discharge Detection Based on Ultrasound Using Optimized Deep Learning Approach," *IEEE Access*, vol. 12, pp. 5151–5162, Jan. 2024, doi: https://doi.org/10.1109/access.2024.3350555.

[21] C. K. Fern et al., "Adaptive Wavelet De-noising Algorithm using Absolute Difference Optimization Technique for Partial Discharge Signal," *Journal of Engineering and Science Research*, vol. 7, no. 3, pp. 26–31, Jun. 2023, doi: https://doi.org/10.26666/rmp.jesr.2023.3.4.

[22] J. Zhong, X. Bi, Q. Shu, D. Zhang, and X. Li, "An Improved Wavelet Spectrum Segmentation Algorithm Based on Spectral Kurtogram for Denoising Partial Discharge Signals," IEEE Transactions on Instrumentation and Measurement, vol. 70, pp. 1–8, Jan. 2021, doi: https://doi.org/10.1109/tim.2021.3071224.

[23] Q. Lin, F. Lyu, S. Yu, H. Xiao, and X. Li, "Optimized denoising method for weak acoustic emission signal in partial discharge detection," IEEE Transactions on Dielectrics and Electrical Insulation, vol. 29, no. 4, pp. 1409–1416, Jun. 2022, doi: https://doi.org/10.1109/tdei.2022.3183662.

[24] X.-C. Hua et al., "A Novel Adaptive Parameter Optimization Method for Denoising Partial Discharge Ultrasonic Signals," IEEE Transactions on Dielectrics and Electrical Insulation, vol. 30, no. 6, pp. 2734–2743, Nov. 2023, doi: https://doi.org/10.1109/tdei.2023.3331663.

[25] Francisco, Rodrigo, George, P. D. Alvim, S. Júnior, and H. S. Silva, "Wavefront Detection and Event Segmentation Method for Partial Discharge Signal Analysis," IEEE Access, vol. 13, pp. 111602–111613, Jan. 2025, doi: https://doi.org/10.1109/access.2025.3582635.

Improving YOLO11 Architecture for Reckless Driving Detection on the Road

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***Abstract*—Reckless driving behavior on the road can increase the risk of traffic accidents for drivers and other road users. Currently, supervision remains weak, particularly in direct supervision, due to the limited number of officers. This study developed an automated system to detect reckless drivers based on their road trajectories. This system comprised three subsystems: car detection, car tracking, and driving trajectory detection. In the driving trajectory detection subsystem, we proposed an improved YOLO11n-cls method developed from YOLO11n-cls by adding convolution and C3k2 blocks. The test results showed that the proposed model achieved an accuracy increase of 4.4% over YOLO11n-cls. The proposed model achieved an accuracy of 0.935 and an inference time of 0.5 ms for car trajectory classification. In addition, the proposed model achieved higher accuracy than all YOLO11 models (YOLO11n-cls, YOLO11s-cls, YOLO11m-cls, YOLO11l-cls, and YOLO11x-cls) and all YOLO12 models (YOLO12n-cls, YOLO12s-cls, YOLO12m-cls, YOLO12l-cls, and YOLO12x-cls). Therefore, the proposed model is better suited to support traffic law enforcement, especially the real-time detection of reckless drivers on highways.**

***Keywords*—Reckless driving detection; improved YOLO11n-cls; added convolution blocks; added C3k2 blocks**

I. Introduction

Deaths from traffic accidents remain a serious global problem. One contributing factor is drivers who disobey traffic regulations, such as dangerous or reckless driving. These violations not only endanger the driver but also put other road users at risk, thereby increasing the likelihood of accidents. Furthermore, many violations still occur. Therefore, it is crucial to strengthen supervision and enforcement of the rules. Currently, supervision is still carried out directly on the road due to limited personnel. This way has the disadvantage of potentially undetected violations. One solution to this problem is to utilize roadside surveillance cameras in conjunction with automated detection systems to identify drivers who drive dangerously or recklessly, thereby preventing traffic accidents. This system requires high accuracy and speed to be implemented in real time.

Research on detecting reckless driving behavior on the highway began about a decade ago. Based on the location of the sensor installation, this research was divided into two categories, namely sensors installed inside the car and surveillance camera sensors installed above the highway. Sensors installed inside the car monitor driver behavior directly. Meanwhile, surveillance camera sensors installed above the highway analyze driver trajectory patterns and speeds. Some methods used for sensor-based car systems included AdaBoost [1], Backpropagation [2], Support Vector Machine (SVM) [3], Graph Convolutional Long Short-term Memory networks (GConvLSTM) [4], YOLOv5 [5], YOLOv8 [6], and ResNet18+SCConv [7]. Meanwhile, some methods using surveillance cameras installed above the highway were SVM [8], Boosting Artificial Intelligence (BAI) [9], Lightweight Graph Convolution (LGC) [10], Convolutional Neural Network (CNN) [11][12], YOLOv2 [13], and YOLOv3 [14].

Cameras installed above the road are better suited for law enforcement, especially for detecting reckless driving. YOLOv2 and YOLOv3 are superior to other methods in single-frame multi-object detection, but they have weaknesses in detecting small objects and require substantial computational resources [13][14]. The models make them challenging to implement in real-time. These models produce low accuracy on small-looking car objects.

YOLO excels because it is fast, accurate, efficient, and easy to implement. It is also suitable for real-time object detection across various applications, including detecting parking space availability [15], video summarization [16], anomaly detection from a video surveillance camera [17], and student behavior detection [18]. Another investigation aimed at detecting pedestrians [19], vehicles [20], and road objects [21]. YOLOv2 and YOLOv3 have been used for reckless driver detection, but these models produce relatively low accuracy and long computation time compared to YOLO11.

This study proposed a system for detecting reckless car drivers on the road based on their trajectories, suitable for real-time conditions. This system comprised three subsystems: car detection, car tracking, and driving trajectory detection. We utilize the modified YOLO11 in the car detection subsystem, the ByteTrack algorithm in the car tracking subsystem, and the improved YOLO11n-cls model for driving trajectory detection. YOLO11n-cls still produces substantial errors in classifying car trajectories on the highway, especially in the smooth lane-change class. This study develops the improved YOLO11n-cls model, which is based on YOLO11n-cls. This model added convolutional layers and C3k2 blocks to expand the model's representation capacity, resulting in a YOLO11n-cls architecture that was more powerful at classifying car driver trajectories on the road. The development of this model aims to improve the accuracy of car trajectory classification on the road while maintaining a consistent speed.

II. Materials and Methods

A. Dataset

The data used in this study are vehicle trajectory images from a 70-minute video recording on a highway. The video has a resolution of 960 × 540 pixels and a frame rate of 30 frames per second (fps). The recording was made with a camera mounted above the highway. The data was recorded on a highway in Semarang City, Indonesia. Fig. 1 is an example of a frame from this video.



Fig. 1. Example of a video frame.

The trajectory data consisted of 153 images across three classes: 87 for straight driving, 30 for smooth lane changes, and 36 for reckless driving. This dataset was split into two parts: 70% for training and 30% for testing. The straight driving class represents the trajectory of a car that does not change lanes, and the smooth lane change class represents the trajectory of a car that changes lanes once. Meanwhile, the reckless driving class represents a car that changes lanes more than once. An example of this dataset is shown in Fig. 2.

B. Proposed System

The method proposed in this study was a reckless road traffic detection system based on the driver's car trajectory. This system consisted of three subsystems: car detection, car tracking, and driving trajectory detection, as illustrated in Fig. 3. The car detection subsystem determined the car's position on the road. The method used was modified YOLO11m, which has been shown to achieve higher mAP than YOLOv8x, YOLOv8m, and all YOLO11 models [22]. The next subsystem was car tracking, which determined each car's trajectory on the road. The method used in this tracking was the ByteTrack algorithm. This algorithm has been demonstrated to outperform other tracking methods, including SORT, DeepSORT, and DeepMOT [23].

The final subsystem, driving trajectory detection, is illustrated in Fig. 4. It comprises several processes: car trajectory reconstruction, Region of Interest (ROI) frame determination, and trajectory classification. The trajectory reconstruction process was used to redraw the car's trajectory on a base frame. This base frame was obtained from one of the video recording frames. Next, the ROI was determined to identify the key areas of the trajectory, namely the road. The ROI was determined by determining 4 points on the highway boundary. The ROI area was left fixed while the others were colored black. The next step was to crop the ROI, then continue the perspective transformation (warping) to produce only the ROI area of the car's trajectory on the highway.

The final process involved classifying the trajectory of the car in this image. This study developed a YOLO11n-cls model for classifying three car-trajectory classes: straight driving, smooth lane change, and reckless driving. The proposed method is named improved YOLO11n-cls, as shown in Fig. 5. The YOLO11n-cls model was essentially a YOLO-based classification model that used a lightweight backbone with convolutional blocks and C3k2 modules for feature extraction, along with a C2PSA (Cross-Stage Partial Squeeze-and-Attention) module to capture spatial and contextual dependencies at a high feature level [24]. This structure is designed to be computationally efficient, while still producing rich feature representations, making it suitable for various image classification tasks, including vehicle movement trajectories.



(a) (b) (c)

Fig. 2. Example of datasets: (a) Straight driving class, (b) Smooth lane change class, (c) Reckless driving class.

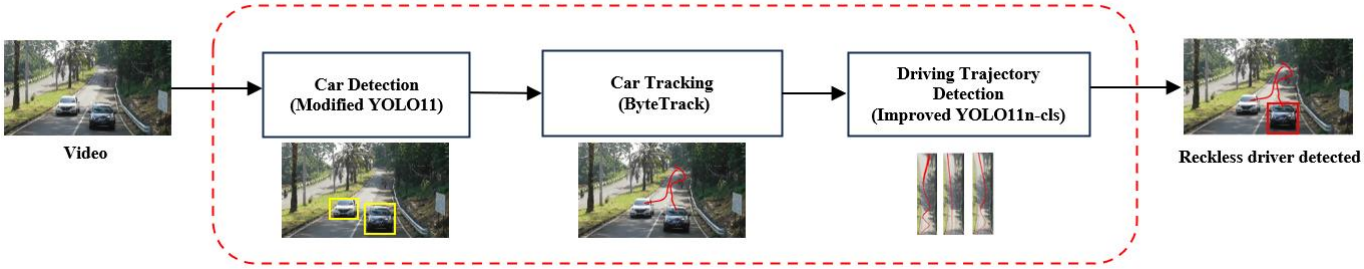


Fig. 3. The proposed system for reckless road traffic detection.

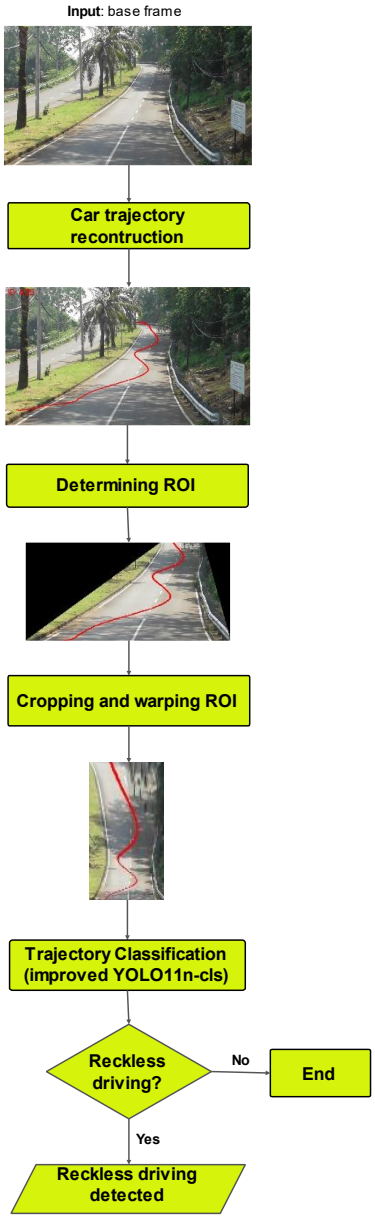


Fig. 4. Driving trajectory detection subsystem.

In the improved YOLO11n-cls model, we modified the backbone to enhance its feature extraction, particularly for complex car trajectory patterns. This modification was achieved by adding a convolutional layer with 2,028 output channels, followed by a C3k2 block at the high-level feature level. This addition aims to expand the model's representation capacity to capture variations in trajectory patterns, increase feature depth, and improve sensitivity to subtle visual differences across trajectory classes. The C3k2 block produces more efficient computation compared to C2f in the previous version of the YOLO model. Furthermore, the C2PSA module was expanded to process higher-resolution features, thereby improving the network's spatial and contextual attention.

The primary objective of this method development is to enhance classification accuracy while maintaining a relatively fast inference time, thereby enabling the model to be applied efficiently in real-time systems. The improved YOLO11n-cls model is expected to deliver more accurate, responsive classification, potentially supporting intelligent transportation systems and real-time driver behavior analysis.

C. Performance Evaluation

The classification model was evaluated using accuracy (Acc), precision, recall, and F1-score as defined by Eq. (1), Eq. (2), Eq. (3), and Eq. (4), respectively [25]. The variable T_{pos} (true positive) represents the number of samples that are correctly classified as belonging to a specific class. In contrast, T_{neg} (true negative) indicates the number of samples that are correctly classified as not belonging to that class. F_{pos} (false positive) refers to the number of samples that are incorrectly classified as belonging to a class when they actually belong to another class, and F_{neg} (false negative) denotes the number of samples that belong to a specific class but are incorrectly classified as another class.

$$Accuration = \frac{T_{pos}+T_{neg}}{T_{pos}+T_{neg}+F_{pos}+F_{neg}} \quad (1)$$

$$Precision = \frac{T_{pos}}{T_{pos}+F_{pos}} \quad (2)$$

$$Recall = \frac{T_{pos}}{T_{pos}+F_{neg}} \quad (3)$$

$$F1-score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

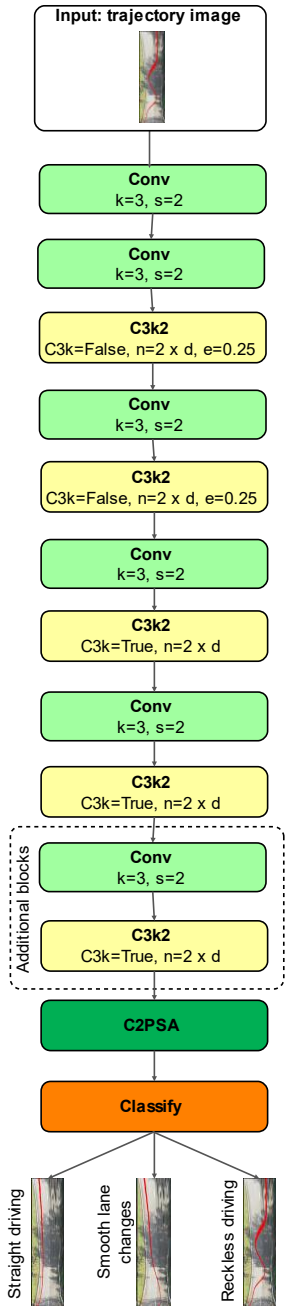


Fig. 5. Improved YOLO11n-cls architecture (proposed model).

III. Experiments and Results

Testing was conducted using several scenarios. First, we tested the proposed method on a dataset. Next, we performed data augmentation to augment the training data. The proposed method was then compared with several other models. The results of the first test using the proposed method are shown in Table I. The precision and recall values for the reckless driving class were quite good. In fact, the recall value was perfect, but the precision and recall for the smooth lane change class could not be classified. Meanwhile, the accuracy, inference time, and training time from this test resulted in 0.891, 0.5 ms, and 0.062 hours, respectively.

The training dataset for the first test was still small—only 107 images—so we augmented the data. The technique used was horizontal scaling. Each vehicle trajectory was scaled proportionally to its starting point, using a scale factor of 0.4-1.5 and a scale increment of 0.1. This technique maintains the original trajectory shape while introducing left-right shifts, making the model more robust to differences in vehicle positions within the lane. The resulting augmented data amounted to 326, so the training data became 433. The test results, incorporating the augmented data, are presented in Table II. The precision and recall values for the reckless driving class were 0.8750 and 1, respectively. The F1-score of the smooth lane change class experienced a significant increase of 0.6667. The confusion matrix of this classification is shown in Table III. The proposed model performs reasonably well at predicting reckless and straight driving, but it still struggles to predict smooth lane changes. Further improvements are needed. Furthermore, additional trajectory datasets are needed to improve accuracy across all classes. Frequent lane changes and high speeds are characteristic of reckless drivers. The proposed method can be combined with speed exceeding threshold detection.

The comparison of accuracy, inference time, and training time between before and after the addition of augmented data is shown in Table IV. From this table, it can be seen that with the addition of augmented data, accuracy increased by 4.4%, while inference time remained the same. Meanwhile, the training time increased threefold. Therefore, it can be concluded that the proposed method, improved YOLO11n-cls, is more suitable for car trajectory classification than YOLO11n-cls.

TABLE I. Test Results of the Proposed Method on the Dataset Without Augmentation

Class	Precision	Recall	F1-score
Reckless driving	0.9375	1.0000	0.9684
Smooth lane change	0.0000	0.0000	0.0000
Straight driving	0.9630	0.8966	0.9285

TABLE II. Test Results of the Proposed Method on the Dataset with Augmentation

Class	Precision	Recall	F1-score
Reckless Driving	0.8750	1.0000	0.9333
Smooth Lane Change	0.6667	0.6667	0.6667
Straight Driving	1.0000	0.9310	0.9646

TABLE III. Confusion Matrix of Trajectory Classification

		Actual Value		
		Reckless driving	***Smooth lane change***	***Straight driving***
Predicted	***Reckless driving***	14	0	0
	Smooth lane change	1	2	0
	Straight driving	1	1	27

TABLE IV. COMPARISON RESULTS WITH AND WITHOUT AUGMENTATION

Augmentasi	Acc	Inference time	Training time
No	0.891	**0.5**	**0.062**
Yes	**0.935**	**0.5**	0.172

Finally, the proposed method was compared with YOLO11 models and YOLO12 models, as shown in Table V. From this table, it is evident that the proposed model's accuracy surpasses that of the other models. At the same time, the inference time is ranked second among all. The proposed method achieves an accuracy of 0.935 and an inference time of 0.5 ms. Therefore, it can be concluded that the proposed method is more suitable for real-time car trajectory classification than all YOLO11 and YOLO12 models. The proposed model improves the average precision of reckless driving detection using vehicle trajectories. Compared to YOLO11, the proposed model achieved higher accuracy due to its enhanced representation capacity and ability to process higher-resolution features.

TABLE V. COMPARISON RESULTS OF THE PROPOSED METHOD WITH ALL YOLO11 AND YOLOV12 MODELS

Model	Acc	Inference time (ms)	Training time (hours)
YOLO11n-cls	0.913	**0.4**	0.170
YOLO11s-cls	0.870	0.5	**0.051**
YOLO11m-cls	0.891	0.5	0.110
YOLO11l-cls	0.891	0.9	0.078
YOLO11x-cls	0.913	0.7	0.100
YOLO12n-cls	0.870	0.8	0.064
YOLO12s-cls	0.848	1.0	0.067
YOLO12m-cls	0.870	0.6	0.076
YOLO12l-cls	0.891	2.0	0.126
YOLO12x-cls	0.870	3.0	0.136
Proposed	**0.935**	0.5	0.172

IV. CONCLUSION

This study developed a system to detect dangerous driving behavior based on vehicle trajectories. The developed system consisted of three subsystems: car detection using a modified YOLO11, car tracking using ByteTrack, and driving trajectory detection using an improved YOLO11n-cls. Improved YOLO11n-cls is a model developed from the original YOLO11n-cls by adding convolution and C3k2 blocks before the C2PSA block. The test results show that the proposed model can improve accuracy by 4.4% compared to YOLO11n-cls. The proposed model achieves an accuracy of 0.935 and an inference time of 0.5 ms. Additionally, the resulting model outperforms all YOLO11-cls and YOLO12-cls models. These results can improve the average precision of reckless driver detection based on their trajectory. However, the proposed model still performs poorly in predicting smooth lane changes. Therefore, the proposed model is better suited to support traffic law enforcement, especially the real-time detection of reckless drivers on highways. Further research can expand the dataset with more diverse traffic conditions and refine the classification model to capture more complex driving patterns.

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REFERENCES

[1] Y. Qiao, K. Zeng, L. Xu, and X. Yin, "A smartphone-based driver fatigue detection using fusion of multiple real-time facial features," in 2016 13th IEEE Annual Consumer Communications & Networking Conference (CCNC), 2016, pp. 230–235, https://doi.org/10.1109/CCNC.2016.7444761.

[2] L. Xu, S. Li, K. Bian, T. Zhao, and W. Yan, "Sober-Drive: A smartphone-assisted drowsy driving detection system," in 2014 International Conference on Computing, Networking and Communications (ICNC), 2014, pp. 398–402, https://doi.org/10.1109/ICCNC.2014.6785367.

[3] A. Dasgupta, D. Rahman, and A. Routray, "A smartphone-based drowsiness detection and warning system for automotive drivers," IEEE Transactions on Intelligent Transportation Systems, vol. 20, no. 11, pp. 4045–4054, 2019, https://doi.org/10.1109/TITS.2018.2879609.

[4] P. Khosravinia, T. Perumal, and J. Zarrin, "Enhancing road safety through accurate detection of hazardous driving behaviors with graph convolutional recurrent networks," IEEE Access, vol. 11, pp. 52983 – 52995, 2023, https://doi.org/10.1109/ACCESS.2023.3280473.

[5] X. G. Zhang and L. Liao, "Identification methods for driver's dangerous driving behavior in low visibility environments," Advances in Transportation Studies, vol. 2, no. Special Issue, pp. 129 – 142, 2024, https://doi.org/10.53136/979122181412511.

[6] F. M. Al Ali, M. J. Alnuaimi, S. A. Alawadhi, and S. Abdallah, "Abnormal driver behavior detection using deep learning," in 2024 7th International Conference on Signal Processing and Information Security (ICSPIS), 2024, pp. 1–4, https://doi.org/10.1109/ICSPIS63676.2024.10812606.

[7] X. Feng, T. Peng, T. Duan, H. Hou, Q. Chen, and Z. Zhang, "DdbiNet: a dangerous driving behavior identification network based on Resnet18," in 2024 5th International Conference on Information Science, Parallel and Distributed Systems, ISPDS 2024, 2024, pp. 565 – 570, https://doi.org/10.1109/ISPDS62779.2024.10667560.

[8] Q. Xue, K. Wang, J. J. Lu, and Y. Liu, "Rapid driving style recognition in car-following using machine learning and vehicle trajectory data," Journal of Advanced Transportation, vol. 2019, no. 1, p. 9085238, 2019, https://doi.org/https://doi.org/10.1155/2019/9085238.

[9] J. Lu, K. Wang, and Y.-M. Jiang, "Real-time identification method of abnormal road driving behavior based on vehicle driving trajectory; [Real-Time Identification Method of Bad Driving Behavior on Road based on Vehicle Driving Trajectory]," Jiaotong Yunshu Gongcheng Xuebao/Journal of Traffic and Transportation Engineering, vol. 20, no. 6, pp. 227 – 235, 2020, https://doi.org/10.19818/j.cnki.1671-1637.2020.06.020.

[10] R. J. Wang, "Identification method for abnormal driving behavior of vehicles based on lightweight graph convolution," Advances in Transportation Studies, vol. 3, no. Special Issue, pp. 97 – 108, 2024, https://doi.org/10.53136/97912218165708.

[11] V. Bhosale, J. Shah, P. Doshi, R. Mangrulkar, and I. Williams, "Enhancing road safety: reckless driver detection via OpenCV in simulated environments," in Intelligent Computing and Big Data Analytics, 2024, pp. 207–222.

[12] X. W. Yang, "Classification recognition for traffic dangerous driving behavior," Advances in Transportation Studies, vol. 1, no. Special Issue, pp. 115 – 124, 2024, https://doi.org/10.53136/979122181230511.

[13] T. Heo, W. Nam, J. Paek, and J. Ko, "Autonomous reckless driving detection using deep learning on embedded GPUs," in 2020 IEEE 17th International Conference on Mobile Ad Hoc and Sensor Systems (MASS), 2020, pp. 464–472, https://doi.org/10.1109/MASS50613.2020.00063.

[14] A. Chauhan, S. Kumar, L. Mahto, and D. N. Jagadish, "Detection of reckless driving using deep learning," in Proceedings - 19th IEEE

International Conference on Machine Learning and Applications, ICMLA 2020, 2020, pp. 853 – 858, https://doi.org/10.1109/ICMLA51294.2020.00139.

[15] M. F. Asy'ari, C. Fatichah, and N. Suciati, "Parking space availability detections from two overlapping cameras using YOLOv5 and image stitching methods," International Journal of Intelligent Engineering and Systems, vol. 16, no. 4, pp. 276–288, 2023, https://doi.org/10.22266/ijies2023.0831.23.

[16] S. K. Jarallah and S. A. Mahmood, "Query-based video summarization system based on lightweight deep learning model," International Journal of Intelligent Engineering and Systems, vol. 15, no. 6, pp. 247–262, 2022, https://doi.org/10.22266/ijies2022.1231.24.

[17] I. A. Alnajjar, L. Almazaydeh, A. A. Odeh, A. A. Salameh, K. Alqarni, and A. A. B. Atta, "Anomaly detection based on hierarchical federated learning with edge-enabled object detection for surveillance systems in industry 4.0 scenario," International Journal of Intelligent Engineering and Systems, vol. 17, no. 4, pp. 649–665, 2024, https://doi.org/10.22266/IJIES2024.0831.49.

[18] M. A. E. Alkhalisy and S. H. Abid, "Students' behavior detection based on improved YOLOv5 algorithm combining with CBAM attention mechanism," International Journal of Intelligent Engineering and Systems, vol. 16, no. 5, pp. 473–487, 2023, https://doi.org/10.22266/ijies2023.1031.41.

[19] K. C. Saranya and A. Thangavelu, "Vulnerable road user detection using YOLOv3," International Journal of Advanced Computer Science and Applications, vol. 10, no. 12, pp. 576–582, 2019, https://doi.org/10.14569/ijacsa.2019.0101275.

[20] O. Bourja, H. Derrouz, H. A. Abdelali, A. Maach, R. O. H. Thami, and F. Bourzeix, "Real Time vehicle detection, tracking, and inter-vehicle distance estimation based on stereovision and deep learning using Yolov3," International Journal of Advanced Computer Science and Applications, vol. 12, no. 8, pp. 915–923, 2021, https://doi.org/10.14569/IJACSA.2021.01208101.

[21] G. Al-refai and M. Al-refai, "Road object detection using Yolov3 and Kitti dataset," International Journal of Advanced Computer Science and Applications, vol. 11, no. 8, pp. 48–53, 2020, https://doi.org/10.14569/IJACSA.2020.0110807.

[22] Sutikno, A. Sugiharto, and R. Kusumaningrum, "Modified YOLO11 for improving car detection perfomance on the highway," Bulletin of the Polish Academy of Sciences Technical Sciences (submitted). 2025.

[23] Z. Dong et al., "Fruit detection and yield estimation in Camellia oleifera based on improved YOLOv8 and ByteTrack algorithm," Smart Agricultural Technology, vol. 12, no. September, p. 101435, 2025, https://doi.org/10.1016/j.atech.2025.101435.

[24] R. Khanam and M. Hussain, "YOLOv11: an overview of the key architectural enhancements," 2024. [Online]. Available: http://arxiv.org/abs/2410.17725.

[25] R. Padilla, S. L. Netto, and E. A. B. Da Silva, "A survey on performance metrics for object-detection algorithms," in International Conference on Systems, Signals, and Image Processing, 2020, pp. 237–242, https://doi.org/10.1109/IWSSIP48289.2020.9145130.

Formal Verification Unified Modeling Language Statechart Using Enhancement Common Modeling Language

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***Abstract*—Modern systems are rapidly evolving and increasing in complexity to satisfy growing requirements. Such systems often incorporate multiple hierarchical statecharts within their behavior modeling diagram, which significantly complicates the verification process. To address this challenge, the Common Modeling Language (CML) was introduced as an intermediate modeling language for formal verification, serving as a bridge between Unified Modeling Language (UML) Statechart and the model checkers. However, CML supports modeling only a single hierarchical statechart, which limits its applicability to complex systems. This study introduces the Enhancement Common Modeling Language (E-CML), an extension of the CML, to support the verification of systems that incorporate multiple hierarchical statecharts. We introduce the group component in E-CML, comprising an initial state, a set of states, transitions, triggers, and a region, to formally differentiate the group components from superstates. We also propose new translation rules to map E-CML into Symbolic Model Verifier (SMV) syntax. E-CML operates through two main processes: transformation and translation. The transformation process transforms an XML Metadata Interchange (XMI) file into E-CML, while the translation process translates E-CML to an Input Symbolic Model Verifier (I-SMV) file. The system is verified using the SMV model checker, with formal properties specified in Computational Tree Logic (CTL) and represented in the I-SMV file. The results demonstrate that the behavior modeling diagram satisfies all formal properties, indicating that E-CML provides an effective framework for the verification of complex systems comprising multiple hierarchical statecharts.**

***Keywords*—CML; E-CML; formal verification; model checkers; UML Statechart**

I. Introduction

The Unified Modeling Language (UML) Statechart is a semi-formal modeling language widely used by software engineers to describe the behavior of software systems, whether simple or complex. In [1], the authors introduced the UML Statechart, which has advanced elements that can describe a complex system's behavior. The simple system's behavior consists of a single hierarchical statechart and a few modules to express the behavior. An example of a simple system is a traffic light system [2], [3]. Meanwhile, the complex system's behavior consists of multiple hierarchical statecharts and multiple modules to express it. The example of complex systems is surgical consultation in the outpatient clinic health system [4]. However, the UML Statechart lacks formal semantics that ambiguously express the behavior modeling. Recent research has addressed the problem that the UML Statechart cannot be used for verification processes [5], [6], even though software engineers widely use the UML Statechart for modeling simple or complex systems. In [7], the authors introduced the Extended Hierarchical Automata (EHA), an extension of finite state machines that supports the hierarchical structure and defines the operational semantics of EHA. The EHA is one of the formal semantics behavior modeling that represents the UML Statechart. Therefore, the UML Statechart can be used for the verification process to check the system's correctness.

Consequently, model checking can be employed as a verification method. Model checking is an automated process for verifying the system's behavior. However, it requires a formal model and a formal temporal logic specification to check the system's correctness. If the model checker does not produce a counterexample, the system is proven to satisfy its requirements [8]. In this context, the Model-Based Software Engineering (MBSE) approach enables the formalization of semi-formal models into formal models through either direct or indirect translation using translation rules. In the case of indirect translation, the model is first transformed into an intermediate modeling language. Examples of such intermediate languages include the Common Modeling Language (CML) [8], Gamma statechart [9], and Abstract Rule-based [10]. CML is an intermediate modeling language for formal verification, serving as a bridge between UML Statechart and the model checkers.

Modern systems are rapidly evolving and increasing in complexity to satisfy growing requirements. Such systems often incorporate multiple hierarchical statecharts within their behavior modeling diagram, which significantly complicates the verification process. Therefore, recent research has proposed numerous methods that can formalize the UML Statechart [11], [12], [13], transforming it into a formal model that can be used for the verification process. Nevertheless, with the complexity of the systems developed nowadays, numerous complex interactions are involved [13]. In [9] and [14], the authors mentioned that integrative approaches are limited to models with fewer modules or lack efficient compatibility with formal verification and validation frameworks. Moreover, reference [15] stated that the CML supports modeling only a single hierarchical statechart, which limits its applicability to complex systems. Therefore, both statements show that recent

approaches have focused on verifying a single hierarchical statechart. However, modeling complex systems involves multiple hierarchical statecharts. It is crucial to address CML's limitations and resolve this problem to ensure the correctness of complex systems. Therefore, this study aims to propose an enhancement of the CML that is capable of verifying systems with multiple hierarchical statecharts, which represent the complex behavior of the systems.

The remainder of this study is organized as follows: Section II reviews related works on formal modeling, semi-formal modeling, theorem proving, model checking, MBSE, and formal verification of UML Statechart, particularly for multiple hierarchical statecharts. Section III presents the research framework and the proposed method, which includes the formal definition of E-CML and the development of new translation rules. Section IV discusses the results and discussion, illustrating the case study using the proposed method. Section V provides a conclusion, summarizes the findings, and outlines potential directions for future work.

II. Related Works

A. Formal Modeling

Formal modeling is an unambiguous language with precise specification built using mathematical and formal methods [16]. Therefore, the formal modeling can specify the requirements, designs, and behavior of the system. It provides the formal semantics of the systems. Examples of formal modeling are Petri Nets, Vienna Development Method (VDM), and Kripke structures. Petri Nets are directed, bipartite multigraphs consisting of places, transitions, and arcs. Fuzzy Petri Nets (FPN) are extensions of Petri Nets and are effective in modeling uncertain biological systems. In [17], the authors reviewed the FPN and categorised it into three types: basic Fuzzy Petri Nets, Fuzzy Quantitative Petri Nets, and Petri Nets with Fuzzy Kinetic Parameters. In [18], the authors proposed an extension of Coloured Petri Nets (CPN) known as catalog-nets (CLog-nets) to integrate business processes with different data types. In [19], the authors utilized Petri Nets to generate secure smart contracts in blockchain systems, enabling the detection of deadlock at an early stage.

Recent studies have used the VDM language to model and verify complex systems. VDM Specification Language (VDM-SL) is a formal specification language with an extensive executable subset and a toolbox that verifies models. In [20], the authors mentioned that the VDM-SL is a robust specification that can define the system's functionality without ambiguity. They proposed an approach that serves as a pre-formal notation for the natural language specification before it is implemented in VDM-SL. In [21], the authors proposed an Internet of Things (IoT) based formal model for vehicle ad hoc networks (VANETs) using VDM-SL. The proposed formal model will be transformed into VDM-SL and verified using the VDM toolbox to check the system's correctness and absence of deadlocks. Meanwhile, reference [22] introduced the first approach to developing the formal semantics of a simulation language in a VDM-SL. They proposed a RE: MODIYC that can describe and examine the formal specification of VDM-SL after initial implementation.

The Kripke structures are a mathematical model used in model logic to represent the possible states and the relationships among them. However, the Kripke structures formalize model logic by extending classical propositional logic with model operators such as necessity and possibility. In [23], the authors proposed an alternative method that transforms a given Kripke structure and the corresponding LTL formal properties into a Buchi automaton, where the number of accepting states is determined based on the LTL formal properties. Meanwhile, reference [24] introduced an approach to verify mobile-interactive systems. They model the properties of dynamic interaction using Variable Petri Nets (VPN). The VPN is transformed into the Kripke structures using a proposed algorithm and verified with a model checker. In [25], the authors proposed formalizing natural language using the UML use case diagram with the Kripke structures. They use the NuSMV model checker to verify whether the formal specification is consistent with the Kripke structures model. However, there are some previous studies that use semi-formal modeling to model the systems.

B. Semi-Formal Modeling

Semi-formal modeling is an ambiguous language in which the modeling lacks formal semantics, but it provides a better understanding of modeling. Therefore, semi-formal modeling is more popular than formal modeling because it does not require as much time and effort to understand the model. Examples of semi-formal modeling are UML and System Modeling Language (SysML). The UML is a graphical notation language used to define and document a system during software development [26]. In [27], the authors introduced a hierarchical modeling formalism based on UML Statechart with generally distributed (GEN) durations, aimed at ensuring modeling simplicity and efficient evaluation of steady-state or transient behavior up to absorption. In contrast, reference [28] used the new semantics of the UML Statechart to model the digital watch. In [29], the authors proposed using a restricted version of the Statechart (Revised Statechart) to model the behavior of autonomous robotic surgery. In [30], the authors used the UML Sequence Diagram to express the requirements of safety-critical systems incrementally.

However, another semi-formal modeling is SysML, which describes a hybrid system of hardware and software. SysML is a graphical modeling language that is intuitive and widely used for modeling complex systems, comprising hardware and software. In [31], the authors proposed an approach to analyze the safety of complex systems. They model the structure of the system using the SysML Block Definition Diagram (BDD) while utilizing the SysML State Machine Diagram to describe the system's behavior. In [32], the authors introduced the transformation of the UML/SysML Activity Diagram to Petri Nets. Meanwhile, reference [33] used the SysML Activity Diagram to model the system's behavior and transform the model into the input language of the Next-generation Unifying Symbolic Model Verifier (nuXmv) model checker. Therefore, there are two types of modeling language, which are formal modeling and semi-formal modeling. However, both models require a formal verification approach to ensure their correctness. Formal verification is the process of ensuring that

a system satisfies certain specifications, typically using two approaches: theorem proving and model checking [34].

C. Theorem Proving

Theorem proving is a formal method that can establish the validity of theorems. The model and specification of the systems are described in a mathematical statement. The verification process of theorem proving involves proving theorems about the system using the rules of the inference process. In [35], the authors introduced the automated prover and proof assistant, GPT-f, to analyze the performance of the Metamath formal language. In [36], the authors proposed the transformation rules from the UML Activity Diagram to Formal Calculus for Liveness and Zero state (FoCaLiZe), a proof-based formal language, and verified the proof-based formal language with the Zenon theorem prover. In [37], the authors identified a barrier for researchers using machine learning for theorem proving in Large Language Models (LLMs). Therefore, they introduced LeanDojo, an open-source Lean framework designed to overcome this barrier, which enables researchers to utilize machine learning with LLMs to enhance the effectiveness of theorem proving.

D. Model Checking

Model checking is one of the formal verification approaches and an automated process for verifying the behavior of a software system. The model checking approach requires a formal model and a formal temporal logic specification to check the correctness of the systems. In [11], the authors enhanced their previous work by formalizing the concurrent element of the UML Statechart, which involves multiple hierarchical statecharts. In [38], the authors used Maude as the formal language for the Internet of Things (IoT) software systems. They use Maude's model checker and Linear Temporal Logic (LTL) specification to verify the IoT software system. Meanwhile, reference [33] utilized the nuXmv to verify Autonomous Artificial Pancreas Systems (AAPS). They used the LTL specification in the nuXmv model checker to verify the APPS system. The model checking approach is widely used due to the MBSE technique, which enables the formalization of modeling language through a process. The transformation process has two types: direct transformation and indirect transformation, which require an intermediate language for the indirect transformation.

E. Model-Based Software Engineering

MBSE provides a platform that enables the definition of complex, multidisciplinary systems. However, the MBSE approach requires formal verification to ensure the correctness of complex systems. Therefore, the MBSE approach provides transformation rules to transform the model, either direct transformation or indirect transformation. Some previous studies use the direct transformation in their approaches.

In [39], the authors identified that the UML State Machine Diagram lacks formal semantics. Therefore, they proposed direct transformation rules from UML State Machine Diagram to Petri Nets and verified them with the Time Petri Nets Analyzer (TINA) to check correctness, safety, and liveness. In [31], the authors verified the Integrated Modular Avionic (IMA) system by proposing the direct transformation rules. They transform the SysML BDD and SysML State Machine Diagram into the input language of the NuSMV model checker. Meanwhile, reference [13] also introduced direct transformation rules from the SysML State Machine Diagram to the input language of the NuSMV model checker for verifying the driving control system. Although both research utilize the SysML State Machine Diagram, their approaches and direct transformation rules differ slightly.

However, some previous studies use the indirect transformation, which introduces an intermediate language to solve their problems. In [8], the authors introduced the CML, an intermediate language to formalize the UML Statechart. They proposed transformation rules to transform the UML Statechart into the CML and translation rules to translate the CML into the input language of the SMV model checker. In [9], the authors proposed the Gamma Statechart, an intermediate language that uses the formal semantics of Yakindu Statechart. They also proposed translation rules to translate the Gamma Statechart into Timed Automata (TA). In [14], the authors proposed transformation rules to transform the SysML State Machine Diagram to the Gamma Statechart. They also proposed the translation rules to translate the Gamma Statechart into the Uppsala Time Automata Laboratory (UPPAAL). Meanwhile, reference [10] used the Abstract Rules-based language as an intermediate language to formalize the UML State Machine Diagram. Previous studies show that most researchers utilize the UML Statechart and SysML State Machine Diagram. However, they may not encompass all elements of the UML Statechart that can represent a complex system.

F. Formal Verification of UML Statechart

Table I illustrates previous studies related to the formal verification of UML Statechart. We consider approaches that use either direct transformation or indirect transformation. We also examine which elements of the UML Statechart are addressed in these approaches. Our focus is on the system complexity, which can be decomposed into multiple modules. Therefore, we consider whether the approaches handle a single hierarchical statechart or multiple hierarchical statecharts. The symbols are indicated as "/" and "X" refer to "have" and "have not", respectively.

TABLE I. PREVIOUS STUDIES RELATED TO THE FORMAL VERIFICATION OF UML STATECHART

Journals	Intermediate Language	Approach	Transformation Rules	Single Hierarchical Statechart	Multiple Hierarchical Statechart
[15]	CML	Indirect	/	/	X
[11]	X	Direct	/	/	X
[12]	X	Direct	/	/	/
[9]	Gamma Statechart	Indirect	X	/	/
[13]	Abstract Rule-based	Indirect	X	/	X
[31]	X	Direct	/	/	X

Some previous studies [15], [9], [13] used an intermediate language to formalize UML Statechart. They employed the indirect transformation approach to verify the models and proposed a few transformation rules to transform the UML Statechart into the intermediate language and subsequently translate it into the model checker's formal model. However, two of these studies [9], [13] used an intermediate language without specifying whether they applied the translation rules in their approaches. The remaining studies [11], [12], [31] did not use an intermediate language; instead, they employed the direct transformation approach, which transforms the UML Statechart directly into the formal model. They also proposed a few transformation rules to guide this transformation.

As mentioned earlier, we focus on system complexity. Most previous studies have addressed a single hierarchical statechart, which represents a relatively simple system. However, only two studies have considered multiple hierarchical statesharts, despite modern systems being built with considerable complexity. Therefore, this observation motivates us to focus on verifying systems with multiple hierarchical statecharts using an indirect transformation approach. Specifically, we aim to enhance the CML by introducing new elements into its formal definition and by creating new translation rules that define multiple hierarchical statecharts and complex systems. The following section will explain the research framework and proposed method.

III. Proposed Method

A. Research Framework

Fig. 1 illustrates the research framework for the proposed method. It involves four processes: 1) Modeling the UML Statechart. 2) Exporting to XML Metadata Interchange (XMI) format. 3) Transforming XMI to Enhancement Common Modeling Language (E-CML). 4) Translating E-CML to Input Symbolic Model Verifier (I-SMV).

Process (1) Modeling the UML Statechart: The behavior of the system is modeled with the UML Statechart by using the Altova UModel software. The Altova UModel software enables modeling of UML Statechart features, including composite state, orthogonal state, history pseudostate (deep and shallow), and inter-level transitions. Process (2) Exporting the UML Statechart to XMI format: The Altova UModel software provides features for exporting the UML Statechart into the XMI format. In the XMI format, there are <region>, <subvertex>, <transition>, and <trigger> tags that refer to the regions, states, transitions, and triggers of the UML Statechart, respectively. Process (3) Transforming XMI to E-CML: The transformation process is based on the tag elements from the XMI format and the formal definition of E-CML. The <region> tags are transformed into the region. The <subvertex> tags are transformed into the state. The <transition> tags are transformed into the transition, and the <trigger> tags are transformed into the trigger. Process (4) Translating E-CML to I-SMV: The translation process is based on the formal definition of I-SMV. Four translation rules are involved in this process, which translate the elements of E-CML into the elements of I-SMV.

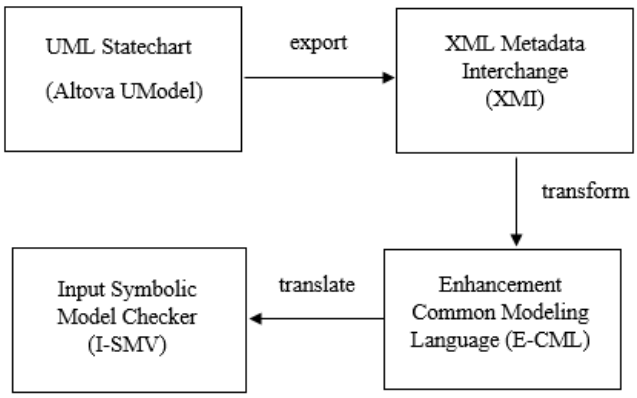


Fig. 1. Research framework.

B. Enhancement of Common Modeling Language

The E-CML is an extension of the CML based on the features of the UML Statecharts. Definition 1 defines the formal definition of E-CML as follows:

Definition 1: Enhancement Common Modeling Language

E-CML = <S, S_0, S_c, G, T, Regions, L, Gp, R>

Where:

S = finite set of states, where each state, s, is declared one of the two types: {AND, OR}.

S_0 = set of initial states ($S_0 \subseteq S$). S_0 forms a valid initial transition relation.

Sc = set of states that form a valid state configuration.

G = finite set of triggers.

T = finite set of transition relations, T = S x G x S'.

Regions = finite set of regions.

Gp = finite set of group components. Each group component consists of states, an initial state, triggers, transitions, and a region. Gp = <S, S_0, S_c, G, T, Regions>.

L = $S \rightarrow Gp'$ is the group component-level function. If $Gp' \subseteq L(S)$, then Gp' is an immediate descendant of S. The function of L describes the hierarchical state of the model.

R = relation between the superstate and group components, Gp.

There are two types of E-CML states: AND and OR. The AND state models concurrency by composing multiple simultaneous group components, Gp. The AND state is a superstate for the group components, Gp, of the statechart that are concurrently active. The descendants of the AND state must always be the OR state. The OR state is a state that supports one of the states inside another, providing a hierarchy in the behavior model. The OR state has states related to each other by an exclusive OR relationship. The leaf states of the E-CML must always be OR states. Each OR state has its region.

Each region is represented as the group component, Gp, in E-CML, consisting of the initial state, S_0, states, S, transitions, T, triggers, G, and the region. This also includes the outermost region represented as a group component, Gp. At runtime, E-CML allows multiple active states, referred to as a state configuration, S_c. A state configuration, S_c, always contains one state from the AND state and all states from the OR states.

Fig. 2 illustrates an example of the UML Statechart model that consists of multiple hierarchical statecharts. It shows there are basic states (A, D, G, H, I, J, M, N, O, and P), AND states (B and C), and OR states (E, F, K, and L). B state contains two OR states (E and F), E state contains two basic states (G and H), and the F state contains two basic states (I and J). Meanwhile, the C state contains two OR states (K and L), the K state contains two basic states (M and N), and the L state contains two basic states (O and P).

The operation of the E-CML is described using the step semantics. The state configuration, S_c, of E-CML starts with the initial state, S_0. In E-CML, when the state configuration, S_c, includes a composite AND state, all of its regions are active concurrently. Each region typically behaves like an OR state, meaning exactly one substate within each region is active at any time.

For example, the state configuration for the AND states in Fig. 2 should be (B, G, I) or (B, H, J) and (C, M, O) or (C, N, P). In E-CML, a transition will always occur at each step in each active state configuration, S_c. An implicit transition is triggered if no explicitly modeled transitions are enabled. The synchronization of E-CML allows it to be flattened into sequential automata, preserving the formal model semantics. Each single flattened component E-CML is equivalent to a sequential automaton [6].

Fig. 3 illustrates the flattened hierarchical E-CML structure of the UML Statechart model in Fig. 2.

Therefore, the single flattened component E-CML is known as the group component, Gp, in Fig. 3 as follows:

Gp_1 = ({A, B, C, D}, A, {E1, E2, E7, E8, E13, E14}, {(A, E1, B), (B, E2, A), (B, E7, C), (C, E8, B), (C, E8, B), (C, E13, D), (D, E14, C)}, Region 1)

Gp_2 = ({G, H}, G, {E3, E4}, {(G, E3, H), (H, E4, G)}, Region 2)

Gp_3 = ({I, J}, I, {E5, E6}, {(I, E5, J), (J, E6, I)}, Region 3)

Gp_4 = ({M, N}, M, {E9, E10}, {(M, E9, N), (N, E10, M)}, Region 4)

Gp_5 = ({O, P}, O, {E11, E12}, {(O, E11, P), (P, E12, O)}, Region 5)

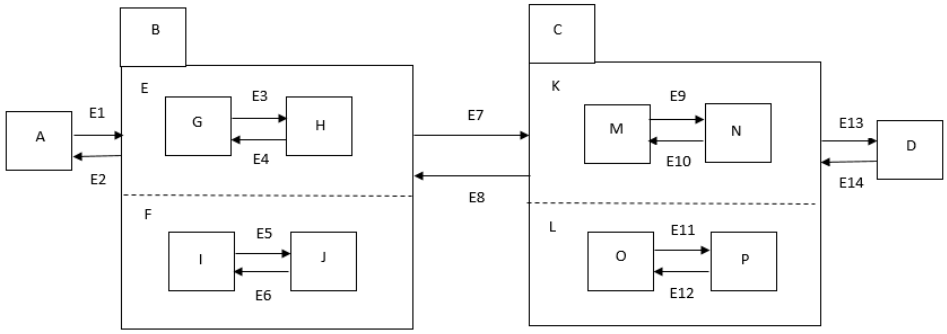


Fig. 2. UML Statechart model.

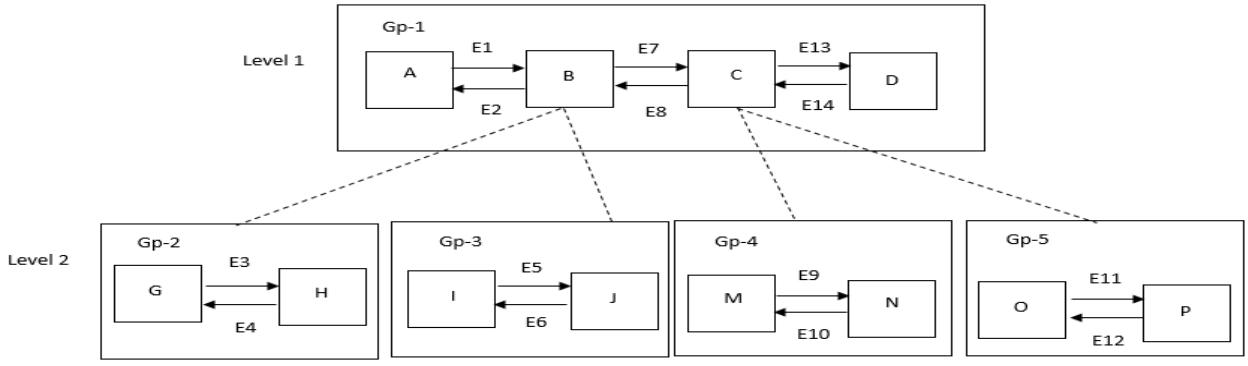


Fig. 3. Flattened hierarchical E-CML structure.

The sequence of elements in the group component, Gp, follows the sequence of variables in the formal definition of the group component, Gp, as given in Definition 1. The group component, Gp, interacts through events. In the following step, an event may trigger a transition in the system's synchronous group component, Gp. If the event triggers a transition from a state and the result is a group component, Gp, then the state is referred to as a superstate. For example, B is the superstate of Gp_2 and Gp_3, while C is the superstate of Gp_4 and Gp_5. This situation creates inter-level transitions. The inter-level

transitions cross hierarchy boundaries. If a transition leaves a superstate, the firing of all transitions containing the group components, Gp, of the superstate is suppressed, as represented by the dotted line in Fig. 3. This creates the relations, R, between the superstate and group components, Gp. Therefore, the group component level function, L, is created. The superstate's group component level function, L, is Level 1. The descendant of the superstate's group component level function, L, is Level 2. Therefore, the relation, R, between superstate and group components, Gp, is defined as follows:

Gp_2: receive a message from Gp_1

Gp_3: receive a message from Gp_1

Gp_4: receive a message from Gp_1

Gp_5: receive a message from Gp_1

Gp_1: receive a message from Gp_2, Gp_3, Gp_4, and Gp_4

In the E-CML, there are two processes involved: transforming the UML Statechart to the E-CML and translating the E-CML to the I-SMV. Therefore, we use the formal definition of I-SMV that is defined by [6]. The formal definition of I-SMV is as follows:

Definition 2: Input Symbolic Model Verifier

I-SMV = <M, V, N, Y>

Where:

M = set of finite modules

V = set of finite state variables

N = set of next states

Y = relation between modules

The I-SMV is modular. The high-level module is called the main module, while the other modules are known as sub-modules. In a module, M, there are state variables, V, to describe the module. A state evolves from one state to another through a next operator, N. The relation, Y, between one module and another is described by using a set of parameters. A set of rules guides the translation from E-CML to I-SMV.

C. Translation Rules of Enhancement of Common Modeling Language

Based on Definition 2, several rules of translation are created to map the E-CML, which is the source model, to the I-SMV, the target model. The translation from the source model to the target model can be defined by using a set of rules [31]. In the I-SMV, the group component, Gp, of E-CML corresponds to the module, M. The set of states, S, and triggers, G, corresponds to the state variables, V. The transitions, T, correspond to the next state, N. Lastly, the relation, R, between the superstate and group components, Gp, corresponds to the relation between modules, Y. The translation rules for mapping the E-CML to the I-SMV are defined as follows:

Rule 1 (Module): Let Grp be the set of group components in the E-CML. Each $Grp_i \in Grp$ is modeled as a module declaration in I-SMV as follows:

Module Grp_i ($arg_i, \ldots\ldots, arg_{i+1}$)

where, i = 1, ..., n, and n is the maximum integer.

If $Grp_i \in Grp$ does not exist, then the execution must be terminated. In I-SMV, arg_i refers to the actual parameter of a module within the main module.

Rule 2 (Variable): Let St be the set of states and Gr be the set of triggers in the E-CML, $St_i \in St$ is declared inside a module as follows:

$St_i : s_1, \ldots., s_{n+1}$; if St is an integer type

$St_i : \{s_1, \ldots., s_n\}$; if St is enumerated type

$St_i : \{\}$; if St is a Boolean type

$Gr_i \in Gr$ is declared inside a module as follows:

$Gr_i : g_1, \ldots., g_{n+1}$; if Gr is an integer type

$Gr_i : \{g_1, \ldots., g_n\}$; if Gr is enumerated type

$Gr_i : \{\}$; if Gr is a Boolean type

Rule 2 is used if and only if the represented module exists and either $St \neq \{\}$ or $Gr \neq \{\}$.

Rule 3 (State change): Tr be the set of transitions. In E-CML, state changes may occur with or without a trigger, Gr. This implies changes between the source state, Ss, and the target state, St, with or without the presence of the trigger. The state changes in I-SMV are defined as follows:

```
next (St): =
  case {
        Tri: St; if gr ∈ Gr, Gr ≠ {}
        Tri: Ss; if gr ∈ Gr, Gr ≠ {}
        default St;
  };
```

The first statement defines the state changes caused by triggered transitions, while the second statement defines the state changes caused by null-triggered transitions.

Rule 4 (Relation between modules): Let $St\text{-}Grp_b.R_b$, $St\text{-}Grp_c.R_c$, $St\text{-}Grp_d.R_d$, and $St\text{-}Grp_e.R_e$ are state variables for Grp_a. Let $St\text{-}Grp_a.R_a$ is the state variable for Grp_b, Grp_c, Grp_d, and Grp_e. The relation between those levels is defined as follows:

Module main()

$St\text{-}Grp_b : Grp_b (St\text{-}Grp_a.R_a)$;

$St\text{-}Grp_c : Grp_c (St\text{-}Grp_a.R_a)$;

$St\text{-}Grp_d : Grp_d (St\text{-}Grp_a.R_a)$;

$St\text{-}Grp_e : Grp_e (St\text{-}Grp_a.R_a)$;

$St\text{-}Grp_a : Grp_a (St\text{-}Grp_a.R_a)$;

$St\text{-}Grp_a$, $St\text{-}Grp_b$, $St\text{-}Grp_c$, $St\text{-}Grp_d$, and $St\text{-}Grp_e$ are state variables in the main module. In I-SMV, the arguments to a module are defined by the state variable of the destination message, followed by the state variable of the source message.

IV. Results and Discussion

In this section, we implement the E-CML for the Surgical Consultation in the Outpatient Clinic Health System as the case study. In general, doctors will refer patients for surgical consultation if they believe the underlying health condition can be effectively treated through surgery. Following the referral, the outpatient clinic schedules an appointment with the surgeon and arranges for samples to be collected if further diagnostic tests are required. The surgeon evaluates the necessity for an operation by analysing symptoms and test results during the consultations. Following a decision to proceed, the patient is registered on a surgical wait list to ensure an appropriate time is booked for use of the operating room. Before surgery, the patient may be educated by the surgeon about the procedure. When the operating room is already booked, the patient waits for their scheduled surgery date. Fig. 4 illustrates the UML Statechart Surgical Consultation in the Outpatient Clinic Health System.

Fig. 4 illustrates that there are two AND states ("Receiving referral" and "Receiving treatment") and four OR states ("Appointment", "Diagnostic Test", "Surgical Waiting List", and "Education"). There are three basic states at the outermost region ("Waiting for referral to clinic", "At consultation", and "Operation booked"), two basic states at the "Appointment" state ("Pending 1" and "Booked"), two basic states at the "Diagnostic Test" state ("Pending 2" and "Sample taken"), two basic states at the "Surgical Waiting List" state ("Pending 3" and "On waiting list"), and two basic states at the "Education" state ("Pending 4" and "Educated"). This model has five regions; each OR state has one region, and the other region is the outermost region. Fig. 5 illustrates the flattened hierarchical E-CML structure for the Surgical Consultation in the Outpatient Clinic Health System.

Based on Fig. 5, each flattened is referring to the group component, Gp, and is defined as follows:

Gp_1 = ({Waiting for referral to clinic, Receiving referral, At consultation, Receiving treatment, Operation booked}, Waiting for referral to clinic, {referral to clinic, patient referral at clinic, treatment decided, booked operation}, {(Waiting for referral to clinic, referral to clinic, Receiving referral), (Receiving referral, patient referral at clinic, At consultation), (At consultation, treatment decided, Receiving treatment), (Receiving treatment, booked operation, Operation booked)}, Region 1).

Gp_2 = ({Pending 1, Booked}, Pending 1, {make booking}, {(Pending 1, make booking, Booked)}, Region 2)

Gp_3 = ({Pending 2, Sample taken}, Pending 2, {take sample}, {(Pending 2, take sample, Sample taken)}, Region 3)

Gp_4 = ({Pending 3, On waiting list}, Pending 3, {register}, {(Pending 3, register, On waiting list)}, Region 4)

Gp_5 = ({Pending 4, Educated}, Pending 4, {educate}, {(Pending 4, educate, Educated)}, Region 5)

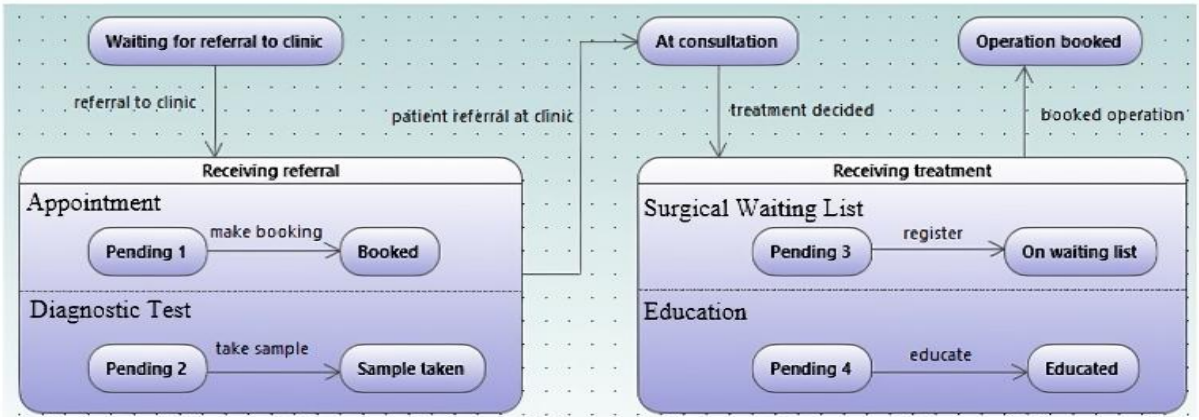


Fig. 4. UML Statechart surgical consultation in the outpatient clinic health system.

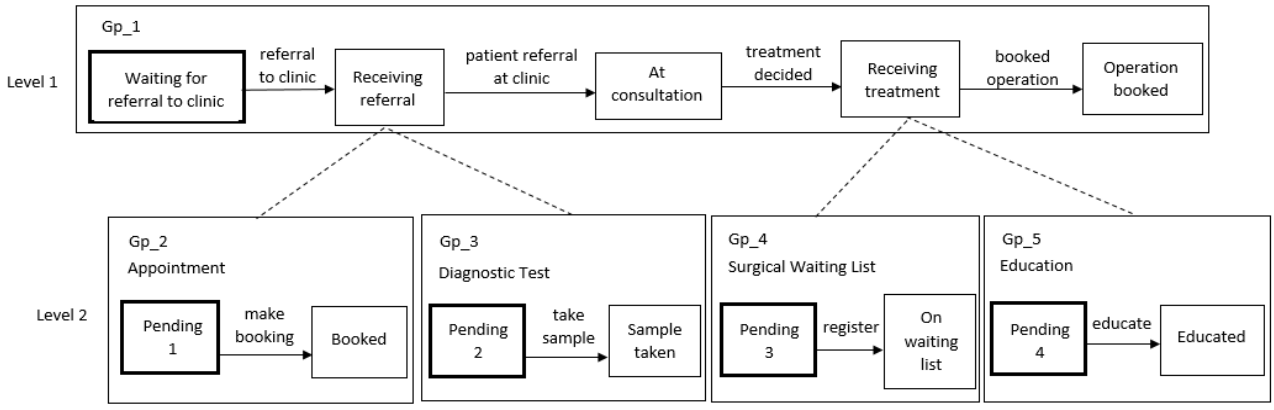


Fig. 5. Flattened hierarchical E-CML structure for surgical consultation in the outpatient clinic health system.

The relation, R, between superstate and group components, Gp, is defined as follows:

Gp_2: receive a message from Gp_1

Gp_3: receive a message from Gp_1

Gp_4: receive a message from Gp_1

Gp_5: receive a message from Gp_1

Gp_1: receive a message from Gp_2, Gp_3, Gp_4, and Gp_4

We use the translation rules of E-CML (Rule 1-4) to translate the E-CML into the I-SMV. Rule 1: Each group component, Gp, in E-CML is translated to the module's name in the I-SMV, followed by the list of arguments. Each module's arguments are based on the relation, R, which is translated in Rule 4. Therefore, the modules are defined as follows:

```
MODULE Gp_2 (gp_1)
MODULE Gp_3 (gp_1)
MODULE Gp_4 (gp_1)
MODULE Gp_5 (gp_1)
MODULE Gp_1 (gp_2, gp_3, gp_4, gp_5)
```

Rule 2 is regarding the variables declared for each module. All states, S, and triggers, G, in E-CML are defined as follows:

```
MODULE Gp_2 (gp_1)
VAR
    state:{Pending 1, Booked};
    trigger2:{make booking};
MODULE Gp_3 (gp_1)
VAR
    state:{Pending 2, Sample taken};
    trigger3:{take sample};
MODULE Gp_4 (gp_1)
VAR
    state:{Pending 3, On waiting list};
    trigger4:{register};
MODULE Gp_5 (gp_1)
VAR
    state:{Pending 4, Educated};
    trigger5:{educate};
MODULE Gp_1 (gp_1)
VAR
    state:{Waiting for referral to clinic, Receiving
    referral, At consultation, Receiving treatment,
    Operation booked};
    trigger6:{referral to clinic, patient referral at clinic,
    treatment decided, booked operation};
```

Rule 3 is regarding the transitions, T, in the E-CML, which are translated to the next (state) in the I-SMV. Therefore, the next (state) in the I-SMV is defined as follows:

```
MODULE Gp_2 (gp_1)
…..
next (state):= case
    ((state = Pending 1) & (trigger2 = make
    booking)): Booked;
1: state;
esac;
MODULE Gp_3 (gp_1)
…..
next (state):= case
    ((state = Pending 2) & (trigger3 = take sample)):
    Sample taken;
1: state;
esac;
MODULE Gp_4 (gp_1)
…..
next (state):= case
    ((state = Pending 3) & (trigger4 = register)): On
    waiting list;
1: state;
esac;
MODULE Gp_5 (gp_1)
…..
next (state):= case
    ((state = Pending 4) & (trigger5 = educate)):
    Educated;
1: state;
esac;
MODULE Gp_1 (gp_2, gp_3, gp_4, gp_5)
…..
next (state):= case
    ((state = Waiting for referral to clinic) & (trigger6 =
    referral to clinic)): Receiving referral;
    ((state = Receiving referral) & (trigger7 = patient
    referral at clinic)): At consultation;
    ((state = At consultation) & (trigger8 = treatment
    decided)): Receiving treatment;
```

((state = Receiving treatment) & (trigger9 = booked operation)): Operation booked;

1: state;

esac;

Rule 4 is regarding the relation, R, between superstate and group components, Gp, in E-CML. In -SMV, Rule 4 is translated into MODULE main. The state variable of the MODULE main is defined as a call module for the corresponding group component. The arguments in each call module are the state variable of the source state, followed by its message passing. The relation between modules is defined as follows:

MODULE main:

VAR

gp_2: Gp_2 (gp_1);

gp_3: Gp_3 (gp_1);

gp_4: Gp_4 (gp_1);

gp_5: Gp_5 (gp_1);

gp_1: Gp_1 (gp_2, gp_3, gp_4, gp_5);

Based on the relation between modules above, gp_2, gp_3, gp_4, and gp_5 are state variables used as arguments for the module in Gp_1. The gp_1 is the state variable for the modules in Gp_2, Gp_3, Gp_4, and Gp_5. We use the SMV model checker to verify the UML Statechart in Fig. 4. The formalized properties need to be specified on the "SPEC" keyword in the I-SMV file. Table II shows the list of formalized properties, descriptions, and the results.

A. Discussion

In this section, we discuss and explain the results that were obtained from the proposed method. All the formalized properties, which cover the multiple hierarchical statecharts, are verified as TRUE. P1 is verified as TRUE because the specification defines that the patient can book an appointment and take the diagnostic test in the future, even though the patient is not waiting for the referral. P2 is verified as TRUE because the specification states that the patient always receives a consultation from the doctor after completing the booking appointment and taking the diagnostic sample test. P3 is verified as TRUE because the specification defines that the patient can always book the operation date after registering on the waiting list and getting education about the surgery from the surgeon. P4 is verified as TRUE because the specification defines that the patient can be on the waiting list for an operation and can receive education about the surgery from the surgeon after the patient receives a consultation from the surgeon.

According to reference [15], correctness is defined as adherence to the specifications and the way software behaves when these correctness specifications are applied. The results indicate that E-CML can serve as an effective intermediate language, as the verification of the specifications returned a result of TRUE. Moreover, E-CML is able to verify complex systems that have multiple hierarchical statecharts, which are a common feature for modern complex systems.

TABLE II. FORMALIZED PROPERTIES, DESCRIPTIONS, AND RESULTS

Property	Description	CTL	Result
P1	A patient who is not waiting for a referral may be able to book an appointment and undergo the diagnostic tests in the future.	AG (!(gp_1.state = Waiting_for_referral_to_clinic) → EF (gp_2.state = Booked & gp_3.state = Sample_taken))	True
P2	A patient who completes a booking and has taken a sample for a diagnostic test is eligible for a consultation.	AG (gp_2.state = Booked & gp_3.state = Sample_taken) → EF (gp_1.state =At_consultation)	True
P3	A patient registered for the operation and received education from the surgeon can book the operation date.	AG ((gp_4.state = On_waiting_list & gp_5.state = Educated) → EF (gp_1.state = Operation_booked))	True
P4	The patient whom the surgeon has consulted can be placed on the waiting list for the operation and receive education on the operation.	AG ((gp_1.state = At_consultation) → EF (gp_4.state = On_waiting_list & gp_5.state = Educated))	True

TABLE III. COMPARISON OF THE E-CML WITH THE OTHER APPROACHES

Method	Approach	Intermediate Language	Substate	Orthogonal State	History State (depp/shallow)
E-CML	Indirect transformation	E-CML	/	/	X
Colored Petri Nets [11]	Direct transformation	-	/	/	/
Gamma Statechart [9]	Indirect transformation	Gamma Statechart	/	X	X

Table III illustrates a comparison between E-CML and other approaches. We compare E-CML with the approaches proposed in [11] and [9]. We also consider the UML Statechart elements covered by each approach during the verification process. The symbols "/" and "X" indicate "supported" and "not supported", respectively.

In [11], the authors proposed a method based on a direct transformation approach, which transforms one model into another without using an intermediate language. The authors utilized UML Statechart to express the system's behavior and formalized it into the CPN. This approach uses the transformation rules to map the elements of the UML Statechart to CPN. In contrast, E-CML provides a formal definition that represents the elements of the UML Statechart. It also includes transformation rules to transform E-CML into an I-SMV file, which is used as the input language for the verification process with the SMV model checker. The E-CML helps and encourages the user to apply the model checking method without requiring knowledge of SMV syntax or CPN.

As discussed, both approaches are capable of verifying multiple hierarchical statecharts. However, some UML Statechart elements are not included in E-CML, whereas they are included in the approach proposed in [11], such as history state (deep and shallow).

Meanwhile, reference [9] proposed a method based on an indirect transformation approach, which same approach used by E-CML and requires an intermediate language. The authors utilized UML Statechart to express the system's behavior and transformed it into the TA. This approach also considers the transformation of ports in the physical components. In contrast, E-CML focuses only on behavioral aspects and does not transform or include physical components. As discussed, both approaches are capable of verifying multiple hierarchical statecharts. However, some UML Statechart elements are not included in the approach proposed in [9], whereas they are included in E-CML, such as orthogonal states. Nevertheless, both approaches do not include the history state (deep and shallow).

V. Conclusion

This study presents a proposed solution for verifying complex systems that are inherently more intricate and difficult to verify. Modern systems often incorporate multiple hierarchical statecharts within their behavior modeling diagram, which significantly complicates the verification process. Therefore, E-CML, an enhancement of CML, helps the users verify complex systems with multiple hierarchical statecharts and ensure their correctness. E-CML introduces group components comprising an initial state, a set of states, transitions, triggers, and a region, to formally differentiate the group components from superstates. It creates new translation rules to define multiple hierarchical statecharts and complex systems that relate to the group components. E-CML demonstrates that it can verify the formalized properties of multiple hierarchical statecharts model. As a result, all of the formalized properties are verified as TRUE. Thus, E-CML enables verification of unverified complex systems. However, E-CML has a limitation in that it cannot verify the history states, including either the deep or shallow pseudostate. This feature is an important element of the UML Statechart that can represent the behavior of complex systems. Some modern systems also include a history state in the behavioral models to store the last active state, such as in air conditioning systems. Therefore, it is important to enhance E-CML to include all UML Statechart elements capable of representing complex systems. This enhancement will enable the verification of all types of complex systems built today.

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References

[1] Harel, D. (1987). Statecharts: A visual formalism for complex systems. *Science of Computer Programming, 8*, 231–274. https://doi.org/10.1016/0167-6423(87)90035-9.

[2] Samat, P. A., Zin, A. M., & Shukur, Z. (2011). Analysis of the model checkers' input languages for modeling traffic light systems. *Journal of Computer Science, 7*(2), 225–233. https://doi.org/10.3844/jcssp.2011.225.233.

[3] Souri, A., Ali, M., & Norouzi, M. (2012). Analyzing SMV & UPPAAL model checkers in real-time systems. *AWERProcedia Information Technology & Computer Science, 1*, 631–639.

[4] Vasilakis, C., Lecznarowicz, D., & Lee, C. (2008). Application of UML to the modeling of health care system: An introduction and literature survey. *International Journal of Healthcare Information Systems and Informatics, 3*(4), 39–52. https://doi.org/10.4018/jhisi.2008100103.

[5] Khalid, M., Zafar, N. A., Afzaal, H., Latif, S., Hassan, S., & Rehman, A. (2019). Automated UML-based formal model of E-Health system. In *2019 13th International Conference on Mathematics, Actuarial Science, Computer Science and Statistics (MACS)* (pp. 1–6). https://doi.org/10.1109/MACS48846.2019.9024830.

[6] Muhamad, Z. H., Abdulmonim, D. A., & Alathari, B. (2019). An integration of UML use case diagram and activity diagram with Z language for formalization of library management system. *International Journal of Electrical and Computer Engineering, 9*(4), 3069–3076. https://doi.org/10.11591/ijece.v9i4.pp3069-3076.

[7] Mikk, E., Lakhnech, Y., & Siegel, M. (1997). Hierarchical automata as model for statecharts (extended abstract). In R. K. Shyamasundar & K. Ueda (Eds.), *Advances in computing science—ASIAN'97* (*Lecture Notes in Computer Science*, Vol. 1345). Springer. https://doi.org/10.1007/3-540-63875-X_52.

[8] Samat, P. A., & Zin, A. M. (2012). Common modeling language for model checkers. *Journal of Computer Science, 8*(1), 99–106. https://doi.org/10.3844/jcssp.2012.99.106.

[9] Molnár, V., Graics, B., Vörös, A., Majzik, I., & Varró, D. (2018). The Gamma statechart composition framework: Design, verification, and code generation for component-based reactive systems. In *Proceedings of the 40th International Conference on Software Engineering: Companion* (pp. 113–116). https://doi.org/10.1145/3183440.3183489.

[10] Grobelna, I. (2020). Formal verification of control modules in cyber-physical systems. *Sensors, 20*(18), Article 5154. https://doi.org/10.3390/s20185154.

[11] André, É., Benmoussa, M. M., & Choppy, C. (2015). Formalising concurrent UML state machines using coloured Petri nets. In V.-H. Nguyen, A.-C. Le, & V.-N. Huynh (Eds.), *Knowledge and Systems Engineering* (pp. 473–486). Springer. https://doi.org/10.1007/978-3-319-11680-8_38.

[12] Guo, C., Ren, S., Jiang, Y., Wu, P., Sha, L., & Jr, R. B. B. (2016). Transforming medical best practice guidelines to executable and verifiable statechart models. In *2016 ACM/IEEE 7th International Conference on Cyber-Physical Systems (ICCPS)* (pp. 1–10). https://doi.org/10.1109/ICCPS.2016.7479121.

[13] Mahani, M., Rizzo, D., Paredis, C., & Wang, Y. (2021). Automatic formal verification of SysML state machine diagrams for vehicular control systems. *SAE Technical Paper*. SAE International. https://doi.org/10.4271/2021-01-0260.

[14] Horváth, B., Molnár, V., Andolfato, L., & Gomes, I. (2020). Model checking as a service: Towards pragmatic hidden formal methods. In *ACM/IEEE 23rd International Conference on Model Driven Engineering Languages and Systems (MODELS '20 Companion)* (pp. 1–5). https://doi.org/10.1145/3417990.3421407.

[15] Samat, P. A., Azwarrudin, M. A., Mohd, N., & Admodisastro, N. (2021). Verifying the correctness of UML Statechart outpatient clinic based on Common Modeling Language and SMV. *The International Journal of Integrated Engineering, 13*(5), 137–145. https://doi.org/10.30880/ijie.2021.13.05.015.

[16] Singh, A., Parizi, R. M., Zhang, Q., Choo, K.-K. R., & Dehghantanha, A. (2020). Blockchain smart contracts formalization: Approaches and challenges to address vulnerabilities. Computers & Security, 88, Article 101654. https://doi.org/10.1016/j.cose.2019.101654.

[17] Liu, F., Heiner, M., & Gilbert, D. (2020). Fuzzy Petri nets for modelling of uncertain biological systems. *Briefings in Bioinformatics, 21*(1), 198–210. https://doi.org/10.1093/bib/bby118.

[18] Ghilardi, S., Gianola, A., Montali, M., & Rivkin, A. (2020). Petri nets with parameterised data: Modelling and verification. In D. Fahland, C. Ghidini, J. Becker, & M. Dumas (Eds.), *Business Process Management*

(BPM) 2020. Lecture Notes in Computer Science, 12168 (pp. 55–74). Springer. https://doi.org/10.1007/978-3-030-58666-9_4.

[19] Zupan, N., Kasinathan, P., Cuellar, J., & Sauer, M. (2020). Secure smart contract generation based on Petri nets. In R. da Rosa Ringhi, A. M. Alberti, & M. Singh (Eds.), *Blockchain Technology for Industry 4.0* (pp. 73–98). Springer. https://doi.org/10.1007/978-981-15-1137-0_4.

[20] Oda, T., Kusakabe, S., Chang, H.-M., & Larsen, P. G. (2022). VDM-SL in action: A FRAM-based approach to contextualise formal specification. In H. D. Macedo & K. Pierce (Eds.), *Proceedings of the 20th International Overture Workshop* (pp. 5–18). https://doi.org/10.48550/arXiv.2208.10233.

[21] Iqbal, S., Zafar, N. A., Ali, T., & Alkhammash, E. H. (2022). Efficient IoT-based formal model for vehicle-life interaction in VANETs using VDM-SL. *Energies, 15*(3). https://doi.org/10.3390/en15031013.

[22] Oda, T., Dur, G., Ducasse, S., & Macedo, H. D. (2023). *Implementation-first approach of developing formal semantics of a simulation language in VDM-SL* (arXiv:2303.14944). arXiv. https://doi.org/10.48550/arXiv.2303.14944.

[23] Rungsetthaphat, N., & Vatanawood, W. (2023). Transformation of Kripke structure with linear temporal logic formula to Büchi automata. In 2023 27th International Computer Science and Engineering Conference (ICSEC) (pp. 1–5). IEEE. https://doi.org/10.1109/ICSEC59635.2023.10329762.

[24] Yang, R., Ding, Z., Guo, T., Pan, M., & Jiang, C. (2022). Model checking of variable Petri nets by using the Kripke structure. *IEEE Transactions on Systems, Man, and Cybernetics: Systems, 52*(2), 7774–7786. https://doi.org/10.1109/TSMC.2022.3163741.

[25] Zaman, Q. uz, Nadeem, A., & Sindhu, M. A. (2020). Formalizing the use case model: A model-based approach. *PLoS ONE, 15*(4). https://doi.org/10.1371/journal.pone.0231534.

[26] Koç, H., Erdogan, A. M., Barjakly, Y., & Peker, S. (2021). UML diagrams in software engineering research: A systematic literature review. *Proceedings 2021*. https://doi.org/10.3390/proceedings2021074013.

[27] Carnevali, L., German, R., Santoni, F., & Vicario, E. (2022). Compositional analysis of hierarchical UML statecharts. IEEE Transactions on Software Engineering, 48(12), 4762–4788. https://doi.org/10.1109/TSE.2021.3125720.

[28] Exelmans, J., Van Mierlo, S., & Vangheluwe, H. (2022). A statecharts interpreter and compiler with semantic variability. In *ACM/IEEE 25th International Conference on Model Driven Engineering Languages and Systems (MODELS '22 Companion)*. ACM. https://doi.org/10.1145/3550356.3561569.

[29] Falezza, F., Piccinelli, N., De Rossi, G., Roberti, A., Kronreif, G., Setti, F., Fiorini, P., Fellow, L., & Muradore, R. (2021). Modeling of surgical procedures using statecharts for semi-autonomous robotic surgery. *IEEE Transactions on Medical Robotics and Bionics, 3*(4), 888–899. https://doi.org/10.1109/TMRB.2021.3110676.

[30] Chen, X., Mallet, F., & Liu, X. (2020). Formally verifying sequence diagrams for safety critical systems. In *International Symposium on Theoretical Aspects of Software Engineering (TASE) 2020* (pp. 217–224). https://doi.org/10.1109/TASE49443.2020.00037.

[31] Wang, H., Zhong, D., Zhao, T., & Ren, F. (2019). Integrating model checking with SysML in complex system safety analysis. *IEEE Access, 7*, 16561–16571. https://doi.org/10.1109/ACCESS.2019.2892745.

[32] Huang, E., McGinnis, L. F., & Mitchell, S. W. (2020). Verifying SysML activity diagrams using formal transformation to Petri nets. *Systems Engineering, 23*(1), 118–135. https://doi.org/10.1002/sys.21524.

[33] Staskal, O., Simac, J., Swayne, L., & Rozier, K. Y. (2022). Translating SysML activity diagrams for nuXmv verification of an autonomous pancreas. *2022 IEEE 46th Annual Computers, Software, and Applications Conference (COMPSAC)* (pp. 1637–1642). https://doi.org/10.1109/COMPSAC54236.2022.00260.

[34] Mahmoud, A. T., Mohammed, A. A., Ayman, M., Medhat, W., Selim, S., Zayed, H., Yousef, A. H., & Elaraby, N. (2024). Formal verification of code conversion: A comprehensive survey. *Technologies, 12*(12), 1–28. https://doi.org/10.3390/technologies12120244.

[35] Polu, S., & Sutskever, I. (2020). Generative language modeling for automated theorem proving. *arXiv*. https://doi.org/10.48550/arXiv.2009.03393.

[36] Abbas, M., Rioboo, R., Ben-Yelles, C., & Snook, C. F. (2021). Formal modeling and verification of UML activity diagrams (UAD) with FoCaLiZe. *Journal of Systems Architecture, 114*(September 2020), 101911. https://doi.org/10.1016/j.sysarc.2020.101911.

[37] Yang, K., Swope, A. M., Gu, A., Chalamala, R., Song, P., Yu, S., Godil, S., Prenger, R., & Anandkumar, A. (2023). LeanDojo : Theorem proving with retrieval-augmented language models. *37th Conference on Neural Information Processing System (NeurIPS 2023)*, 1–40. https://doi.org/https://doi.org/10.48550/arXiv.2306.15626.

[38] Fortas, A., Kerkouche, E., & Chaoui, A. (2022). Formal verification of IoT applications using rewriting logic: An MDE-based approach. *Science of Computer Programming, 222*, 102859. https://doi.org/10.1016/j.scico.2022.102859.

Detecting Low-Quality Deepfake Videos Using 3D Residual Vision Transformer

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***Abstract*—The rapid evolution of deep generative models has facilitated the creation of "Deepfakes", enabling the synthesis of hyper-realistic facial manipulations that threaten the trustworthiness of digital media. While forensic countermeasures have been developed to identify these forgeries, deepfake detection in real-world scenarios is severely hampered by video compression artifacts, which often obscure the subtle pixel-level traces exploited by conventional Convolutional Neural Networks (CNNs). This study introduces a robust detection framework designed specifically to withstand the aggressive compression inherent to social media dissemination. We present a hybrid 3D architecture that integrates the local spatiotemporal feature extraction capabilities of a 3D-ResNet-50 backbone with the global context modeling of a temporal Video Vision Transformer. Unlike frame-based or joint spatiotemporal attention approaches, the proposed model performs fully video-level reasoning and utilizes a factorized self-attention mechanism to decouple spatial and temporal modeling, thereby preserving stable temporal cues under compression while minimizing computational costs. Experimental results on the compressed protocols of the FaceForensics++ dataset as well as Celeb-DF-v2 and DFDC datasets, including cross-dataset generalization evaluation, validate the efficacy of this design, demonstrating that our method achieves superior detection accuracy and generalization compared to existing baselines, particularly on low-quality inputs.**

Keywords*—Deepfake detection; compressed deepfake videos; low-quality deepfakes; 3D convolutional neural networks; Video Vision Transformer

I. Introduction

Recent advances in deep generative modeling have enabled the creation of highly realistic synthetic audiovisual content, giving rise to what are commonly referred to as deepfakes [1]. A deepfake is a piece of media; typically a video, image, or audio clip, created or manipulated using deep neural networks to convincingly imitate real individuals or events. Although the term has become strongly associated with disinformation and online abuse, the underlying technologies offer several legitimate and beneficial applications [2]. These include privacy-preserving data generation for machine learning, synthetic training datasets for rare-event detection, improved dubbing in film production, educational reenactments, and assistive technologies for individuals with speech impairments.

Despite these positive uses, deepfakes pose significant societal and security risks. High-fidelity manipulations can be leveraged to spread political misinformation, facilitate identity or financial fraud, generate non-consensual explicit content, or erode public trust in digital media [3]. As generative models continue to improve in resolution, coherence, and computational efficiency, distinguishing authentic content from manipulated media becomes increasingly challenging. The pervasive dissemination of deepfake videos across social platforms exacerbates this issue, contributing to large-scale misinformation campaigns and undermining the reliability of digital communication ecosystems.

In response to this adversarial landscape, the forensic community has developed a variety of detection algorithms designed to identify the subtle, distinct trace anomalies left by generative models. However, a critical disparity exists between the performance of these detectors in controlled environments and their efficacy in real-world deployment [4]. While deepfake generation has become increasingly sophisticated, often outpacing conventional detection cues, the primary challenge in practical application lies in the transmission medium itself. To accommodate bandwidth constraints and storage limitations, online distribution platforms routinely subject video content to aggressive lossy compression standard H.264. This compression process introduces a complex, two-fold impediment to forensic analysis. First, the quantization inherent in lossy compression acts as a low-pass filter, effectively smoothing out the high-frequency noise patterns and subtle pixel-level artifacts that many detectors rely upon as fingerprints of manipulation. Second, the compression algorithms introduce their own structural noise, such as blocking artifacts and ringing, which can mask manipulation traces or mimic them, leading to increased false positives. Consequently, the robustness of existing state-of-the-art detectors degrades precipitously when applied to low-quality, highly compressed media [5]. Addressing this vulnerability created by compression, remains one of the most pressing open challenges in multimedia forensics.

This study presents a fully video-level approach for robust deepfake detection in highly compressed videos, a setting in which conventional frame-based detectors often fail due to the suppression of spatial and frequency-domain forensic cues. While most existing detection methods process videos on a frame-by-frame basis using 2D representations, contemporary deepfake generation pipelines operate sequentially across time, inherently introducing temporal patterns that persist even under aggressive compression. Motivated by this mismatch, we

formulate compression-robust deepfake detection as an end-to-end spatiotemporal learning problem.

To this end, we propose a hybrid spatiotemporal architecture that integrates the local representational capacity of a 3D convolutional neural network (3D-CNN) with the global temporal modeling capability of a factorized self-attention video vision transformer. By consistently operating in the 3D domain, from feature extraction to long-range temporal reasoning, the proposed model jointly captures localized spatiotemporal artifacts and global temporal dependencies, enabling improved robustness under severe compression and in-the-wild video conditions.

The primary contributions of this work can be summarized as follows:

- We introduce a fully video-level detection framework that departs from the dominant frame-based paradigm by employing a pretrained 3D-CNN backbone to extract joint spatial–temporal representations directly from video clips, allowing the model to exploit motion and temporal coherence that remain informative in low-quality, compressed video streams.
- We employ a factorized attention mechanism that separately models spatial and temporal dependencies. Ablation experiments demonstrate that this decoupled formulation yields more robust performance than joint spatiotemporal attention under severe compression, suggesting that preserving distinct spatial and temporal representations is beneficial for low-quality video forensic analysis.
- We conduct extensive experiments including comparisons with state-of-the-art spatial and frequency-domain methods, and detailed ablation studies which demonstrate that the proposed fully 3D spatiotemporal approach achieves competitive performance under mild compression and consistently superior robustness under aggressive compression across multiple benchmarks.

The remainder of this study is structured as follows: Section II introduce deepfake generation and reviews existing detection approaches. Section III details the proposed hybrid 3D-CNN and transformer-based architecture. Section IV describes the experimental setup and reports the results. Section V provides discussion, analysis, and insights. Section VI concludes the study.

II. Related Work

A. Deepfake Generation

Deepfake videos are commonly produced through deep generative models that learn statistical representations of facial structure, appearance, and motion. Early face-swapping systems employed autoencoder-based architectures in which a shared encoder mapped facial inputs into a latent representation, and identity-specific decoders reconstructed the manipulated output. These methods enabled basic identity replacement, but were often limited in realism.

Subsequent advancements in generative adversarial networks (GANs) [6] and variational autoencoders (VAEs) [7] marked a significant leap in synthesis quality. GAN-based models introduced adversarial training mechanisms that encouraged the generator to produce content indistinguishable from real data, resulting in improved texture fidelity, lighting realism, and temporal smoothness. More recently, diffusion models have demonstrated state-of-the-art performance in photorealistic image and video generation by iteratively denoising latent representations and capturing fine-grained visual structures.

These generative architectures underpin the two most prevalent and impactful categories of facial manipulation: Face Swap and Face Reenactment.

- Face Swap: This technique involves transferring the facial identity of a source individual onto a target person within a video. Initial approaches relied heavily on autoencoder architectures; however, recent advances predominantly utilize generative adversarial networks (GANs) to achieve higher-quality and more seamless facial replacements, surpassing the limitations of earlier methods.
- Face Reenactment: Unlike identity transfer, face reenactment manipulates the facial expressions, head poses, and movements (such as mouth and eye dynamics) of the target video to mimic those of a source video, while preserving the target's inherent identity. This is commonly realized by extracting facial landmarks or action units from the source and applying them to the target, followed by a GAN-based synthesis to produce photorealistic frames faithfully reflecting the altered expressions and movements.

The rapid evolution of these generative technologies has triggered an ongoing arms race between increasingly sophisticated forgery techniques and the development of advanced detection methodologies aimed at mitigating emerging threats posed by highly realistic digital manipulations.

B. Deepfake Detection Approaches

Despite continuous advancements, deepfake synthesis methods remain bound by inherent architectural limitations which, inevitably introduce subtle digital artifacts embedded within manipulated media. These artifacts can be visually identified within individual frames as spatial features, such as unnatural facial textures or lighting inconsistencies. Additionally, they may manifest as temporal features reflecting unnatural movements or inconsistent transitions between frames, including irregular expressions or blinking patterns. The spatial and temporal cues, while often imperceptible to the human visual system, provide critical forensic traces (i.e. fingerprints). The challenge of reliably detecting these traces has given rise to a diverse spectrum of detection methodologies and approaches, which broadly fall into three main categories: handcrafted-based feature, deep learning-based feature, and multi modal approaches.

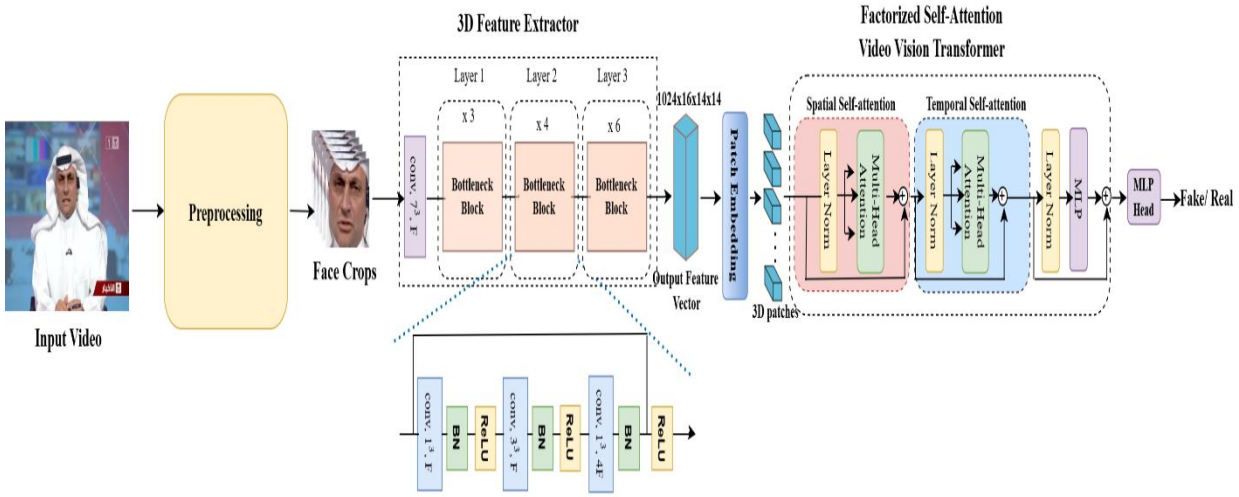


Fig. 1. Illustration of the proposed deepfake detection system.

1) Handcrafted-based features approach: This approach exploits traditional forensic cues such as inconsistencies in color blending, illumination, facial boundaries, and compression artifacts. For instance, inconsistent head poses indicate manipulation through unnatural geometric variations [8]. Face warping artifacts, introduced by affine transformations during deepfake synthesis, serve as discriminative signals [9]. Detection of blending boundary inconsistencies between the forged face and background is addressed by the face X-ray technique [10]. Another line of research leverages subtle physiological and behavioral inconsistencies inherent in deepfakes. Eye blinking patterns, typically involuntary and natural, are often absent or abnormal in synthesized videos, providing temporal cues for detection [11]. Heartbeat-induced photoplethysmographic (PPG) signals, reflecting blood flow and skin color variations, are also lacking in forgeries, effectively leveraged by Ciftci et al. [12]. Furthermore, phoneme-viseme mismatches, arising from a lack of synchronization between audio phonemes and lip movements (visemes), expose audiovisual inconsistencies unique to manipulated content [13].

While handcrafted-based methods are effective against early deepfakes, it often struggle to generalize to advanced generation techniques.

2) Deep learning-based feature approach: Deep learning-based feature approaches primarily leverage convolutional neural networks (CNNs), vision transformers (ViTs) [14], and hybrid spatiotemporal architectures to automatically learn discriminative representations. These models capture subtle spatial distortions, temporal inconsistencies, and generator-specific fingerprints that are typically imperceptible to human observers, thereby enabling robust detection of deepfake content. Afchar et al. [15] proposed MesoNet, a lightweight CNN that targets mesoscopic spatial features for detecting forged faces. Capsule-forensics [16] employed Capsule networks, which are known by their ability to catch hierarchical relationships and preserve spatial features better than convolutional neural networks. F^3Net is a dual-branch network that captures both local and global frequency features, employing a CNN for classification in deepfake detection [17]. SurFake model [18], which identifies manipulations by analyzing the surface geometry of faces to capture anomalies in surface caused by the forging process. FreMask [19] is a method that enhances deepfake detection by applying random masks to frequency components during training. This frequency-domain augmentation improves model robustness and generalization. The work in [20] employs a learnable uniform visibility matrix to guide the model in emphasizing subtle, imperceptible artifacts that remain in videos even after compression. Additionally, plug-and-play modules [21] with adaptive notch filters specifically remove compression noise while multi-task learning optimizes detection across domains, boosting robustness.

Deep learning methods have become central in deepfake detection due to their ability to autonomously learn intricate spatial and temporal features that reveal subtle manipulations.

3) Multimodal approach: Multimodal deepfake detection approach integrates multiple sources of information, typically combining visual and audio data, to improve detection accuracy and robustness. By fusing complementary features such as facial expressions, lip movements, voice characteristics, and audio-visual synchronization, these methods aim to capture inconsistencies that are difficult to detect using single-modality models. Salvi et al. [22] proposed an integrated system combines CNN-based visual frame analysis with audio spectrogram processing, jointly exploiting visual and auditory cues to detect deepfakes. Gandhi et al. [23] introduced a framework that jointly analyzes facial characteristics and mel-spectrogram audio features using machine learning models, achieving high detection accuracy by fusing these modalities. Alsaeedi et al. [24] proposed a multimodal fusion mechanism that integrates pre-trained audio, visual, and textual emotion features, leveraging speech sentiment and facial expressions to enhance detection robustness and accuracy.

These multimodal methods demonstrate the power of combining multiple modalities to detect subtle and sophisticated deepfake manipulations.

III. Proposed Method

To address the problem of performance degradation in videos affected by compression, this study proposes an end-to-end learning framework that transcends conventional frame-level analysis. The model comprises two primary units: first, a spatiotemporal feature extractor utilizing 3D convolutional layers to process video segments of fixed spatial and temporal dimensions; second, a transformer-based classifier that leverages factorized attention mechanisms to effectively integrate spatial and temporal features. This design enables the model to robustly distinguish between authentic and manipulated videos, maintaining high detection accuracy even under varying compression levels and quality impairments. Detailed architectural specifications are provided in the following sections:

1) Feature extraction unit: To extract robust spatiotemporal representations from the input video sequences, we employ a 3D-CNN backbone derived from the 3D-ResNet-50 architecture [25]. This framework extends the standard ResNet-50 into the temporal domain, utilizing three-dimensional convolutional kernels to inherently model volumetric video data.

The baseline architecture consists of 50 layers organized into four stages of residual bottleneck blocks. As illustrated in Fig. 1, each bottleneck unit comprises a sequence of three convolutional layers: a 1×1 convolution for dimensionality reduction, a 3×3 convolution for joint spatial and temporal features extraction, and a final 1×1 convolution for restoring the dimensionality. These layers are interleaved with Batch Normalization (BN) and Rectified Linear Unit (ReLU) activation functions. A residual skip connection bridges the input and output of each block, preserving signal integrity during backpropagation and facilitating the convergence of deep architectures. To ensure robust initialization, the model is pretrained on the Kinetics-700 dataset [26], leveraging learned weights optimized for large-scale action recognition.

To tailor this architecture specifically for the detection of fine-grained manipulation artifacts, we introduce two critical modifications: 1) Temporal Resolution Preservation: We adjusted the stride of the initial max-pooling layer from the default (*2, 2, 2,)* to (*1, 2, 2)*. By removing the temporal downsampling at this early stage, we preserve the full temporal resolution of the input sequence, allowing the network to capture subtle high-frequency frame-to-frame inconsistencies. 2) Mid-Level Feature Extraction: We truncated the network by removing the final residual block (Layer 4) and the fully connected layer. Consequently, feature maps are extracted from the output of the third residual block (Layer 3). Unlike the high-level semantic abstractions found in Layer 4, Layer 3 features retain the fine-grained spatiotemporal details essential for identifying the minute artifacts introduced by neural rendering.

The video clip consists of t consecutive frames, denoted as $\{I_1, I_2, \ldots, I_t\}$ where each frame I_i is an RGB image of fixed spatial resolution; h and w represent the height and width of the image, respectively. The corresponding clip's label is $y \in \{0, 1\}$, where $y = 0$ indicates an authentic (Real) video, while $y=1$ indicates a manipulated (Fake) video. The input tensor for the network is represented by the following shape [see Eq. (1)]:

$$X \in R^{B \times C \times T \times H \times W} \quad (1)$$

where, B denotes the batch size, $C = 3$ is the number of input channels corresponding to the RGB image, T is the temporal dimension (number of frames), and $H = W$ represent the height and width of each frame. The network processes this input as a video volume producing a feature tensor of shape:

$$F=f(X) \in R^{B \times C' \times T' \times H' \times W'} \quad (2)$$

where, $B = 1$, $C' = 1024$, $T' = 16$, $H' = W' = 14$, are the batch size, channel, temporal, height, and width dimensions of the output feature map, respectively. This tensor F encapsulates spatiotemporal feature maps, encoding both spatial patterns per frame and temporal dynamics across frames, and serves as the input to the classification module.

2) Classification unit: The Vision Transformer (ViT) is a transformer-based architecture designed for image recognition tasks, which divides an input image into small patches and processes them as a sequence of tokens. The core component of ViT is the self-attention mechanism, which enables the model to adaptively weight the importance of different patches in the image by computing pairwise interactions. This mechanism allows the transformer to capture long-range dependencies and global context from the earliest layers, unlike convolutional neural networks that rely on local receptive fields.

Our model leverages a factorized self-attention transformer inspired by the Video Vision Transformer (ViViT) [27] architecture. Unlike conventional Vision Transformers (ViT), which operate on 2D patch embeddings extracted from individual frames, the proposed transformer processes 3D patch embeddings derived from the output of a 3D-ResNet backbone, enabling the modeling of volumetric spatiotemporal representations. As illustrated in Fig. 1, the factorized self-attention module decomposes self-attention into separate spatial and temporal components: spatial self-attention is first applied independently within each frame to capture local appearance relationships, followed by temporal self-attention across frames at each spatial location to model motion and temporal dynamics.

While similar factorized attention designs have been explored in prior video transformer architectures, their adoption has largely been motivated by computational efficiency. In contrast, our use of factorized spatial–temporal attention is driven by robustness considerations in compressed video. Under aggressive compression, spatial features are disproportionately degraded, whereas temporal structure often remains more stable. By explicitly decoupling spatial and temporal attention, the model avoids entangling corrupted spatial cues with temporal reasoning. As confirmed by our ablation studies, this design consistently outperforms joint spatiotemporal attention in highly compressed settings, indicating that factorized attention is better aligned with the characteristics of low-quality video forensic analysis.

The 3D-ResNet output features tensor F from Eq. (2) is divided into nonoverlapping 3D patches across temporal and spatial dimensions. Given a patch size (p_t, p_h, p_w), where p_t, p_h, p_w are the temporal, height, and width dimensions of each patch, respectively, the number of temporal patches N_T and spatial patches N_S is given by Eq. (3) and Eq. (4):

$$N_T = \frac{T'}{p_t} \quad (3)$$

$$N_S = \frac{H'}{p_h} \times \frac{W'}{p_w} \quad (4)$$

While the total number of patches is calculated by Eq. (5):

$$N = \frac{T'}{p_t} \times \frac{H'}{p_h} \times \frac{W'}{p_w} \quad (5)$$

Each 3D patch x_i for (i = 1, ..., N) is then flattened into a vector and linearly projected into a fixed-dimensional embedding [see Eq. (6)]:

$$z_i = E(x_i) \quad (6)$$

where, $E \in R^{D \times (C' \cdot p_t \cdot p_h \cdot p_w)}$ is a learnable matrix, B is the batch size, and D is the embedding dimension. Thus, linearly projected N patches form a sequence of discrete tokens as follows [Eq. (7)]:

$$Z_0 = [z_1, z_2, \ldots, z_N] \in R^{B \times N \times D} \quad (7)$$

An extra class token Z_{cls} and positional embedding P are prepended and added as follows [Eq. (8)]:

$$Z' = [z_{cls}; Z_0] + P \quad (8)$$

This patch embedding step converts the volumetric feature maps into a tokenized sequence suitable for the architecture of the video transformer.

The transformer encoder processes the tokens Z' with alternating spatial and temporal self-attention blocks:

The spatial attention is applied independently on tokens from each temporal slice, modeling spatial relationships within each frame as follows [Eq. (9)]:

$$Z_{spa} = Sp - attn(Z') \in \mathbb{R}^{B \times N_T \times N_S \times D} \quad (9)$$

Following the spatial attention, the temporal attention integrates the spatial encodings across all temporal slices by applying self-attention along the temporal dimension over the class tokens output from the spatial attention. The output of the temporal attention is given by Eq. (10):

$$Z_{tmp} = tmp - attn(Z_{spa}) \in \mathbb{R}^{B \times N_S \times N_T \times D} \quad (10)$$

Finally, the output class token from the temporal attention block is passed through a Multi-layer Perceptron (MLP) head and sigmoid activation function to estimate probabilities for the classes (Real vs. Fake) [see Eq. (11)]:

$$\hat{y} = \sigma(MLP(Z_{cls})) \quad (11)$$

IV. Experiments

A. Datasets

To evaluate the proposed model, experiments are conducted on three widely used public deepfake detection benchmarks: FaceForensics++ (FF++) [28], Celeb-DF-v2 [29], and the DeepFake Detection Challenge (DFDC) [30] dataset. These datasets collectively cover controlled and in-the-wild scenarios, multiple manipulation techniques, and varying levels of video quality and compression.

1) FaceForensics++: FaceForensics++ (FF++) is a public dataset containing 1,000 authentic videos collected from YouTube and 4,000 manipulated videos generated using four manipulation techniques: Deepfakes (DF), Face2Face (F2F), FaceSwap (FS), and NeuralTextures (NT). The FaceForensics++ videos are compressed using the H.264 codec, with each manipulation technique provided in three compression variants: c0 represents raw or uncompressed videos, c23 represents high-quality videos with medium compression, and c40 represents low-quality videos under a high compression level. In this work, FF++ enables systematic evaluation of detection robustness across different manipulation types and compression regimes.

2) Celeb-DF-v2: This dataset is an extension of the original Celeb-DF dataset, which consists of 590 real videos for 59 celebrities collected from YouTube and 5639 fake videos generated from the real videos using an advanced face-swapping technique. Compared to earlier datasets, Celeb-DF-v2 exhibits significantly improved visual quality and reduced synthesis artifacts, making it one of the most challenging benchmarks for deepfake detection. The dataset is commonly used to assess generalization performance under high-fidelity manipulation conditions.

3) DeepFake Detection Challenge (DFDC): The DeepFake Detection Challenge (DFDC) dataset is a large-scale benchmark released as part of a competition organized by Meta (formerly Facebook). It contains over 128,000 videos generated from 3,426 paid actors spanning diverse ethnicities, genders, and age groups. Videos are captured under varying poses, lighting conditions, and recording environments to reflect real-world scenarios. Fake videos are generated using multiple manipulation techniques, including face swapping and expression manipulation.

In this work, DFDC is used exclusively to evaluate cross-dataset generalization. Models are trained on the FaceForensics++ dataset and tested on DFDC without fine-tuning, allowing assessment of robustness to unseen identities, manipulation pipelines, and real-world capture conditions.

B. Dataset Preprocessing

The auxiliary preprocessing unit takes the raw input MP4 video and transforms it into a standardized data format suitable for subsequent deepfake detection analysis. Initially, video frames are extracted sequentially using the OpenCV (cv2) library. For each extracted frame, the face detection and localization are performed via the Multi-task Cascaded Convolutional Networks (MTCNN) algorithm. The identified facial regions are then cropped and uniformly resized to 224×224 pixels to ensure network compatibility.

To enhance model robustness and generalization, a combination of both spatial augmentations (e.g., horizontal

flipping, rotation, color jitter) and temporal augmentations (e.g., frame shuffling, dropouts) is applied. The face crops are then normalized using the mean and standard deviation values derived from the Kinetics dataset to standardize feature distribution. The final output of this unit is a tensor representing a face clip (a stack of T=16 cropped and processed frames) and a corresponding ground-truth label tensor (indicating Real or Fake) for supervised training.

C. Experimental Setup

All experiments were conducted on the Google Colaboratory (Colab) platform using Python 3.11.13 and PyTorch 2.6.0, running on an NVIDIA L4 GPU. The model dimension was set to 384, with 6 attention heads and an MLP dimension of 1536. Training utilized the Adam optimizer with a learning rate of $1\times10-4$ and a weight decay of $1\times10-3$ to mitigate overfitting. The Focal Loss function was employed with a focusing parameter $\gamma=2$ and balancing factor $\alpha=0.25$. The model was trained for up to 30 epochs with a batch size of 32. The best checkpoint was selected based on performance. Evaluation metrics reported include:

- Accuracy (ACC): This metric measures the proportion of correct predictions (both true positives and true negatives) out of the total number of predictions made. If TP, TN, FP, FN denote true positives, true negatives, false positives, and false negatives, respectively. Accuracy is calculated as:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

Accuracy reflects the overall correctness of the model's predictions but can be misleading on imbalanced datasets.

- Area Under the Curve (AUC): AUC is the area under the Receiver Operating Characteristic (ROC) curve, which plots the true positive rate (TP) against the false positive rate (FP) at varying classification thresholds. It quantifies the model's ability to distinguish between classes irrespective of any threshold. The AUC value ranges from 0 to 1, with 0.5 representing a random guess and 1.0 a perfect classifier. Higher AUC values indicate better model discrimination, especially useful for imbalanced classes.

D. Results

1) Model performance: In this experiment, we evaluated the effectiveness of the proposed model on detecting deepfake. We trained and tested the model on FF++ (raw), which composed of raw uncompressed videos, FF++ (high quality) consists of videos with medium compression (c23), FF++ (low quality), which includes videos with aggressive (c40) compression level, and the Celeb-DF-v2 datasets. The results of these experiments are presented in Table I.

2) Comparative study: To evaluate the effectiveness of the proposed model and establish a fair benchmark, a comparative study was conducted involving six state-of-the-art methods: MesoInception4 [15], F^3Net [17], SurFake [18], FreMask [19], Unseen Artifacts [20], and Multi-domain [21]. These methods were selected to represent a broad range of spatial-domain and frequency-domain detectors, which primarily rely on frame-level cues, enabling direct assessment of the benefit of explicit temporal modeling in comparison to non-temporal approaches. All models were trained and tested on four subsets of the FaceForensics++ (FF++) dataset, Deepfakes (DF), Face2Face (F2F), FaceSwap (FS), and NeuralTextures (NT), with consistent compression levels applied during both training and testing. Performance metrics for the baseline methods were cited from [21], ensuring consistency with previously established evaluation protocols. Table II presents the comparative performance results, while Fig. 2 further facilitates comparative analysis by visualizing the detection performance in terms of AUC across the four subsets of the FaceForensics++ dataset.

TABLE I. PERFORMANCE OF THE PROPOSED MODEL ON FACEFORENSICS++ DATASET AT VARYING COMPRESSION LEVELS AND ON THE CELEB-DF-V2 DATASET

Dataset							
FF++ (Raw)		***FF++ (High quality)***		***FF++ (Low quality)***		***CDF-v2***	
ACC	***AUC***	***ACC***	***AUC***	***ACC***	***AUC***	***ACC***	***AUC***
97.05	99.88	93.00	98.40	90.38	92.50	94.98	98.78

TABLE II. COMPARATIVE PERFORMANCE OF THE PROPOSED MODEL AND STATE-OF-THE-ART METHODS ON FACEFORENSICS++ SUBSETS UNDER CONSISTENT COMPRESSION LEVELS IN TERMS OF ACCURACY

Method	**Dataset**							
	DF		**F2F**		**FS**		**NT**	
	C23	**C40**	**C23**	**C40**	**C23**	**C40**	**C23**	**C40**
Meso4 [15]	90.09	88.06	82.19	76.64	89.63	77.89	55.33	52.86
F^3-Net [17]	97.34	92.13	97.72	84.72	98.19	88.84	89.13	58.28
SurFake [18]	98.52	88.46	97.34	75.62	98.34	84.87	90.17	52.81
FreMask [19]	98.15	92.09	98.26	85.16	99.01	87.11	88.75	58.41
Unseen Artifacts [20]	98.14	94.19	98.12	87.12	97.32	88.14	89.23	64.81
Multi-domain [21]	**99.02**	**95.17**	98.58	86.87	**99.22**	90.19	91.80	70.37
Ours	96.79	94.29	**98.93**	**91.07**	97.50	**91.43**	**92.86**	**76.79**

TABLE III. CROSS-DATASET EVALUATION IN TERMS OF (AUC) MODELS ARE TRAINED ON FF++ AND EVALUATED ON DFDC DATASET

Model	Train dataset	Test dataset
		DFDC
MesoInception4	FF++	56.42
F^3-Net		63.72
SurFake		59.15
FreMask		68.23
Unseen Artifacts		64.81
Multi-domain		67.13
Ours		**71.33**

3) Cross-dataset evaluation: While our work objective is to detect deepfake in a compressed video setting, we additionally evaluated the generalization ability of our method to detect unseen deepfake. Table III summarizes the cross-dataset detection performance on the challenging DFDC test set.

4) Ablation study: To evaluate the impact of key components in the proposed model, several ablation studies were conducted. These studies included evaluating: 1) the choice between 2D and 3D convolutions for the backbone model, 2) the impact of the transformer self-attention design, and 3) the performance sensitivity to the patch size. The experiments were conducted using the Deepfakes (DF) and Face2Face (F2F) subsets under heavy compression, as they represent the two main types of Deepfakes. The results of these studies are presented in Table IV.

TABLE IV. AN ABLATION STUDY PERFORMANCE OF DIFFERENT CONFIGURATIONS ON DEEPFAKES (DF) AND FACE2FACE (F2F) DATASETS AT C40

Parameter	Setup	DF		F2F	
		ACC	AUC	ACC	AUC
Backbone	2D-ResNet50	89.64	95.17	75.36	84.57
	3D-ResNet50	93.93	97.83	82.50	91.16
Self-Attention Design	Joint Self-attention Encoder	92.50	97.80	84.29	92.81
	Factorized Self-attention Encoder	94.29	98.43	91.07	94.94
Patch size	(1, 7, 7)	92.50	96.21	86.43	93.41
	(1, 14, 14)	94.29	98.43	91.07	94.94
Hybrid Architecture	3D-Resnet50 + Factorized self-attention ViViT with patch size (1, 14, 14)	94.29	98.43	91.07	94.94

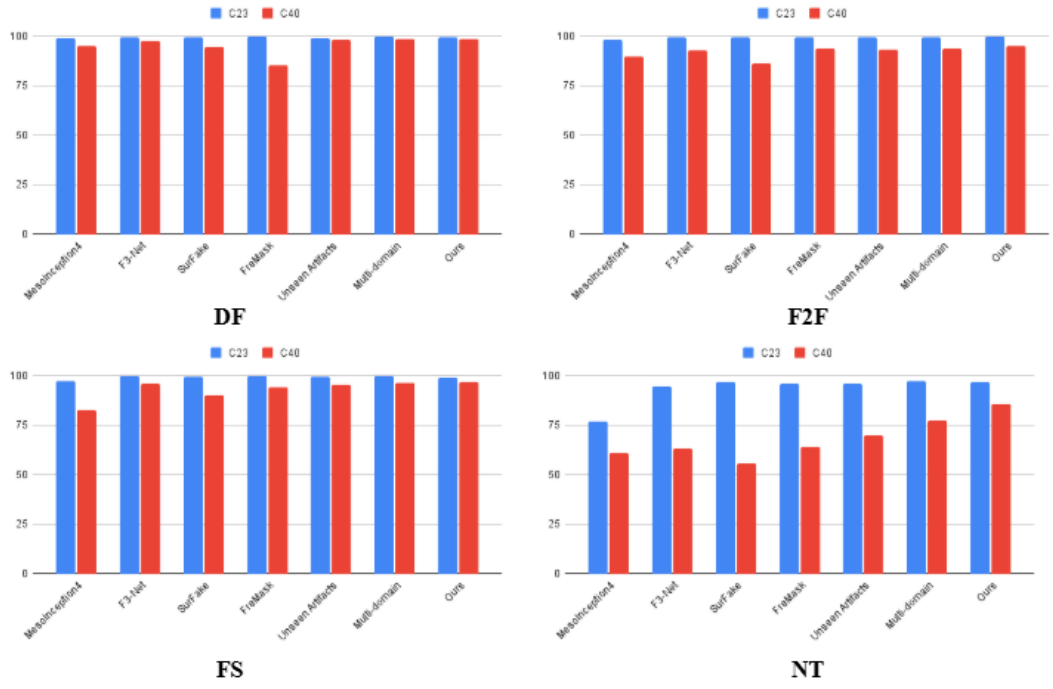


Fig. 2. Illustration of performance degradation on the four subsets of FF++ dataset, as compression increased from medium (c23) to aggressive (c40).

V. Discussion

From the extensive experimental work, we summarize our key findings as follows:

The comparative results in Table II illustrate the performance of the proposed method against representative spatial-domain and frequency-domain detectors under both medium (c23) and high (c40) compression settings across four manipulation types. Under c23, most methods achieve strong performance across datasets, indicating that moderate compression preserves sufficient manipulation artifacts for reliable detection. In this setting, the proposed method achieves competitive performance comparable to state-of-the-art approaches.

As compression increases to c40, a clear performance gap emerges between frame-based detectors and methods that explicitly leverage temporal information. While frequency-based and multi-domain approaches maintain reasonable performance on DeepFakes (DF) and FaceSwap (FS), their detection accuracy degrades substantially on Face2Face (F2F) and NeuralTextures (NT), which involve more complex motion and expression manipulations. In contrast, the proposed method consistently achieves the highest performance on F2F and NT under c40, with AUC improvements of up to +5.72% compared to the strongest baseline on NT.

This trend highlights the advantage of fully video-level spatiotemporal modeling under aggressive compression. When spatial and frequency-domain cues are suppressed by lossy encoding, temporal inconsistencies remain more reliable indicators of manipulation. By jointly leveraging a 3D convolutional backbone and factorized temporal attention, the proposed method is better suited to capture these cues, resulting in improved robustness in low-quality video scenarios.

Table III reports the cross-dataset detection performance on the DFDC dataset, where all models are trained on FaceForensics++ and evaluated on an unseen dataset without fine-tuning. Across all baselines, detection performance decreases substantially compared to within-dataset evaluation, reflecting the well-known domain gap between curated benchmarks and in-the-wild deepfake content.

Despite this challenge, the proposed method achieves the highest performance, with an AUC of 71.33%, outperforming all compared approaches. This improvement indicates stronger generalization to unseen identities, manipulation pipelines, and real-world capture conditions. The observed gains can be attributed to the model's fully video-level spatiotemporal modeling, which reduces reliance on dataset-specific spatial or frequency artifacts that do not transfer well across domains. By emphasizing temporal consistency cues, the proposed architecture demonstrates improved robustness in cross-dataset deepfake detection scenarios.

The ablation results in Table IV provide insight into the contribution of each architectural component under heavy compression. Replacing the 2D-ResNet50 backbone with a 3D-ResNet50 yields a substantial improvement across both manipulation types, increasing AUC from 95.17% to 97.83% on DeepFakes and from 84.57% to 91.16% on Face2Face. This confirms that explicitly modeling temporal information at the feature extraction stage is critical for robust deepfake detection in compressed videos, where frame-level spatial cues are often degraded.

The impact of the self-attention design is further evidenced by comparing joint spatiotemporal attention with the proposed factorized spatial–temporal attention. While joint attention improves performance over convolution-only baselines, factorized attention consistently achieves higher accuracy and AUC, particularly on Face2Face, where AUC increases from 92.81% to 94.94%. This result suggests that decoupling spatial and temporal attention enables more stable temporal reasoning by preventing compression-corrupted spatial features from dominating temporal modeling.

The effect of patch size is also evident, with larger spatiotemporal patches (1, 14, 14) outperforming smaller ones (1, 7, 7). Larger patches capture richer contextual information across both space and time, which is beneficial for detecting subtle temporal inconsistencies under compression. Finally, the complete hybrid architecture, combining a 3D backbone with factorized self-attention and an optimized patch size, achieves the best overall performance, validating the complementary role of each design choice.

VI. Conclusion

In this work, we proposed a 3D spatiotemporal deepfake detection framework that integrates a 3D convolutional backbone with a vision transformer to enable fully video-level reasoning. Unlike prior approaches that primarily rely on frame-based spatial or frequency-domain cues, the proposed model explicitly captures long-range temporal inconsistencies, resulting in improved robustness under aggressive video compression. The use of factorized spatial–temporal self-attention further enhances detection reliability by decoupling temporal modeling from compression-degraded spatial features.

Extensive experiments demonstrate that the proposed approach achieves competitive or superior performance across multiple manipulation types, particularly under low-quality compression and in cross-dataset generalization settings. With 62.7 million parameters and a model size of 361 MB, the proposed model is best suited for server-side or offline forensic analysis, where robustness and accuracy are prioritized over strict real-time constraints. Future work will focus on improving computational efficiency and further enhancing generalization to emerging deepfake generation techniques.

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References

[1] F.-A. Croitoru et al., "Deepfake Media Generation and Detection in the Generative AI Era: A Survey and Outlook," IEEE Trans Pattern Anal Mach Intell, vol. 50, no. NO. 1, Nov. 2024, Accessed: Dec. 22, 2025. [Online]. Available: https://arxiv.org/pdf/2411.19537

[2] N. Hynek, B. Gavurova, and M. Kubak, "Risks and benefits of artificial intelligence deepfakes: Systematic review and comparison of public attitudes in seven European Countries," Journal of Innovation &

Knowledge, vol. 10, no. 5, p. 100782, Sep. 2025, doi: 10.1016/J.JIK.2025.100782.

[3] S. Singh and A. Dhumane, "Unmasking digital deceptions: An integrative review of deepfake detection, multimedia forensics, and cybersecurity challenges," MethodsX, vol. 15, p. 103632, Dec. 2025, doi: 10.1016/J.MEX.2025.103632.

[4] M. Alrashoud, "Deepfake video detection methods, approaches, and challenges," Alexandria Engineering Journal, vol. 125, pp. 265–277, Jun. 2025, doi: 10.1016/J.AEJ.2025.04.007.

[5] Y. Lu and T. Ebrahimi, "Assessment framework for deepfake detection in real-world situations," EURASIP Journal on Image and Video Processing 2024 2024:1, vol. 2024, no. 1, pp. 6-, Feb. 2024, doi: 10.1186/S13640-024-00621-8.

[6] I. J. Goodfellow et al., "Generative Adversarial Nets," Adv Neural Inf Process Syst, pp. 2672–2680, 2014, [Online]. Available: http://www.github.com/goodfeli/adversarial

[7] D. P. Kingma and M. Welling, "Auto-Encoding Variational Bayes," in 2nd International Conference on Learning Representations, ICLR 2014, Banff, AB, Canada, April 14-16, 2014, Conference Track Proceedings, 2014., Dec. 2013. [Online]. Available: http://arxiv.org/abs/1312.6114

[8] X. Yang, Y. Li, and S. Lyu, "Exposing Deep Fakes Using Inconsistent Head Poses," ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings, vol. 2019-May, pp. 8261–8265, May 2019, doi: 10.1109/ICASSP.2019.8683164.

[9] Li Y and Lyu S, "Exposing DeepFake Videos By Detecting Face Warping Artifacts," IEEE Conference on Computer Vision and Pattern Recognition (CVPR) Workshops, pp. 1–6, Jun. 2019.

[10] L. Li et al., "Face X-Ray for More General Face Forgery Detection," 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pp. 5000–5009, Jun. 2020, doi: 10.1109/CVPR42600.2020.00505.

[11] Y. Li, M. C. Chang, and S. Lyu, "In Ictu Oculi: Exposing AI Created Fake Videos by Detecting Eye Blinking," International Workshop on Information Forensics and Security, Jul. 2018, doi: 10.1109/WIFS.2018.8630787.

[12] U. A. Ciftci, I. Demir, and L. Yin, "FakeCatcher: Detection of Synthetic Portrait Videos using Biological Signals," IEEE Trans Pattern Anal Mach Intell, pp. 1–1, Jul. 2020, doi: 10.1109/TPAMI.2020.3009287.

[13] S. Agarwal, H. Farid, O. Fried, and M. Agrawala, "Detecting deep-fake videos from phoneme-viseme mismatches," IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops, vol. 2020-June, pp. 2814–2822, Jun. 2020, doi: 10.1109/CVPRW50498.2020.00338.

[14] A. Dosovitskiy et al., "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale," International Conference on Learning Representations, 2020.

[15] D. Afchar, V. Nozick, J. Yamagishi, and I. Echizen, "MesoNet: A compact facial video forgery detection network," 10th IEEE International Workshop on Information Forensics and Security, WIFS 2018, Jan. 2019, doi: 10.1109/WIFS.2018.8630761.

[16] H. H. Nguyen, J. Yamagishi, and I. Echizen, "Capsule-forensics: Using Capsule Networks to Detect Forged Images and Videos," ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings, vol. 2019-May, pp. 2307–2311, May 2019, doi: 10.1109/ICASSP.2019.8682602.

[17] Y. Qian, G. Yin, L. Sheng, Z. Chen, and J. Shao, "Thinking in Frequency: Face Forgery Detection by Mining Frequency-Aware Clues," Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol. 12357 LNCS, pp. 86–103, 2020, doi: 10.1007/978-3-030-58610-2_6.

[18] A. Ciamarra, R. Caldelli, F. Becattini, L. Seidenari, and A. Del Bimbo, "Deepfake detection by exploiting surface anomalies: the SurFake approach."

[19] C. T. Doloriel and N. M. Cheung, "FREQUENCY MASKING FOR UNIVERSAL DEEPFAKE DETECTION," ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings, pp. 13466–13470, 2024, doi: 10.1109/ICASSP48485.2024.10446290.

[20] S. Chhabra, K. Thakral, S. Mittal, M. Vatsa, and R. Singh, "Low-Quality Deepfake Detection via Unseen Artifacts," IEEE Transactions on Artificial Intelligence, vol. 5, no. 4, pp. 1573–1585, Apr. 2024, doi: 10.1109/TAI.2023.3299894.

[21] Y. Wang, Q. Sun, D. Rong, and R. Geng, "Multi-domain awareness for compressed deepfake videos detection over social networks guided by common mechanisms between artifacts," Computer Vision and Image Understanding, vol. 247, p. 104072, Oct. 2024, doi: 10.1016/J.CVIU.2024.104072.

[22] D. Salvi et al., "A Robust Approach to Multimodal Deepfake Detection," J Imaging, vol. 9, no. 6, p. 122, Jun. 2023, doi: 10.3390/JIMAGING9060122.

[23] K. Gandhi, P. Kulkarni, T. Shah, P. Chaudhari, M. Narvekar, and K. Ghag, "A Multimodal Framework for Deepfake Detection," Journal of Electrical Systems, Oct. 2024, doi: 10.53555/jes.v20i10s.6126.

[24] A. Alsaeedi, A. AlMansour, and A. Jamal, "Audio-Visual Multimodal Deepfake Detection Leveraging Emotional Recognition," International Journal of Advanced Computer Science and Applications, vol. 16, no. 6, pp. 213–226, Jun. 2025, doi: 10.14569/IJACSA.2025.0160622.

[25] K. Hara, H. Kataoka, and Y. Satoh, "Can Spatiotemporal 3D CNNs Retrace the History of 2D CNNs and ImageNet?," Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pp. 6546–6555, Nov. 2017, doi: 10.1109/CVPR.2018.00685.

[26] J. Carreira, E. Noland, C. Hillier, and A. Zisserman, "A Short Note on the Kinetics-700 Human Action Dataset," Oct. 2022, [Online]. Available: http://arxiv.org/abs/1907.06987

[27] A. Arnab, M. Dehghani, G. Heigold, C. Sun, M. Lučić, and C. Schmid, "ViViT: A Video Vision Transformer," Proceedings of the IEEE International Conference on Computer Vision, pp. 6816–6826, Mar. 2021, doi: 10.1109/ICCV48922.2021.00676.

[28] A. Rossler, D. Cozzolino, L. Verdoliva, C. Riess, J. Thies, and M. Niessner, "FaceForensics++: Learning to Detect Manipulated Facial Images," in 2019 IEEE/CVF International Conference on Computer Vision (ICCV), IEEE, Oct. 2019, pp. 1–11. doi: 10.1109/ICCV.2019.00009.

[29] Y. Li, X. Yang, P. Sun, H. Qi, and S. Lyu, "Celeb-DF: A Large-Scale Challenging Dataset for DeepFake Forensics," Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, pp. 3204–3213, 2020, doi: 10.1109/CVPR42600.2020.00327.

[30] B. Dolhansky et al., "The DeepFake Detection Challenge (DFDC) Dataset.," arXiv: Computer Vision and Pattern Recognition, 2020.

Contact-Free Cardiovascular Monitoring Using AI-Driven Radar and Sensor Fusion on a Hybrid Edge-Cloud Platform

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***Abstract*—Access to essential cardiovascular parameters such as heart rate (HR), heart rate variability (HRV), and blood pressure (BP) remains limited in low-income and remote populations, particularly among older adults in developing regions. Continuous, simultaneous, and contact-free monitoring of these parameters beyond close proximity can enhance early detection, screening, and management of cardiovascular and related conditions. This study presents a real-time, contact-free health monitoring system based on millimeter-wave (mmWave) FMCW radar, phase demodulation, and digital signal processing (DSP), integrated with multimodal sensor fusion and artificial intelligence (AI)-driven inference. Sub-millimeter chest wall displacements are captured using radar in-phase and quadrature (I/Q) signals to extract beat-to-beat physiological features, including ECG-correlated waveform components, HR, and HRV, while non-invasive blood pressure is indirectly estimated using a physics-informed adaptive learning framework. A custom Long Short-Term Memory (LSTM) neural network is employed for temporal smoothing and stabilization of HRV signals, improving robustness under real-world conditions. The system is implemented within a hybrid edge–cloud architecture, enabling on-device inference for real-time monitoring and cloud-based analytics for long-term analysis and integration. Clinical-like validation conducted on over 100 adult participants demonstrates measurement accuracy comparable to clinically accepted reference devices, and statistical analysis confirms the robustness and reliability of the proposed system.**

Keywords*—Wireless sensing; radar signal processing; sensor fusion; contact-free monitoring; heart rate; heart rate variability; blood pressure; deep learning

I. Introduction

Cardiovascular diseases (CVDs) remain among the leading causes of morbidity and mortality worldwide, accounting for a significant proportion of sudden cardiac deaths and long-term disability [1]. Early detection and continuous monitoring of cardiovascular function are therefore critical for preventive care, timely intervention, and effective disease management. Key physiological indicators such as heart rate (HR), heart rate variability (HRV), and blood pressure (BP) provide essential insights into cardiac health, autonomic nervous system regulation, and overall physiological resilience [2]. Abnormalities in these parameters—such as arrhythmias, reduced HRV, or sustained hypertension—are strongly associated with increased risk of stroke, heart failure, and other chronic conditions.

Despite their clinical importance, continuous and simultaneous monitoring of HR, HRV, and BP remains difficult to achieve in a practical, scalable manner, particularly in low-income, rural, and resource-constrained settings. Conventional measurement techniques, including electrocardiography (ECG), photoplethysmography (PPG) [3], and cuff-based sphygmomanometers, require physical contact with the subject and are often episodic, obtrusive, or dependent on trained personnel. These constraints limit their suitability for long-term monitoring, mass screening, and deployment in mobile or community-based healthcare programs. Additionally, contact-based systems pose challenges related to hygiene, patient comfort, and compliance, especially in elderly populations and infectious-disease scenarios.

Recent advances in contactless sensing technologies have opened new possibilities for non-invasive physiological monitoring. Radar-based systems, particularly those operating in the millimeter-wave (mmWave) spectrum, can detect sub-millimeter chest wall displacements caused by cardiac and respiratory activity, enabling remote measurement of vital signs without physical contact. Several studies have demonstrated the feasibility of using radar, cameras, or acoustic sensors to estimate heart rate and respiration. However, existing approaches remain limited in clinical applicability. Many focus on single-parameter estimation, rely on extensive subject-specific calibration, or exhibit reduced robustness under real-world conditions involving motion artifacts, environmental interference, or physiological variability. Most notably, accurate contactless estimation of blood pressure continues to be an unresolved challenge, with prior methods often depending on pulse transit time (PTT) models, multiple synchronized sensors, or regression-based techniques that may not generalize well across populations.

This disconnects between clinical requirements—namely, reliable, continuous, and multi-parameter cardiovascular monitoring and the capabilities of existing contactless systems represent a critical research gap. There is a lack of integrated, field-deployable platforms capable of simultaneously extracting HR, HRV, and BP from a single sensing modality, while maintaining medical-grade accuracy, interpretability, and scalability. Furthermore, many reported solutions remain at a

proof-of-concept stage and do not address system-level considerations such as real-time processing, deployment in non-controlled environments, or integration with digital health infrastructure.

A. Research Objectives

In response to the identified limitations of existing contactless cardiovascular monitoring approaches, this study aims to investigate the feasibility of a single, contact-free radar-based sensing system combined with multimodal sensor fusion and adaptive artificial intelligence for accurate, real-time estimation of heart rate (HR), heart rate variability (HRV), and blood pressure (BP) in clinical-like and real-world environments, without reliance on physical contact or wearable sensors.

The primary objective of this research is to design, develop, and experimentally validate a contact-free cardiovascular monitoring platform that integrates millimetre-wave radar sensing, advanced digital signal processing, and AI-driven inference within a hybrid edge–cloud architecture. Specifically, the study seeks to:

- Extract beat-to-beat cardiac features from radar in-phase and quadrature (I/Q) signals using physics-guided signal processing techniques;
- Improve the stability and robustness of HR and HRV estimation through temporal modelling based on Long Short-Term Memory (LSTM) networks;
- Estimate blood pressure indirectly from radar-derived cardiac waveform features using adaptive learning methods, without the use of cuff-based measurements; and
- Evaluate system performance through comparative validation against clinically accepted reference devices under controlled and semi-controlled conditions.

B. Contribution and Significance

The proposed approach advances deployable contactless cardiovascular monitoring by translating laboratory-scale sensing into an integrated, system-level solution. By combining radar-based sensing with adaptive learning and multimodal sensor fusion, the platform supports concurrent estimation of multiple cardiovascular parameters using a single, non-intrusive device. A hybrid edge–cloud architecture enables low-latency, real-time inference at the point of care while supporting scalable cloud-based analytics for longitudinal and population-level assessment. Collectively, this work establishes a practical, scalable framework for hygienic, continuous cardiovascular monitoring in distributed, resource-constrained healthcare environments beyond conventional clinical settings and equitable access.

C. Organization of the Study

The remainder of this study is structured as follows: Section II discusses the motivation for contact-free cardiovascular monitoring. Section III reviews existing contactless monitoring techniques, identifies their limitations, and positions the proposed approach relative to prior work while highlighting its novel contributions. Section IV details the system architecture, sensing framework, and signal processing methodology. Section V presents experimental results and clinical validation. Section VI explores future research directions and potential applications. Section VII addresses data privacy and ethical considerations, and Section VIII concludes the study.

II. Motivation for Contact -Free Measurement of HR, HRV, BP, and Other Vitals in this Research

With advancements in medical devices, there is a growing demand to measure multiple vital and non-vital parameters simultaneously with a single device. However, current scientific and engineering limitations often necessitate multiple devices, complicating the process. This research aims to develop a non-invasive, hygienic, and efficient contactless method for measuring blood pressure and other vitals, enhancing patient comfort, reducing infection risk, and enabling continuous remote monitoring. To achieve this, innovative techniques are required to accurately capture vitals without altering established scientific frameworks. This study focuses on the contactless measurement of derived parameters, which can improve safety, comfort, and efficiency across various fields. The proposed method is particularly valuable in healthcare and holds promise for industrial, consumer, medical, and enterprise applications. By enabling indirect parameter measurement, this research seeks to drive innovation across multiple sectors. Specifically, it demonstrates how the radar signals can be used to measure heart rate (HR), heart rate variability (HRV), blood pressure (BP), and other dynamic vitals. Using a sensor fusion approach, the system processes data from sensors and transducers to provide accurate physiological insights through advanced digital signal processing and phase demodulation techniques.

In this research, the I (In Phase) and Q (Quadrature) components form the basis of complex signal representation, widely used in signal processing, communications, and radar systems. For orthogonal receiver radar with I/Q channels, phase information is obtained using arctangent demodulation, providing critical data for precise parameter estimation.

III. Literature Review

A. Existing Approaches

The evolution of radar-based, contactless systems for health monitoring holds transformative potential in non-invasive, patient-centered care. Building upon conventional technologies, recent research explores the unique benefits and expanded applications of radar systems, particularly in environments where physical contact with sensors may be undesirable or impractical. Zhang et al. [4] introduced "Radar-Beat", a breakthrough radar-based system capable of continuous beat-by-beat heart rate monitoring. The system leverages radar signals to measure heart rate accurately, even in dynamic settings where traditional contact-based methods might fail, marking a significant advancement for healthcare monitoring in real-life scenarios. Similarly, Maji et al. [5] explored an alternative approach using standard RGB cameras for contactless heart rate monitoring, which, while less costly and more accessible than radar, generally lacks the precision

radar provides in tracking vital signs reliably in non-static environments.

The development of millimeter wave radar has been especially influential in expanding the possibilities for real-time, contactless vital sign monitoring. Gao et al. [6] demonstrated the effectiveness of millimeter wave radar for tracking both heart rate and respiratory rate simultaneously. The study highlights radar's versatility and its applications in healthcare settings, where it can offer reliable, real-time monitoring without requiring any physical contact, thereby enhancing both patient comfort and data accuracy. Deep learning integration further amplifies radar-based systems' capabilities, as explored by Ni et al. [7], who reviewed deep learning approaches to contactless heart rate measurement. By leveraging machine learning algorithms, these systems can adapt to varying signal conditions, significantly reducing noise and improving measurement accuracy, even in non-ideal conditions.

Radar-based health monitoring systems are further enriched through hybrid solutions that incorporate AI, camera, and radar technologies for a more robust measurement approach. Kolosov et al. [8] demonstrated a camera-based system enhanced by AI for monitoring heart and respiratory rates. Such multi-sensor setups, which combine data from both radar and camera sources, increase the reliability of readings, addressing potential challenges associated with either technology alone. Expanding the scope of contactless monitoring to more accessible technologies, Wang et al. [9] illustrated the use of smart speakers for heart rhythm monitoring, showcasing the flexibility of contactless technology to adapt to household devices. This expands the use of contactless systems into home environments, offering a convenient solution for ongoing monitoring outside clinical settings.

Further innovations in wearable and radar-based monitoring were presented by De Pinho Ferreira et al. [10], who reviewed non-invasive heart rate monitoring for wrist-worn devices, providing insights into the growing role of wearable applications for real-time health monitoring. Similarly, Esgalhado et al. [11] evaluated heart rate variability (HRV) derived from ECG and PPG signals, emphasizing the effectiveness of multimodal approaches that improve accuracy by drawing from multiple sources of physiological data. Zhang et al. [12] took this concept further by employing a CNN-LSTM model to detect arrhythmias in medical IoT systems, illustrating deep learning's value in enhancing diagnostic capabilities by detecting subtle patterns in heart rate data that may indicate health risks.

Radar technology has made strides in signal processing methods that enhance measurement accuracy. Park and Lubecke [13] developed a critical technique involving arctangent demodulation with DC offset compensation for Doppler radar systems, improving the precision of heart rate detection by isolating vital signals from noise and background interferences. Further refinement of signal accuracy in radar systems was achieved by Sameera et al. [14], who worked on reducing respiratory harmonics within heart signal analysis. This is crucial for radar-based systems to accurately distinguish heart rate data from respiratory noise, improving the system's overall effectiveness in diverse monitoring environments.

Nonlinear HRV analysis has also contributed to a deeper understanding of heart rate dynamics in patients with cardiovascular disease. Krstacic et al. [15] examined HRV's nonlinear dynamics in patients with coronary artery disease, illustrating how complex HRV behaviour can serve as a critical indicator of cardiovascular health and disease progression. Similarly, Kondo et al. [16] investigated laser-based monitoring of chest wall movements, presenting a promising alternative for non-contact respiratory rate tracking. This further validates radar's complementary role in continuous respiratory monitoring, especially in high-risk or critically ill patient scenarios where accurate respiratory tracking is vital.

Wearable technologies for HRV monitoring have also progressed, as evidenced by Eguchi and Aoki [17], who developed R-R interval editing techniques for single-channel ECG devices. This is essential in wearable applications, as it ensures data reliability by providing clean, precise HRV measurements even in continuous monitoring scenarios. Longitudinal studies such as Schroeder's [18] study on HRV determinants in the Atherosclerosis Risk in Communities Study provided foundational insights into how HRV changes over time can signal early indicators of cardiovascular disease, supporting the utility of continuous monitoring in preventive care.

Patented advancements have also driven innovation in radar-based health monitoring. KRS [19, 20] proposed adaptive learning-based techniques for radar signal enhancement, which enable the system to dynamically adjust and enhance input features based on rank and event-driven causes. This adaptive capability represents a major leap toward intelligent monitoring systems that can self-optimize for accuracy in real-time scenarios. Schellenberger et al. [21] contributed to this field by providing a clinically recorded radar dataset with synchronized reference sensor signals, an invaluable resource for developing, validating, and training radar-based health monitoring algorithms.

The application of ultra-wideband radar, particularly in paediatric and early childhood health monitoring, is another area of emerging interest. Arasteh et al. [22] utilized ultra-wideband radar for simultaneous monitoring of respiratory and heart rates in young children, achieving high accuracy by implementing a deep transfer learning approach. This study underscores radar's potential for non-intrusive monitoring in sensitive populations, like infants and young children, where conventional methods may not be feasible. Finally, Udupa et al. [23] investigated the applicability of HR and HRV in mental health assessments, finding that HRV can indicate autonomic dysfunction in patients with major depression. This connection between HRV and mental health broadens radar's applicability, potentially allowing healthcare providers to monitor psychological as well as physiological health indicators non-invasively.

B. Comparative Evaluation of Existing Approaches and Novel Contributions of the Present Study

Our research work represents a significant departure from prior art, introducing a clinically validated, scalable, and AI-driven contactless health monitoring system suited for low-resource and mobile healthcare settings. Existing academic and commercial efforts in radar-based vital sign monitoring often depend on pulse transit time (PTT) models or signal regression techniques requiring multiple sensors or calibration. Prior works—such as those by Mase et al. (2011), Kim & Ling (2017) [24], and Huang et al. (2016)—struggle with limited accuracy under dynamic, real-world conditions. In contrast, the presented system enables real-time blood pressure estimation using a single radar by extracting dynamic PQRS waveform segments from micro chest wall displacements. This bypasses the need for PTT calibration and enhances diagnostic precision using physics-informed modelling. A custom Long Short-Term Memory (LSTM) model, implemented in C++, ensures temporal smoothing of heart rate variability signals under fluctuating conditions. Unlike deep-learning-only prototypes such as the Smart Health mmWave Radar (UT Austin) and Convolution Neural Network (CNN) based models, Li et al. (2021), this system fuses empirical and AI-driven inference for robustness and interpretability. Patents like US11,076,522B2 (UC) and US10,995,684B2 (Google) disclose radar-based BP estimation, yet none offer a unified signal processing framework for simultaneous extraction of over 18 parameters in a validated field-deployable device. Additionally, unlike exploratory efforts like Project Soli (Google) or WO2022174460A1 (Huawei). This work has achieved Technology Readiness Level (TRL) 7 through multi-site functional validation. To the best of the authors' knowledge, it represents the first integrated platform that combines single-radar PQRS waveform generation, physics-guided modelling, hybrid AI processing (on-device and cloud), and multimodal sensor fusion. The system's industrial scalability is supported by seven patent applications, with regulatory submissions currently in progress through the US FDA 510(k) pathway under the Class B medical device category. No prior academic or commercial effort, to the authors' knowledge, demonstrates a comparable combination of parameter richness, medical-grade accuracy, model transparency, and operational readiness. These distinctions represent a significant advancement toward scalable, contact-free health monitoring platforms designed for integration into large-scale public health systems.

IV. Methodology

Although contactless monitoring of vital signs has been investigated across various research domains, the presented system represents a distinct advancement through its emphasis on clinical-grade accuracy at short-range, person-specific distances (1.25–1.75 meters). The solution combines radar-based physiological sensing with adaptive signal processing and machine learning, including a purpose-built Long Short-Term Memory (LSTM) neural network for real-time signal stabilization. Integration with a hybrid edge-cloud framework facilitates continuous, secure, and remote access to health data, enabling deployment in primary care centers, mobile clinics, and underserved healthcare environments.

In this research, a multi-sensor framework was employed that integrates multi-point temperature sensors, multimedia sensors, transducers, and millimeter-wave (mmWave) radar, all operating within the Industrial, Scientific, and Medical (ISM) radio bands. These sensors were deployed in compact integrated circuit (IC) packages, with all electronics custom-designed by Impilo Sensys and certified under CE (Conformité Européenne) and FCC (Federal Communications Commission) standards, and are lead (Pb)-free. The radar module utilizes Frequency-Modulated Continuous Wave (FMCW) technology and operates at 120 GHz (Indie Semiconductor). The study primarily focuses on three ISM-band ICs functioning at approximately 24 GHz, 61 GHz, and 120 GHz. The mmWave radar modules are responsible for non-contact measurement of human heart rate (HR), heart rate variability (HRV), and blood pressure (BP).

Due to intellectual property and regulatory considerations, detailed electronic schematics have been limited to block-level architecture, as shown in Fig. 1 and Fig. 2. Technical schematics can be made available to the editorial board under confidentiality agreements, if required.

A. Test Population

Clinical validation of the system was conducted at renowned tertiary care hospitals in Bengaluru, India, involving a diverse cohort of over 100 adult participants aged 18 to 88 years. The study included both healthy individuals and patients with known health conditions, provided they could remain still for at least two minutes. Exclusion criteria included individuals with implanted cardiac devices, movement disorders, or those undergoing beta-blocker therapies.

To ensure data privacy, only anonymized vital and non-vital parameters are shared publicly. The radar and reference signals are one-dimensional electrical signals, inherently preserving participant anonymity. Full datasets can be made available upon request under appropriate ethical data sharing agreements. Additionally, a live system demonstration with a volunteer subject can be arranged by the corresponding author for interested researchers.

B. Reference Instrument

A medical-grade pulse oximeter and stethoscope were used to measure heart rate, while a sphygmomanometer (BP cuff) was employed to measure blood pressure, serving as reference tools to validate our findings.

C. System Architecture and Sensing Framework

In alignment with the global shift toward proactive, decentralized, and digitally enabled healthcare, this research presents a contact-free, AI-powered health screening and monitoring system. Rather than a product promotion, the system serves as an illustrative example of a scalable medical device ecosystem built on artificial intelligence, sensor fusion, and hybrid edge-cloud architecture. It features a tablet-sized, portable device capable of real-time, contactless measurement of over 18 physiological parameters, including heart rate, respiratory rate, SpO_2, non-invasive blood pressure, and heart rate variability. Central to the system is a proprietary AI foundation model, HealthGPT, operating in two modes:

HealthGPT Lite for on-device inference and HealthGPT Pro for cloud-based contextual analysis. The platform is designed for standalone use or integration with external medical devices and health records, offering localized data visualization and secure cloud synchronization. Validated in clinical-like settings, the system has achieved Technology Readiness Level (TRL) 7.0, confirming its suitability for real-world healthcare deployment.

Inside the system enclosure, a tightly integrated sensor fusion framework is implemented, comprising intelligent computing hardware and analytical software modules. As illustrated in Fig. 1, this framework includes two primary subsystems: 1) a radar-based sensing unit and 2) a complementary suite of sensors contributing to multimodal data fusion. The radar subsystem operates within the Industrial, Scientific, and Medical (ISM) radio bands and is configured to initiate signal acquisition upon receiving a predefined trigger frequency. A 16-bit Analog-to-Digital Converter (ADC) samples incoming radar signals at a programmable sampling frequency, initiating processing of a defined number of data samples.

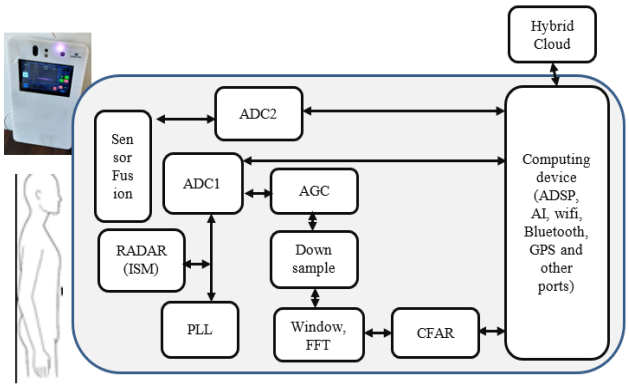


Fig. 1. Integrated sensor fusion architecture for health monitoring using radar and auxiliary sensors.

Signal strength is optimized using an Auto Gain Control (AGC) mechanism, and DC offset cancellation is performed when enabled. A Phase-Locked Loop (PLL) ensures frequency stability during operation. The acquired radar data is downsampled and processed through a Hanning window function to reduce spectral leakage, followed by a Fast Fourier Transform (FFT) with selectable lengths of 128, 256, 512, or 1024 points, depending on the sampling rate and ramp duration. From the FFT output, signal features such as magnitude and phase are extracted for target characterization. Target detection is performed using a Constant False Alarm Rate (CFAR) algorithm, which applies tuneable parameters including CFAR window size, guard bands, and threshold levels to suppress noise and false positives.

Both raw and transformed radar data are transmitted to an embedded computing device running a Linux operating system. This device also receives inputs from additional sensing modalities such as infrared sensors, camera modules, and air quality sensors via separate ADC interfaces. The aggregated multimodal data is processed using digital signal processing (DSP) algorithms and machine learning (ML) models to infer vital and non-vital health parameters through direct and indirect computational methods.

A custom web-based application is deployed locally on the device for real-time visualization and interaction. This interface also enables secure bidirectional communication with a hybrid cloud server, facilitating extended analytics, secure storage, and integration within this system platform's white-labelled device architecture.

D. MM Wave Radar Setup

The primary approach of Frequency Modulated Continuous Wave (FMCW) radar-based vital sign detection is to measure chest vibrations resulting from the mechanical effects of breathing and the cardiac cycle. The heartbeat signal typically has a fundamental frequency between 0.75 Hz and 2.5 Hz (45 to 150 beats per minute) and an amplitude of approximately 0.45 mm from the chest. In contrast, the breathing signal has a fundamental frequency between 0.1 and 0.7 Hz (6 to 42 breaths per minute) with an amplitude range of 3.5 mm to 11.5 mm. In this research, we present results obtained using a 120 GHz radar system from Indie Semiconductor FFO GmbH.

The general block diagram of the radar system is shown in Fig. 2. The antennas, labelled T(x) and R(x), correspond to the transmit and receive channels, respectively. A frequency-modulated radio frequency (RF) signal is emitted toward the subject's chest for non-contact physiological sensing.

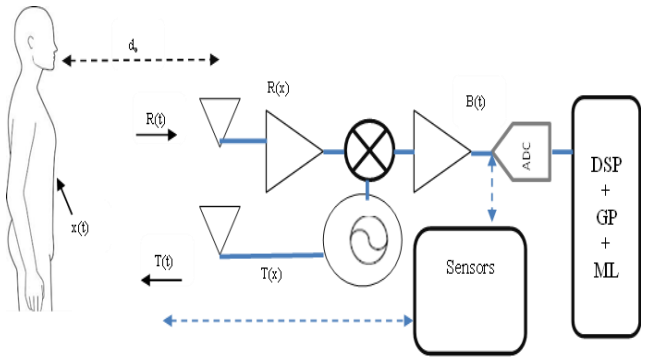


Fig. 2. Block diagram of a radar system to measure heart rate and heart rate variability wirelessly.

The received signal is first pre-processed before being sent to an analog-to-digital converter (ADC) and is then transmitted to digital signal processing (DSP) and other modules for further analysis.

The radar transmits signal T(t) via T(x) antenna to the subject at a distance of d_o :

$$T(t) = A_T COS(2\pi f\, t + \theta(t)) \quad (1)$$

where, f is the carrier frequency, A_T is the power amplitude and $\theta(t)$ is the phase noise from waveform generator.

Chest displacement caused by breathing and heartbeat is measured through phase modulation in the received signal, yielding a signal that encapsulates the effects of both breathing and heartbeat.

R(t) is the signal which the radar receives after it is reflected by the subject's chest displacement:

$$R(t) \cong A_R COS(2\pi f\, t - 4\pi \frac{d_0}{\lambda} - 4\pi \frac{x(t)}{\lambda} + \theta(t - 2\frac{d_0}{c})) \quad (2)$$

where, A_R is the received power, λ is the carrier wavelength, c is the speed of light in free space, $x(t)$ is the chest wall movement due to heartbeat and respiration, and $\theta(t - 2d_o/c)$ is the phase noise with a delay of $2d_o/c$.

The same T(x) is used as local oscillator (LO) signal to down-convert R(t) to baseband B(t):

$$B(t) = \cos(\theta_0 + 4\pi \frac{x(t)}{\lambda} + \triangle\theta(t)) \quad (3)$$

where, $\theta_0 = 4\pi d_0/\lambda + \sigma$ is the summation of phase shift from the nominal distance d_o and at the reflection surface, $\Delta\theta(t) = \theta(t) - \theta(t - 2d_o/c)$ is the residual phase noise.

E. Experimental Procedure

The test subject is seated between 1.25 m and 1.75 m from the radar device, with a medical-grade pulse oximeter and blood pressure monitor attached in accordance with standard clinical protocols. Data collected by the radar over a one-minute interval is processed through a series of digital signal processing (DSP) steps. These include adaptive filtering, phase demodulation, and feature extraction, followed by a Fast Fourier Transform (FFT) for frequency domain analysis.

To enhance temporal stability and reduce physiological noise, a customized Long Short-Term Memory (LSTM) neural network developed in C and C++ is employed for post-processing. Final results are transmitted securely to a hybrid cloud platform, enabling remote access to derived metrics such as heart rate (HR), heart rate variability (HRV), blood pressure (BP), and other auxiliary parameters from any connected device. Fig. 3 illustrates the overall architecture of the hybrid cloud integration.

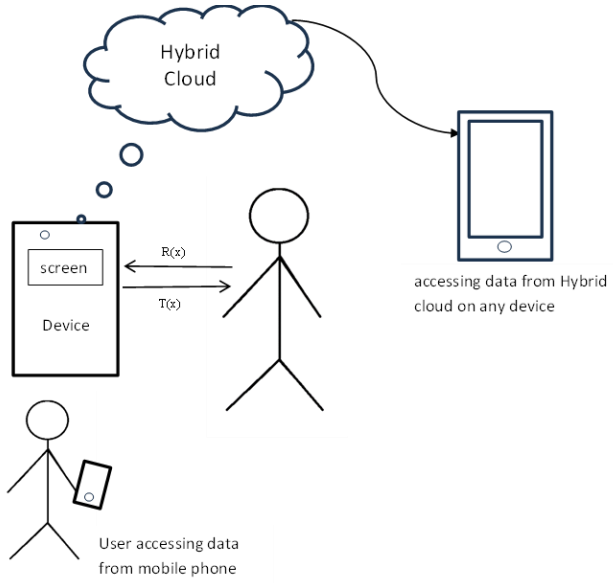


Fig. 3. Overview of device architecture and hybrid cloud integration flow.

The radar subsystem operates across widely accessible ISM frequency bands at 24 GHz, 61 GHz, and 120 GHz, capturing minute chest wall displacements associated with cardiac and respiratory activity. Signals within the 0.75–2.5 Hz range (corresponding to 45 150 BPM) are segmented into 10-second windows, producing six HR estimations per minute. These radar readings are then fused with auxiliary sensor data, including motion, temperature, and air quality, using an adaptive signal fusion framework. In future work, this multimodal sensing framework is expected to enable not only the estimation of primary vital parameters (HR, HRV, and BP) but also the inference of secondary physiological indicators, such as stress levels, brain health, mental health and fatigue states.

Preprocessing begins with phase demodulation using an arctangent-based algorithm that incorporates noise suppression mechanisms. This is followed by baseband conversion and adaptive bandpass filtering to isolate relevant physiological signals. FFT is applied to extract frequency-domain features, while template matching identifies PQRS or PQRST waveform patterns in the time domain. These extracted features are then passed to the LSTM module for signal stabilization and used in the system's indirect BP estimation module, thereby maintaining both high signal fidelity and diagnostic accuracy.

F. Temporal Smoothing Using LSTM

To address signal noise, motion artifacts, and temporal inconsistencies inherent in radar-derived HR measurements, the authors developed a C++ based LSTM neural network. Operating on 10-second radar-derived HR segments, the LSTM model was chosen over conventional smoothing techniques due to its ability to learn and retain both short- and long-term dependencies. This approach enhances the stability of HRV signals, which are further used to estimate BP and assess physiological variability under real-world conditions.

Each 10-second radar-derived reading is scaled by dividing the value by 100 to normalize it below 1 and is then fed into the LSTM model. The LSTM operates in three iterations, each using four consecutive readings: the first iteration uses readings values in a sequence 1, 2, 3, and 4; the second uses 2, 3, 4, and 5; and the third uses 3, 4, 5, and 6. Each iteration generates a predicted HR value, and the final output is calculated as the average of these three predictions. This iterative approach ensures the stabilization of the final HR value by smoothing out any inconsistencies or noise present in the raw radar data.

The internal structure of the LSTM node, as shown in Fig. 4, consists of a forget gate, input gate, and output gate, which collaboratively regulate the flow of information through the network. This architecture enables the LSTM to retain relevant patterns and discard noise, ensuring robust and accurate heart rate predictions. The LSTM's role in refining and stabilizing the HR output is integral to the system's ability to provide reliable and medically accurate real-time monitoring.

In this LSTM model, the Long-Term Memory (LTM) and Short-Term Memory (STM) values generated from the first iteration are passed forward to the next iteration, along with a new set of four HR readings. This allows the model to build

upon the prior memory states, incorporating information from previous HR data to enhance accuracy and stability in the output. Specifically, the LTM and STM values calculated from readings 1, 2, 3, and 4 in the first iteration serve as the initial memory states for the next set of inputs (readings 2, 3, 4, and 5) in the second iteration. This process is repeated across iterations, with each successive iteration updating and carrying forward the LTM and STM values, thereby reinforcing the model's understanding of temporal patterns in the data. Fig. 5 provides a visual of this iterative process, illustrating how the memory states are updated and propagated, ultimately ensuring a stabilized output across multiple LSTM iterations.

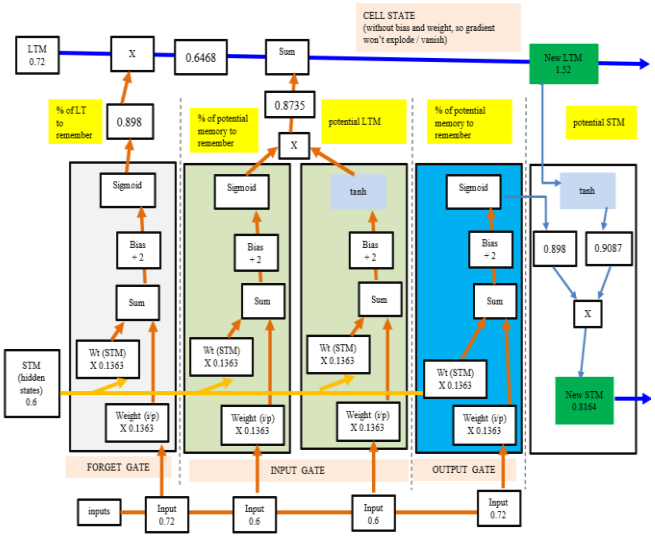


Fig. 4. Single LSTM node showing the flow of data.

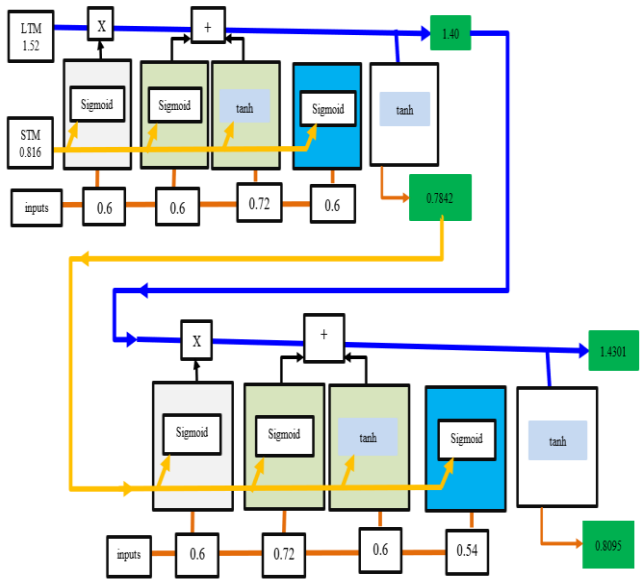


Fig. 5. Multiple iteration of the LSTM model.

G. Blood Pressure Estimation: A Physics-Informed AI Approach

A systematic approach was presented for estimating blood pressure (BP) parameters from reflected radar signals, enabling fully contactless monitoring. This methodology integrates fundamental scientific principles with adaptive artificial intelligence and advanced digital signal processing (DSP) techniques. As illustrated in Fig. 6, the process involves a series of signal transformations and algorithmic steps designed to extract vital cardiovascular information without the use of physical probes or direct contact with the subject.

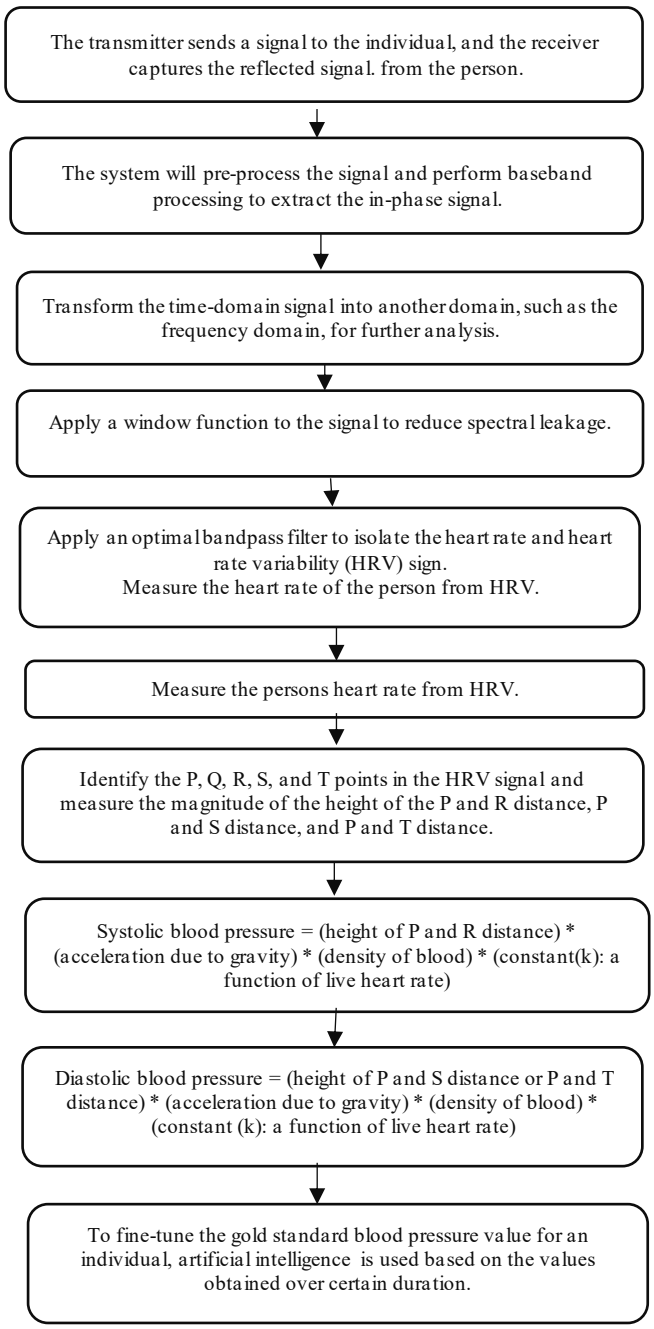


Fig. 6. Step-by-step method and data flow for measuring blood pressure wirelessly without any contact.

The radar system continuously tracks heart rate variability (HRV) signals to identify PQRST intervals, which are then analysed using adaptive learning DSP algorithms. From these features, systolic and diastolic pressures are estimated using the following equations:

Systolic blood pressure = (height of P and R distance(h)) * (acceleration due to gravity(g)) * (density of blood(ρ)) * (constant(k): a function of live heart rate) (4)

Diastolic blood pressure = (height of P and S distance or P and T distance (h)) * (acceleration due to gravity(g)) * (density of blood (ρ)) * (constant(k): a function of live heart rate) (5)

Here, h denotes the amplitude difference between specific cardiac waveform peaks, g is the gravitational acceleration, ρ is the blood density, and k is a constant dynamically derived from an adaptive learning AI model, which depends on the live heart rate value. This indirect estimation technique has been validated against a conventional sphygmomanometer, achieving measurement accuracy in the 90 to 98% range, as detailed in Table II.

H. User Experience and Operational Simplicity

Although supported by advanced AI and digital signal processing backends, the system is designed to offer a straightforward, hygienic, and contactless user experience. Users interact with the system via an integrated touchscreen interface or a mobile application, with measurements obtained while the individual remains seated within the operational range—without the need for physical contact or wearable sensors. This user-centric, non-intrusive design makes the system particularly suitable for deployment in eldercare facilities, infectious disease control scenarios, primary care centers, and community health programs.

The actual device, as shown in Fig. 7, is compact—approximately the size of a traditional tablet—making it both portable and unobtrusive.



Fig. 7. Contactless health screening product.

For each measurement session, the reference person (RP) or subject follows a simple and repeatable protocol to ensure accurate and consistent readings:

- The RP is seated in front of the radar and sensor-enabled device, as illustrated in Fig. 8.
- Prior to starting, the RP should ensure their bladder is nearly empty and relax for at least 5 minutes to stabilize physiological parameters.
- The RP should sit upright on a chair, facing the device at a distance of 1.1 to 1.75 meters, with both feet flat on the floor and legs uncrossed.
- The RP is encouraged to take a few deep breaths, then continue with normal, relaxed breathing throughout the measurement period.
- Measurements are recorded for a minimum of 2 minutes, extendable to 5, 10, or 15 minutes based on the use case.
- The recorded values are displayed in real time via the user interface (UI), as shown in Fig. 9, and are also transmitted to the RP's mobile device and uploaded to the cloud for secure, remote access and further analysis.
- To ensure consistency and long-term reliability, the procedure should be repeated daily at approximately the same time.

Fig. 8 shows the live demonstration of the device. The device includes a screen that displays the data. Additionally, any other device can access the same data via the hybrid cloud, ensuring flexibility and remote monitoring capabilities.

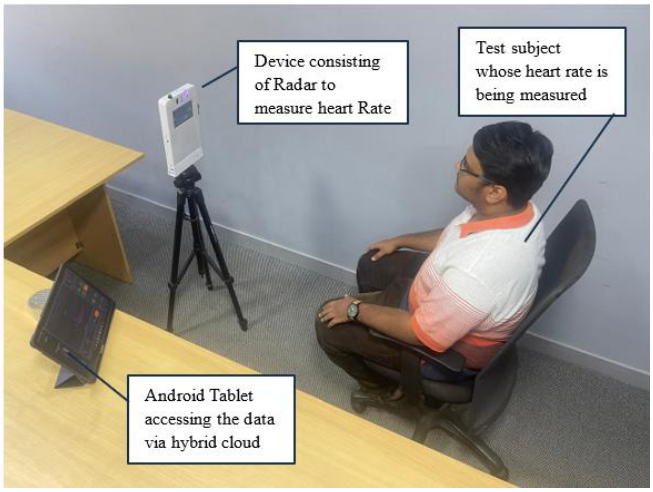


Fig. 8. Live demo of the device. (Subject is the co-author, journal is free to use their image and associated data in publication).

The device screen, as shown in Fig. 9, displays the heart rate, BP and other vitals

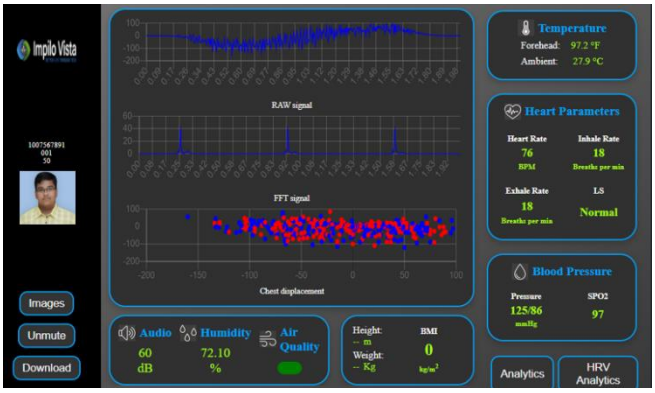


Fig. 9. Device screen showing heart rate, BP and other vitals.

I. Heart Rate Variability

The number of beats per minute is referred to as the heart rate, measured in beats per minute (BPM). Heart rate variability (HRV) represents the variation in the time intervals between consecutive heartbeats. HRV is visualized by the changes in R-R intervals over time, as shown in Fig. 10.

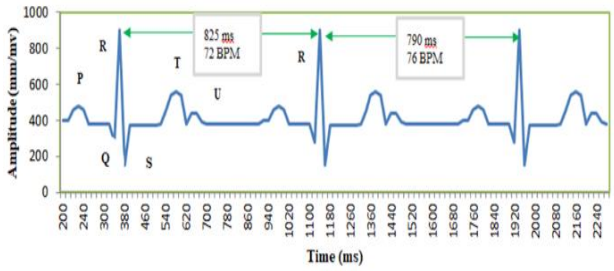


Fig. 10. Heart rate variability (HRV) visualized with R-R interval changes.

Heart rate variability (HRV) is a critical marker of autonomic nervous system function, providing valuable insights into an individual's cardiovascular fitness and stress levels. Fig. 12 illustrates a graphical representation of a heart rate variability (HRV) meter, displaying live HRV data along with the activities of the sympathetic nervous system (SNS) and the autonomic nervous system (ANS).

On the left side of the diagram, the variations and activities of the SNS are shown, highlighting its role in controlling the "fight-or-flight" response, such as reactions to fear, anxiety, or being startled. Typically, the SNS signals the adrenal glands to release adrenaline, leading to an increase in heart rate (HR) and blood pressure (BP).

On the right side, the ANS is depicted as regulating the "rest-and-digest" response, which counteracts the effects of the SNS. The diagram also outlines three conditions: rest, previous status, and live (current) status.

Low HRV is often linked to an increased risk of cardiovascular disease, as it indicates a reduced ability of the heart to adapt to changing physiological demands. Conversely, higher HRV reflects better cardiovascular health and a more flexible, responsive autonomic system. Fig. 11 illustrates human age variation as a function of heart rate variability (HRV), with the green-colored region representing the normal recommended values.

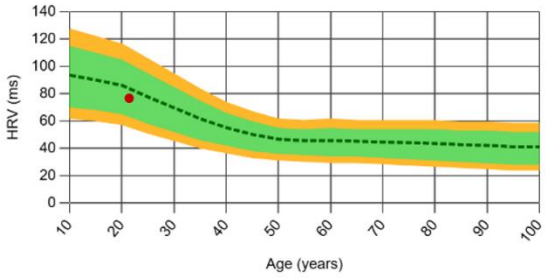


Fig. 11. Age variation as a Function of Heart Rate Variability (HRV).

V. Results

The proposed contact-free, radar-based health monitoring system demonstrates strong potential for accurate, non-intrusive estimation of key physiological parameters, including heart rate (HR), heart rate variability (HRV), and blood pressure (BP). Validation was performed on more than one hundred adult participants aged 18 to 88 years, using both the authors' vitals and those of external volunteers. Clinical-grade reference instruments—a Class B BP monitor, a manual sphygmomanometer (gold standard), a pulse oximeter, and a stethoscope—served as comparative benchmarks. The consolidated quantitative outcomes for HR and BP are summarized in Table I and Table II, respectively.

Under controlled indoor conditions (ambient temperature 18°C–32°C in an air-conditioned setting), the system achieved 90%–98% accuracy for BP estimation relative to the sphygmomanometer and 90%–95% accuracy for HR estimation compared with pulse oximeter and stethoscope readings. Each participant underwent three consecutive daily measurements to ensure statistical rigor and account for day-to-day variability.

A comprehensive quantitative analysis was performed to evaluate agreement, correlation, and precision. Bland–Altman plots demonstrated strong agreement between the contactless device and reference instruments. Pearson and Spearman correlation coefficients confirmed both linear and monotonic relationships between measured and gold-standard values. Additionally, Mean Absolute Error (MAE) with 95% confidence intervals provided insight into the system's consistency and repeatability. These findings were benchmarked against state-of-the-art radar-based literature and certified clinical devices, offering a robust comparative framework for assessing real-world applicability.

The system is implemented on a portable, tablet-sized platform integrating radar sensing, multimodal sensor fusion, signal processing, embedded AI models, and hybrid edge–cloud connectivity. This architecture enables real-time inference and supports longitudinal monitoring. The adaptive inference framework further enhances contextual interpretation of physiological signals while maintaining user simplicity and fully non-contact operation.

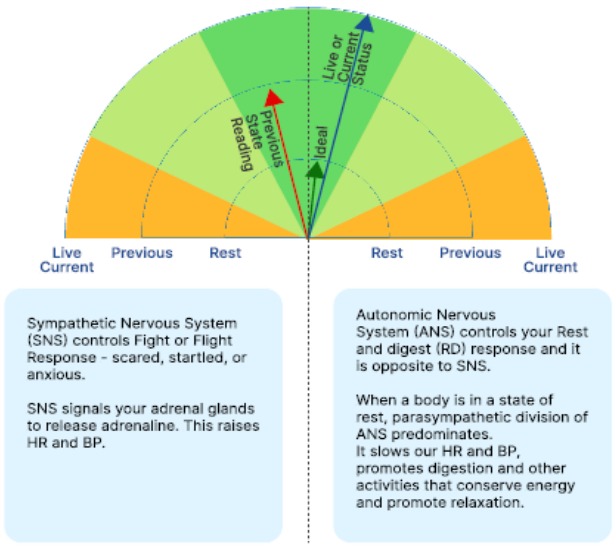


Fig. 12. Live heart rate variability (HRV) with SNS and ANS activities.

TABLE I. TEST RESULTS: COMPARISON OF HEART RATE MEASUREMENTS FROM OUR DEVICE AND REFERENCE DEVICES (BEFORE AND AFTER APPLYING LSTM MODEL): HEART RATE (HR), BEATS PER MINUTE (BPM), LONG SHORT-TERM MEMORY (LSTM)

Description Candidates/ Subjects.	HR measured using medical grade Pulse Oximeter (BPM)	HR measured using medical grade blood pressure (BP) and HR meter (BPM)	HR from our radar based contactless method. (BPM)	HR from our radar based contactless method, (BPM) with LSTM	Accuracy w.r.to medical grade pulse oximeter. (%)	Accuracy w.r.to medical grade B and HR meter. (%).
Subject 1	81	80	72	76.33	94.23	95.41
Subject 2	89	91	82	81	91.01	89.01
Subject 3	78	77	73	76	97.43	98.70
Subject 4	70	74	70	68	97.14	91.89
Subject 5	91	89	88	70	76.92	78.65
Subject 6	92	95	88	87	94.56	91.57
Subject 7	61	62	57	60	98.36	96.77
Subject 8	62	67	60	61	98.38	91.04
Subject 9	67	64	62	62	92.53	96.87
Subject 10	77	77	74	75	97.40	97.40
Subject 11	90	89	88	88	97.77	98.87
Subject 12	92	90	82	87	94.56	96.66
Subject 13	93	91	88	89	95.69	97.80
Subject 14	99	100	94	94	94.94	94.00
Subject 15	102	105	98	99	97.05	94.28
Subject 16	65	68	61	64	98.46	94.11
Subject 17	67	67	67	66	98.50	98.50
Subject 18	78	79	76	73	93.58	92.40
Subject 19	84	85	78	81	96.42	95.29
Subject 20	89	92	85	84	94.38	91.30

Note: We conducted clinical trials for this experiment at renowned hospitals in India with several test candidates. Due to data privacy concerns, we are only disclosing the data of the authors and a few selected subjects. However, researchers can contact the corresponding author for a live demo of the research work for validation.

TABLE II. TEST RESULTS: COMPARISON OF BLOOD PRESSURE (BP) MEASUREMENT FROM OUR DEVICE AND REFERENCE DEVICES BEFORE AND AFTER APPLYING THE LONG SHORT-TERM MEMORY (LSTM) TEST DURATION: 2 MINUTES

Description Candidates/ Subjects.	BP measured using medical grade BP meter. (systolic /diastolic)	BP measured using medical grade sphygmomanometer. (systolic / diastolic)	BP measured using contactless method (systolic /diastolic)	BP measured using contactless method (systolic /diastolic) with LSTM	Accuracy w.r.to BP meter. (systolic /diastolic) (%)	Accuracy w.r.to sphygmomanometer) Gold standard. (systolic /diastolic) (%).
Subject 1	120 / 84	118 / 80	116 / 82	117 / 81	97/96	99/98
Subject 2	180 / 110	170 / 105	173 / 98	168 / 95	93/86	98/90
Subject 3	130/85	140/87	122/80	123/84	94/98	87/96
Subject 4	125/84	125/90	118/87	122 /80	97/95	97/88
Subject 5	110 /75	115 / 80	102 / 75	108 /70	98/ 93	93/87
Subject 6	145 / 95	150 /100	140 /85	142 / 90	97/ 94	94/ 90
Subject 7	175 / 115	180 / 115	175 / 115	173 /113	98/98	96/98
Subject 8	125 / 85	118 / 90	116 / 82	115 / 82	92/96	97/91
Subject 9	170 / 120	180 / 105	163 / 98	165 / 95	97/ 79	91/90
Subject 10	140/95	145/ 90	122/80	133/85	95/89	91/94
Subject 11	185 / 110	175 / 105	173 / 98	168 / 100	90/90	94/98
Subject 12	135/85	140/87	122/80	123/84	91/98	87/96
Subject 13	110 /75	115 / 80	102 / 75	108 /70	98/93	93/87
Subject 14	135/85	140/87	122/80	123/84	91/98	87/96
Subject 15	120 / 84	118 / 82	116 / 82	117 / 81	97/96	97/98
Subject 16	170 / 110	170 / 105	163 / 98	168 / 95	98/86	98/90
Subject 17	115 /75	125 / 80	102 / 75	108 /70	93/93	86/87
Subject 18	165 / 110	170 / 105	155 / 98	162 / 102	98/92	95/97
Subject 9	130/85	140/87	122/80	123/84	94/98	87/96
Subject 20	120 / 88	118 / 85	116 / 82	117 / 81	97/92	99/95

Note: We conducted clinical trials for this experiment at renowned hospitals in India with several test candidates. Due to data privacy concerns, we are only disclosing the data of the authors and a few selected subjects. However, researchers can contact the corresponding author for a live demo of the research work for validation.

From a translational standpoint, the system has reached Technology Readiness Level (TRL) 7, having undergone functional validation and demonstrating readiness for controlled real-world deployment. Regulatory assessments and hospital-based evaluations are underway to advance clinical translation.

Despite its encouraging performance, certain limitations remain. The validation was restricted to adults, controlled posture, and short-range indoor operation, which may limit generalizability to dynamic or high-motion environments, paediatric populations, or broader demographic groups. Residual noise and motion artifacts, inherent to radar-based sensing, can still influence measurements. Ongoing work focuses on improving digital signal processing pipelines, minimizing internal and external artifacts, and refining real-time deep learning models to enhance robustness and statistical confidence.

Collectively, the results confirm the feasibility of contact-free estimation of cardiovascular parameters from micro chest wall displacements without wearable sensors or cuff-based methods. This represents a significant advance in remote and continuous health monitoring. Continued research and broader community validation are encouraged to further develop and expand this promising approach.

VI. Future Works

The future of medical devices is moving towards compact, portable, and contact-free systems that can securely integrate personal health data into hybrid cloud environments. This shift emphasizes the need for continuous, non-invasive monitoring solutions, adaptable across clinical, public, and home settings. Upcoming research will focus on new algorithms, multi-sensor integration, and enhanced radar signal processing to improve these devices' capabilities.

A. Advanced Algorithms for Comprehensive Monitoring

Research in advanced algorithms will be essential to capture multiple health parameters—heart rate, variability, blood pressure, glucose levels, and more, with high accuracy. These algorithms will need to account for environmental complexities, handling multiple persons, ensuring accurate, real-time, contactless readings, even in varied conditions.

B. Enhanced Accuracy with Multi-Radar Interference

Experiments with multi-radar interference techniques will boost the precision of complex measurements, such as blood pressure and respiration rates. Testing these in high-interference settings, like public areas, will provide robust, reliable radar-based monitoring and help optimize both direct and indirect measurement methods.

C. Parameter Modeling and Dependency Analysis

Studying the interdependencies between physiological parameters offers deeper insight into personalized health trends. This research will support the design of monitoring devices that adapt to individual variability, enhancing the precision and relevance of health assessments.

D. Expanding Use Cases

Contactless monitoring has wide applications, including:

- Proactive Health Monitoring for Aging Populations: Accessible devices for early health indicators could support independent living for seniors.
- Clinical and Non-Clinical Use: Psychiatry, yoga, and fitness settings can use these devices to track mental and physical well-being.
- Military and Industry Applications: Military personnel monitoring and machine health tracking (Industry 4.0/5.0) are emerging fields for this technology.
- Financial Services: Health data integration in loan and insurance processes offers new avenues for risk assessment and underwriting.

E. Miniaturization and Mobile Integration

Embedding compact monitoring modules into mobile devices will make health screening universally accessible. This requires miniaturized sensors that maintain high performance while optimizing power use, leading to future smartphones and wearables with advanced health-monitoring capabilities.

VII. Data Privacy, Ethics, Research Work Demo

1) Data privacy: This study exclusively uses the vital and non-vital parameters of the authors. Additionally, the method has been validated with data from over 100 subjects at leading hospitals in India, with all personally identifiable information removed. The radar and reference signals used are one-dimensional electrical signals, ensuring a high level of anonymity.

2) Data availability: The validated test data used for this research, obtained from ImpiloVista and other gold-standard medical devices, are available from the corresponding author upon reasonable request.

3) Ethics statement: In the initial phase, data were collected solely from the researchers themselves. All mmWave radars operate within the ISM band, and all electronic components used are CE and FCC compliant.

4) Product demo and supplementary materials: Upon request, the corresponding author can arrange a live demonstration of our research findings using the complete system with a subject for interested researchers.

5) Ethics and consent to participate declarations: We confirm that all methods were conducted in accordance with relevant guidelines and regulations, including the Declaration of Helsinki and applicable local regulatory standards. This study involved the use of medically approved international Industrial, Scientific, and Medical (ISM) band radar and medical-grade sensors, classified as a Class B medical product, without administering medication or inserting probes into the participants' bodies. All data were collected from subjects at a 1-meter distance with prior informed consent, ensuring strict privacy and confidentiality.

VIII. Conclusion

This research presents a novel, non-invasive method for accurate, real-time measurement of heart rate (HR), heart rate

variability (HRV), blood pressure (BP), and other vital signs from a distance, offering dynamic and continuous monitoring without physical contact. By leveraging the same signal, HRV can be derived, providing insights into brain-heart interactions critical for optimal health and supporting real-time adjustments for well-being. Through advanced sensor fusion techniques, this study demonstrates a reliable, efficient approach to indirect measurement of both vital and non-vital parameters, positioning contactless health monitoring as a promising advancement for remote and continuous healthcare.

ACKNOWLEDGMENT

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REFERENCES

[1] N. T. Srinivasan and R. Schilling, "Sudden cardiac death and arrhythmias," *Arrhythmia & Electrophysiology Review*, vol. 7, no. 2, pp. 111–117, 2018.

[2] J. Sacha, "Interaction between heart rate and heart rate variability," *Annals of Noninvasive Electrocardiology*, vol. 19, no. 3, pp. 207–216, 2014.

[3] Ş. C. Mirescu and S. W. Harden, "Photoplethysmography as a potential alternative to electrocardiography for recording heart rate intervals used in variability analysis," *Journal of Medicine and Life*, vol. 5, Spec. Issue, pp. 123–128, 2012.

[4] H. Zhang *et al.*, "Radar-Beat: Contactless beat-by-beat heart rate monitoring for life scenes," *Biomedical Signal Processing and Control*, vol. 86, p. 105360, 2023.

[5] S. Maji, C. Massaroni, E. Schena, and S. Silvestri, "Contactless heart rate monitoring using a standard RGB camera," in *Proc. IEEE Int. Workshop on Metrology for Industry 4.0 & IoT*, Rome, Italy, 2020, pp. 729–733.

[6] Z. Gao *et al.*, "Real-time non-contact millimeter wave radar-based vital sign detection," *Sensors*, vol. 22, no. 19, p. 7560, 2022.

[7] A. Ni, A. Azarang, and N. Kehtarnavaz, "A review of deep learning-based contactless heart rate measurement methods," *Sensors*, vol. 21, no. 11, p. 3719, 2021.

[8] D. Kolosov *et al.*, "Contactless camera-based heart rate and respiratory rate monitoring using AI on hardware," *Sensors*, vol. 23, no. 9, p. 4550, 2023.

[9] A. Wang *et al.*, "Using smart speakers to contactlessly monitor heart rhythms," *Communications Biology*, vol. 4, p. 319, 2021.

[10] N. De Pinho Ferreira, C. Gehin, and B. Massot, "A review of methods for non-invasive heart rate measurement on wrist," *IRBM*, vol. 42, no. 1, pp. 4–18, 2021.

[11] F. Esgalhado *et al.*, "Peak detection and HRV feature evaluation on ECG and PPG signals," *Symmetry*, vol. 14, no. 6, p. 1139, 2022.

[12] P. Zhang *et al.*, "A united CNN-LSTM algorithm combining RR wave signals to detect arrhythmia in the 5G-enabled medical Internet of Things," *IEEE Internet of Things Journal*, early access, 2021.

[13] B.-K. Park, O. Boric-Lubecke, and V. M. Lubecke, "Arctangent demodulation with DC offset compensation in quadrature Doppler radar receiver systems," *IEEE Transactions on Microwave Theory and Techniques*, vol. 55, no. 5, pp. 1073–1079, 2007.

[14] J. N. Sameera *et al.*, "Enhancing beat-to-beat analysis of heart signals with respiration harmonics reduction through demodulation and template matching," *IEEE Transactions on Microwave Theory and Techniques*, early access, 2023.

[15] G. Krstacic *et al.*, "Dynamic nonlinear changes in heart rate variability in patients with coronary heart disease and arterial hypertension treated by amlodipine besylate," in *Proc. Computers in Cardiology*, 2003, pp. 485–488.

[16] T. Kondo *et al.*, "Laser monitoring of chest wall movements," *European Respiratory Journal*, vol. 10, pp. 1865–1869, 1997.

[17] K. Eguchi and R. Aoki, "Practical R–R interval editing for heart rate variability analysis using single-channel wearable ECG devices," *IEEE Access*, vol. 11, pp. 25543–25582, 2023.

[18] E. B. Schroeder, *Determinants of the Longitudinal Change in Heart Rate Variability: The Atherosclerosis Risk in Communities Study*, Univ. of North Carolina, Chapel Hill, NC, USA, 2003.

[19] K. R. Shetty, "Adaptive learning-based enhancement of input features with rank and event-based causes of output for intelligent systems," Indian Patent Application 202241072404, 2022.

[20] K. R. Shetty, "A novel method to measure parameters of objects and matter," Indian Patent Application 202441040135, 2024.

[21] S. Schellenberger *et al.*, "A dataset of clinically recorded radar vital signs with synchronised reference sensor signals," *Scientific Data*, vol. 7, p. 291, 2020.

[22] E. Arasteh *et al.*, "Ultra-wideband radar for simultaneous and unobtrusive monitoring of respiratory and heart rates in early childhood: A deep transfer learning approach," *Sensors*, vol. 23, p. 7665, 2023.

[23] Udupa *et al.*, "Alteration of cardiac autonomic functions in patients with major depression: A study using heart rate variability measures," *Journal of Affective Disorders*, vol. 100, nos. 1–3, pp. 137–141, 2007.

[24] Y. Kim and H. Ling, "Human activity classification based on micro-Doppler signatures using a support vector machine," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 47, no. 5, pp. 1328–1337, 2009.

Choosing the Arena: A Systematic Review of Simulators for Deep Reinforcement Learning in Mobile Robot Navigation

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***Abstract*—This study presents a formal Systematic Literature Review (SLR) to address a critical methodological question in robotics research: "Which simulator is most suitable for a given Deep Reinforcement Learning (DRL) algorithm and mobile robot navigation task?" The choice of a simulation environment profoundly impacts policy robustness, data efficiency, and sim-to-real transfer, yet the community has lacked an evidence-based guide for this decision. Following PRISMA guidelines, we methodically searched and analyzed 87 peer-reviewed studies published between January 2020 and June 2025 to map the contemporary research landscape. Our synthesis introduces a novel, theory-informed taxonomy that classifies simulators into three archetypes based on their empirical use. Archetype I, ROS-centric standards (e.g., Gazebo), are chosen for algorithmic novelty with low-dimensional sensor inputs. Archetype II, versatile platforms (e.g., CoppeliaSim), are favored for rapid prototyping. Archetype III, GPU-native engines (e.g., NVIDIA Isaac Sim), have emerged for large-scale, perception-heavy challenges, leveraging photorealism and parallelization to mitigate the perception gap and enable zero-shot transfer. This review reveals a paradigm shift towards data-driven methodologies and culminates in a prescriptive decision-making framework, transforming simulator selection from an incidental detail into a strategic choice.**

***Keywords*—Simulator; mobile robot; Deep Reinforcement Learning; navigation**

I. Introduction

The autonomous navigation of mobile robots remains a cornerstone challenge in robotics, with Deep Reinforcement Learning (DRL) emerging as a powerful paradigm for learning adaptive control policies directly from sensor data [1]. However, the data-intensive nature of DRL makes training on physical hardware impractical due to time, cost, and safety constraints [2], [3], making simulation an indispensable tool. This reliance on simulation introduces the pervasive "sim-to-real gap"—the discrepancy between simulation and reality that hinders policy transfer [4]. The choice of simulator is therefore a foundational methodological decision, as it dictates the available strategies for mitigating this gap, defines the fidelity of sensor models (the "perception gap"), and sets the performance ceiling for data collection, which is critical for modern DRL algorithms [5], [6]. Despite the existence of numerous simulators, researchers lack a systematic, evidence-based guide to inform their selection, often leading to a methodological mismatch between the tool and the research objective. This study addresses this significant void by conducting a formal Systematic Literature Review (SLR) to provide a data-driven answer to the central research question: "Which simulator should a researcher choose for a specific DRL algorithm and mobile robot navigation task?"

While prior surveys have provided excellent overviews of DRL algorithms for navigation [7] or sim-to-real techniques [8], they are largely simulator-agnostic. They identify the sim-to-real gap as a key challenge, but do not offer a comparative analysis of the simulation tools themselves as the primary variable influencing research outcomes. Our work is fundamentally different. By employing a formal SLR methodology focused specifically on the simulator, we move beyond simple cataloging to provide a novel, archetype-based synthesis. This approach allows us to uncover causal links between simulator choice, research focus (e.g., algorithmic novelty vs. perception challenges), and the adopted sim-to-real strategy—insights that remain obscured in conventional narrative reviews. We frame our resulting taxonomy not as a mere descriptive grouping but as a theory-informed abstraction that reveals the underlying structure of current research practices. Furthermore, by analyzing literature from 2020 to 2025, our review captures and contextualizes a critical paradigm shift in the field: the move away from purely CPU-bound simulation towards GPU-native engines and data-driven methodologies for achieving robust real-world deployment.

This review makes several distinct contributions to the field. Our methodological contribution is the application of the rigorous PRISMA framework to a simulator-centric analysis, providing a transparent and reproducible evidence base. Our conceptual contribution is the novel taxonomy of simulator archetypes, which serves as a new analytical lens for understanding research trends and trade-offs. Finally, our practical contribution is a prescriptive, data-driven decision-making framework designed to guide researchers in strategically aligning their choice of simulator with their specific research objectives, thereby enhancing methodological rigor and research efficiency.

To achieve these aims, this study is structured as follows: Section II reviews related survey literature, sharpening the novel positioning of our work. Section III details our systematic review methodology, adhering to the PRISMA

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guidelines. Section IV presents the data extraction and synthesis process. In Section V, we present the results, introducing our taxonomy of simulator archetypes and analyzing their use in the literature. Section VI provides a detailed discussion, formalizing our findings into a prescriptive decision-making framework and articulating key research gaps. Finally, Section VII concludes the study with a reflective synthesis of our findings and their implications for future research.

II. Related Work

Several survey papers have explored the intersection of RL and robotics. Seminal works provided a comprehensive overview of RL in robotics before the deep learning era [9]. More recent reviews have focused on DRL for robotics, but often with accomplishments primarily in simulation or with a broad scope covering many tasks like manipulation and locomotion [7]. Other reviews focus specifically on sim-to-real transfer techniques, such as domain randomization and adaptation, but are generally simulator-agnostic [8].

A few studies have compared simulation environments directly. A study in [10] benchmarked the performance of four simulators on different hardware, focusing on computational speed rather than the broader research context. A recent review in [11] also reviewed popular simulation engines, highlighting MuJoCo and Unity, but not focusing specifically on the mobile robot navigation domain. Most closely related are recent reviews such as [5], [7], and [12]. A foundational review of DRL methods and navigation frameworks is provided in [7]. A systematic review focusing on navigation in dynamic environments is offered in [5]. Similarly, a comprehensive overview of DRL's integration in mobile robotics, analyzing its evolution and identifying key challenges and future directions, is presented in [12]. While these studies provide excellent, broad surveys of the algorithmic landscape, they identify the sim-to-real gap as a challenge without offering a comparative analysis of the simulation tools themselves. Our work differentiates itself by using a formal SLR methodology to specifically analyze and synthesize the literature based on the choice of simulator, thereby providing a novel, evidence-based framework that directly links simulator characteristics to DRL algorithms and navigation tasks.

III. Systematic Review Methodology

To ensure a transparent, reproducible, and rigorous review, we adopted the PRISMA 2020 statement as our methodological framework [13]. The process consists of defining research questions, a search strategy, study selection criteria, and a data extraction plan [14].

This review is guided by four central research questions (RQs) designed to systematically map the literature:

- RQ1: What is the distribution of simulators (e.g., Gazebo, Webots, CoppeliaSim, NVIDIA Isaac Sim) used in the recent literature for DRL-based mobile robot navigation?
- RQ2: What are the reported capabilities and limitations of these simulators concerning sensor modeling (perception gap) and performance/scalability for DRL training?
- RQ3: Which DRL algorithms (e.g., PPO, SAC, DQN, DDPG) are predominantly paired with each simulator, and for which specific navigation tasks (e.g., obstacle avoidance, end-to-end visual navigation)?
- RQ4: What trends and patterns emerge from the literature regarding sim-to-real transfer strategies associated with each simulator archetype?

A. Search Strategy

To gather a comprehensive body of literature, we implemented a structured search strategy across several major scientific databases. We conducted a systematic search of three major scientific databases: IEEE Xplore, Scopus, and arXiv. The search was performed in June 2025, covering publications from January 2020 to June 2025 to capture the most recent trends. The following search string was adapted for each database's syntax: ("reinforcement learning" OR "RL") AND ("mobile robot" OR "robot navigation") AND ("simulation" OR "simulator") AND ("Gazebo" OR "Webots" OR "CoppeliaSim" OR "Isaac Sim" OR "PyBullet").

B. Study Selection: Inclusion and Exclusion Criteria

We conducted the study selection in two phases: 1) title and abstract screening, and 2) full-text review[15]. To be included, a paper had to meet all of the following inclusion criteria:

- I1: The paper is a full-text, peer-reviewed conference paper, journal article, or a publicly available preprint (from arXiv).
- I2: The paper was published between January 2020 and June 2025.
- I3: The paper explicitly uses a physics-based simulator for training or evaluating a DRL agent for a mobile robot navigation task.
- I4: The paper is written in English.

Papers were excluded based on the following exclusion criteria:

- E1: The paper is a review, survey, or abstract-only publication.
- E2: The work does not involve a mobile ground robot (e.g., focuses only on manipulators, drones, or underwater vehicles).
- E3: The work uses RL but not deep learning (i.e., no deep neural networks).
- E4: The simulator is used for purposes other than DRL (e.g., only for visualization or classical controller testing).

C. Selection Results

The systematic search and screening process yielded a final corpus of literature that forms the evidence base for this review. Initially, 173 papers were selected based on the research query and inclusion criteria. After the removal of

duplicates, 143 unique studies remained. These were subjected to a full-text review, and after applying the exclusion criteria, a final set of 87 papers were deemed eligible for inclusion in our qualitative synthesis. The complete study selection process is visually detailed in the PRISMA flow diagram shown in Fig. 1.

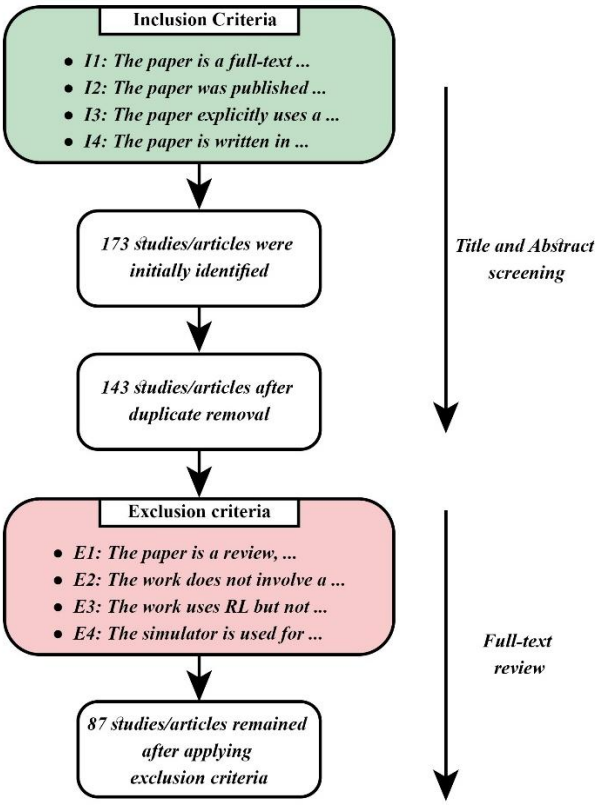


Fig. 1. Study selection process based on inclusion and exclusion criteria.

IV. Data Extraction and Synthesis

For each study that met the criteria, we performed a detailed data extraction process to gather key information for our synthesis. For each included study, we extracted the following data points: 1) Simulator used; 2) Mobile robot platform; 3) Navigation task description; 4) DRL algorithm implemented; 5) Sensor modalities simulated; 6) Stated reasons for simulator choice; 7) Reported performance metrics; and 8) Sim-to-real transfer methodology and results. The extracted data was then synthesized qualitatively to answer the research questions and identify overarching trends. Table I provides a summary of a representative selection of the reviewed literature, illustrating the connections between simulators, algorithms, and tasks that form the basis of our analysis.

The data summarized in Table I reveal several distinct trends that underpin our analysis. A clear majority of the studies leverage Gazebo, pairing it with a wide array of DRL algorithms—from value-based methods like D3QN to policy-gradient methods like PPO and DDPG—for tasks centered on map-less navigation and obstacle avoidance. This reinforces its role as a versatile, community-standard testbed. In contrast, papers utilizing NVIDIA Isaac Sim consistently tackle complex, often end-to-end, navigation tasks and are frequently paired with data-hungry algorithms like PPO or advanced methods like Imitation Learning. This highlights its adoption for research pushing the boundaries of sim-to-real transfer and performance.

Webots and CoppeliaSim are used for a range of tasks, including multi-robot systems and learning from demonstration, often employing algorithms like PPO and GAIL, respectively, showcasing their utility in specialized research areas [37]. Collectively, the table illustrates a strong correlation between the choice of simulator and the scope of the research problem, a central theme explored in this review.

TABLE I. Summary of Selected Literature on Simulators for DRL-based Mobile Robot Navigation

Reference	*Used Simulator(s)*	*DRL Algorithm(s)*	*Task(s)*
[16]	Isaac Sim, Gazebo	PPO	End-to-end local planning and obstacle avoidance.
[17]	Gazebo	DDPG, PPO	Autonomous navigation, target seeking and obstacle avoidance.
[18]	Unity, Gazebo	Double DQN	Map-less navigation to a random target.
[19]	Gazebo	SAC, PPO, DDPG, Q-learning	Path planning and obstacle avoidance
[20]	Gazebo	D3QN (Dueling Double Deep Q-Network)	End-to-end navigation and obstacle avoidance in an unknown environment with static and dynamic obstacles.
[21]	Gazebo	DDPG, PPO	Map-free navigation for an omnidirectional robot.
[22]	Gazebo	DDPG (customized with guiding points)	Navigation in crowded environments with dynamic pedestrians.
[23]	Gazebo	Parallel Distributional Actor-Critic Networks	Map-less navigation for terrestrial mobile robots
[24]	Gazebo	DDQN (Double Deep Q-Network)	Map-less navigation and obstacle avoidance for a TurtleBot3 robot.
[25]	Webots	PPO (enhanced with Curriculum Learning)	Shortest path planning for an E-puck robot using IR sensors.
[26]	Webots	DQN, PPO	Pedestrian avoidance for autonomous vehicles in simulated scenarios.
[27]	Webots	DQN, PPO, A2C	The inverted pendulum task
[28]	Webots	DQN, NSQ, DDQN, PPO	Multi-robot swarm navigation.
[29]	CoppeliaSim	GAIL (Generative Adversarial Imitation Learning)	Learning navigation behaviors from expert demonstrations for mobile robots.
[30]	CoppeliaSim	Adaptive TD3	Navigation in dynamic environments
[31]	Gazebo (via FRobs RL)	PPO, SAC, TD3	Map-less navigation for a mobile robot.
[32]	Isaac Sim	RMA (Rapid Motor	Legged mobile robot walking on different

Reference	Used Simulator(s)	DRL Algorithm(s)	Task(s)
		Adaptation)	types of ground surfaces.
[33]	Isaac Sim	NavACL-Q (curriculum learning method with soft actor-critic algorithm)	Map-less navigation for an Automatic Guided Vehicle (AGV) in a warehouse scenario.
[34]	Isaac Sim	Imitation Learning (IL) and Curriculum Learning (CL)	Map-less navigation of a wheeled robot using open-vocabulary 3D scene graphs.
[35]	Isaac Sim	Imitation Learning (IL) with an auto-regressive world model	Generalizable end-to-end navigation.
[36]	Isaac Sim	Asymmetric Actor Critic	Visual goal-tracking
[37]	Gazebo	DDPG	Map-less path planning in an unknown environment
[38]	Gazebo	DQN, DDQN	Map-less navigation and obstacle avoidance
[39]	Custom Simulator	DWA-RL	Mobile robot navigation without prior exploration

V. Results of the Systematic Review

A. Distribution of Simulators

An analysis of the selected corpus of literature reveals a distinct distribution in the adoption of simulation platforms. Gazebo emerged as the predominant simulation environment, utilized in a substantial majority of the reviewed studies, thereby establishing its position as a de facto standard within the research community.

NVIDIA Isaac Sim was identified as the second most prevalent platform, indicating its significant and growing adoption in recent research. Following these, Webots and CoppeliaSim were also frequently employed, albeit to a lesser extent. A smaller subset of the literature utilized alternative simulators, such as PyBullet, particularly in studies concentrating on specialized applications like mobile navigation.

B. Simulator Capabilities, DRL Algorithms, and Tasks

Our synthesis of the literature revealed distinct patterns that link the choice of simulator with its technical capabilities, the selected DRL algorithms, and the complexity of the navigation task. We present these findings through our proposed taxonomy of simulator archetypes.

1) Archetype I: ROS-Centric Open-Source Standards (Gazebo, Webots). These simulators are predominantly selected for their seamless integration with the ROS ecosystem[40]. The literature consistently cites the benefit of architectural parity, where the same ROS2 control software can be deployed in simulation and on the real robot, simplifying the sim-to-real process[16]. However, their CPU-bound performance is a frequently acknowledged limitation, making them less suitable for training on high-dimensional visual data. Sensor modeling is functional, but studies note that default noise parameters often require manual tuning to match real hardware, presenting a perception gap challenge[41]. Consequently, the majority of studies using these platforms focus on navigation tasks with low-dimensional inputs, primarily 2D LiDAR scans[24]. The most common DRL algorithms are off-policy methods like DDPG/TD3 and SAC, alongside the on-policy PPO[24]. The research contribution in these papers often lies in algorithmic enhancements, such as novel reward shaping [37] or modified network architectures for safer navigation, rather than tackling the perception gap itself.

2) Archetype II: The Versatile Multi-Physics Platform (CoppeliaSim) CoppeliaSim's unique value proposition in the literature is its versatility. Several papers leverage its support for multiple physics engines to conduct comparative analyses. The high-speed PyRep interface is frequently cited as a key advantage for accelerating DRL training cycles compared to the overhead of ROS-based communication1. The tasks explored in CoppeliaSim are diverse, often involving complex kinematics or prototyping novel robot designs. The DRL algorithms used are varied, with studies employing GAIL for imitation learning [28] and DDPG for control tasks. The focus is often on rapid algorithm development and validation in a flexible environment.

3) Archetype III: The GPU-Native High-Performance Engine (NVIDIA Isaac Sim) Papers using Isaac Sim are almost exclusively focused on tackling large-scale DRL problems and bridging the sim-to-real gap for perception-heavy tasks. The ability to run thousands of parallel simulations on the GPU is the most cited advantage, as it enables the collection of massive datasets required to train robust policies[42]. Its use of RTX rendering for photorealistic sensor data is highlighted as a direct strategy to mitigate the perception gap, making it the platform of choice for end-to-end, vision-based navigation[42]. The dominant algorithm in the Isaac Sim literature is PPO, whose on-policy nature benefits immensely from the massive parallel data collection capabilities. The tasks are ambitious, often involving navigation in complex, cluttered environments using only camera images or a fusion of camera and LiDAR data, with the primary research contribution often being the demonstration of successful zero-shot sim-to-real transfer.

C. Sim-to-Real Transfer Strategies

Our review confirms that the choice of simulator strongly influences the sim-to-real strategy.

With Gazebo/Webots, the strategy is an architectural alignment. Researchers leverage the native ROS integration to ensure the software stack is nearly identical between simulation and the real robot, minimizing transfer errors related to control and communication logic.

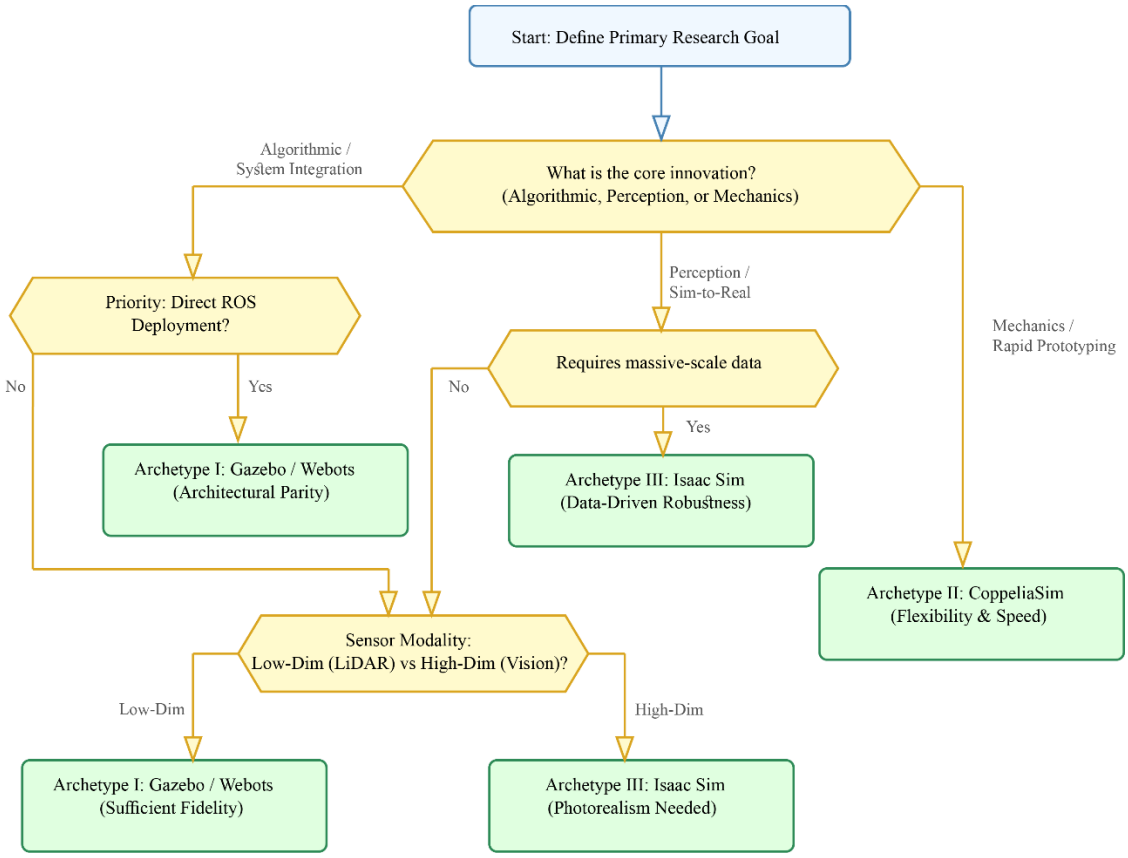


Fig. 2. A prescriptive decision flowchart for simulator selection. This flowchart formalizes the selection logic by guiding a researcher from their primary research goal through key technical requirements to the most appropriate simulator archetype, highlighting the core trade-offs at each stage.

With NVIDIA Isaac Sim, the strategy is data-driven robustness. Researchers leverage massive parallelization and photorealistic rendering to train policies on an extremely wide distribution of scenarios via domain randomization. This forces the policy to become invariant to simulation-specific artifacts, making it robust enough for zero-shot transfer. A powerful emerging trend is the "sim-to-sim-to-real" pipeline, where policies trained in Isaac Sim are first validated in Gazebo before real-world deployment, providing strong evidence of their generalization capabilities.

VI. Discussion: A Decision-Making Framework

Based on our comprehensive literature synthesis, we propose a structured decision-making framework (see Fig. 2) to guide the selection of robotic simulators according to two pivotal dimensions: 1) the primary source of methodological innovation, and 2) the complexity of required sensory data.

When the research novelty lies in algorithmic improvements—such as novel reward functions, enhanced safety-aware exploration strategies [43], or gains in sample efficiency—and the underlying task can be addressed with low-dimensional sensor inputs (for example, 2D LiDAR), established platforms like Gazebo and Webots are recommended (see Fig. 2). These environments not only offer robust, community-validated benchmarks, but their seamless ROS integration also streamlines the transition from simulation to real-world deployment under manageable computational loads.

In contrast, if the principal innovation revolves around comparative physics analyses or the rapid prototyping of intricate mechanical systems, CoppeliaSim emerges as the superior choice. Its unique support for multiple physics engines, combined with the high-speed PyRep API, accelerates development cycles beyond what ROS-centric alternatives typically allow.

Finally, for investigations explicitly targeting sim-to-real transfer—particularly those focused on vision-based, end-to-end navigation in visually complex domains—NVIDIA Isaac Sim provides indispensable capabilities. Its photorealistic rendering and exceptional parallel training performance make it the de facto standard for experiments aiming to achieve zero-shot policy transfer. Through a sim-to-sim-to-real validation pipeline, researchers can rigorously demonstrate methodological advances in direct policy transfer, thus reinforcing the scientific contribution of their work.

VII. Conclusion and Future Directions

This systematic literature review has provided a rigorous, evidence-based analysis of the simulator landscape for DRL-based mobile robot navigation. The central, definitive insight from our synthesis of 87 recent studies is that simulator selection is not an incidental technical detail but a foundational methodological decision that shapes research outcomes. Our work conclusively changes how this choice should be viewed: from a matter of convenience to a strategic alignment of tool, task, and objective. We have formalized the community's

implicit practices into an explicit taxonomy of simulator archetypes, demonstrating a clear correlation between a simulator's architectural principles and its application in the literature.

What this review definitively establishes is a tripartite structure of the current research landscape. First, ROS-centric platforms like Gazebo are the established workhorses for algorithmic development with low-dimensional sensors, where architectural parity with the real world is the primary sim-to-real strategy. Second, GPU-native engines, epitomized by NVIDIA Isaac Sim, have become the standard for tackling the perception gap in vision-based navigation, enabling data-driven robustness through massive parallelization and domain randomization. Third, versatile engines like CoppeliaSim occupy a vital niche for rapid prototyping and specialized mechanical analysis. By making these distinctions explicit, our framework provides immediate, practical guidance that can prevent methodological mismatches and enhance research efficiency.

However, our review also illuminates what remains uncertain. While we identify a strong trend towards data-driven sim-to-real transfer, the precise metrics for quantifying the "reality gap" remain ad-hoc and study-specific. It is still an open question how to create a universal benchmark that can compare the transferability of policies from different simulators in a scientifically rigorous manner. Furthermore, the long-term viability and interoperability of vendor-specific, high-performance ecosystems versus open-source standards is an unresolved tension that will shape the field's future accessibility and direction.

Looking forward, the capabilities of Archetype III simulators serve as a crucial technological bridge to the next paradigm: persistent, bi-directional Robotic Digital Twins. Yet, to realize this future and improve scientific rigor, the community must move beyond the current state. We strongly advocate for the development of a Standardized Sim-to-Real Navigation Benchmark. Such a framework would enable true apples-to-apples comparisons, fostering more generalizable and robust solutions. By clarifying the present state of simulation, separating validated insights from open questions, and illuminating the path toward standardized benchmarking, this work aims to accelerate the development of intelligent systems capable of operating safely and effectively in the complexity of the real world.

REFERENCES

[1] R. Hoseinnezhad, “A Comprehensive Review of Deep Learning Techniques in Mobile Robot Path Planning: Categorization and Analysis,” Appl. Sci. 2025, Vol. 15, Page 2179, vol. 15, no. 4, p. 2179, Feb. 2025, doi: 10.3390/APP15042179.

[2] Y. Li, B. W. Min, and H. Liu, “Deep Q-Learning-Based Optimization of Path Planning and Control in Robotic Arms for High-Precision Computational Efficiency,” Int. J. Adv. Comput. Sci. Appl., vol. 16, no. 1, pp. 1199–1207, Jan. 2025, doi: 10.14569/IJACSA.2025.01601115.

[3] W. Zhao, J. P. Queralta, and T. Westerlund, “Sim-to-Real Transfer in Deep Reinforcement Learning for Robotics: a Survey,” 2020 IEEE Symp. Ser. Comput. Intell., pp. 737–744, Jul. 2021, doi: 10.1109/SSCI47803.2020.9308468.

[4] T. Chaffre, J. Moras, A. Chan-Hon-Tong, and J. Marzat, “Sim-to-real transfer with incremental environment complexity for reinforcement learning of depth-based robot navigation,” ICINCO 2020 - Proc. 17th Int. Conf. Informatics Control. Autom. Robot., pp. 314–323, 2020, doi: 10.5220/0009821603140323.

[5] Y. Zhu, W. Z. Wan Hasan, H. R. Harun Ramli, N. M. H. Norsahperi, M. S. Mohd Kassim, and Y. Yao, “Deep Reinforcement Learning of Mobile Robot Navigation in Dynamic Environment: A Review,” Sensors (Basel)., vol. 25, no. 11, p. 3394, Jun. 2025, doi: 10.3390/S25113394.

[6] F. Rosique, P. J. Navarro, C. Fernández, and A. Padilla, “A Systematic Review of Perception System and Simulators for Autonomous Vehicles Research,” Sensors 2019, Vol. 19, Page 648, vol. 19, no. 3, p. 648, Feb. 2019, doi: 10.3390/S19030648.

[7] K. Zhu and T. Zhang, “Deep reinforcement learning based mobile robot navigation: A review,” Tsinghua Sci. Technol., vol. 26, no. 5, pp. 674–691, Oct. 2021, doi: 10.26599/TST.2021.9010012.

[8] D. Han, B. Mulyana, V. Stankovic, and S. Cheng, “A Survey on Deep Reinforcement Learning Algorithms for Robotic Manipulation,” Sensors 2023, Vol. 23, Page 3762, vol. 23, no. 7, p. 3762, Apr. 2023, doi: 10.3390/S23073762.

[9] J. Kober, J. A. Bagnell, and J. Peters, “Reinforcement learning in robotics: A survey,” Int. J. Rob. Res., vol. 32, no. 11, pp. 1238–1274, Sep. 2013.

[10] M. Körber, J. Lange, S. Rediske, S. Steinmann, and R. Glück, “Comparing Popular Simulation Environments in the Scope of Robotics and Reinforcement Learning,” Mar. 2021, [Online]. Available: https://arxiv.org/pdf/2103.04616

[11] M. Kaup, C. Wolff, H. Hwang, J. Mayer, and E. Bruni, “A Review of Nine Physics Engines for Reinforcement Learning Research,” Aug. 2024, [Online]. Available: https://arxiv.org/pdf/2407.08590v1

[12] Z. Haja et al., “Deep Reinforcement Learning for Mobile Robots: Overview and Issues,” Lect. Notes Networks Syst., vol. 1100 LNNS, pp. 523–532, 2024, doi: 10.1007/978-3-031-68660-3_48.

[13] M. J. Page et al., “The PRISMA 2020 statement: an updated guideline for reporting systematic reviews,” BMJ, vol. 372, Mar. 2021, doi: 10.1136/BMJ.N71.

[14] S. Leone, F. Lago, D. Pisla, and G. Carbone, “A Systematic Approach for Robotic System Development,” Technol. 2025, Vol. 13, Page 316, vol. 13, no. 8, p. 316, Jul. 2025, doi: 10.3390/TECHNOLOGIES13080316.

[15] A. Carrera-Rivera, W. Ochoa, F. Larrinaga, and G. Lasa, “How-to conduct a systematic literature review: A quick guide for computer science research,” MethodsX, vol. 9, p. 101895, Jan. 2022, doi: 10.1016/J.MEX.2022.101895.

[16] S. Salimpour, J. Peña, P. Peña-Queralta, D. Paez-Granados, J. Heikkonen, and T. Westerlund, “Sim-to-Real Transfer for Mobile Robots with Reinforcement Learning: from NVIDIA Isaac Sim to Gazebo and Real ROS 2 Robots,” Jan. 2025, Accessed: Jan. 25, 2025. [Online]. Available: https://arxiv.org/abs/2501.02902v1

[17] H. Taheri, S. R. Hosseini, and M. A. Nekoui, “Deep Reinforcement Learning with Enhanced PPO for Safe Mobile Robot Navigation,” May 2024, [Online]. Available: https://arxiv.org/pdf/2405.16266

[18] E. Marchesini and A. Farinelli, “Discrete Deep Reinforcement Learning for Mapless Navigation”, [Online]. Available: http://wiki.ros.org/move

[19] T. Saravanan et al., “‘Deep Reinforcement Learning for Autonomous Navigation in Unknown Environments,’” J. Inf. Syst. Eng. Manag., vol. 10, no. 22s, pp. 782–793, Mar. 2025, doi: 10.52783/JISEM.V10I22S.3620.

[20] R. Van Hoa, L. K. Lai, and L. T. Hoan, “Mobile Robot Navigation Using Deep Reinforcement Learning in Unknown Environments,” Int. J. Electr. Electron. Eng., vol. Volume 7, no. 8, pp. 15–20, Sep. 2020, doi: 10.14445/23488379/IJEEE-V7I8P104.

[21] M. Heidari, S. Ali, and K. Nylaender, “Autonomous Robot Navigation Using Deep Reinforcement Learning in Office Environments,” 2025, [Online]. Available: https://oda.oslomet.no/oda-xmlui/handle/11250/3206164

[22] G. Yang and Y. Guo, “Deep Reinforcement Learning Based Mobile Robot Navigation in Crowd Environments,” 2024 21st Int. Conf. Ubiquitous Robot. UR 2024, pp. 513–519, 2024, doi: 10.1109/UR61395.2024.10597481.

[23] V. A. Kich et al., "Parallel Distributional Deep Reinforcement Learning for Mapless Navigation of Terrestrial Mobile Robots," Int. Conf. Control. Autom. Syst., pp. 978–983, 2024, doi: 10.23919/ICCAS63016.2024.10773323.

[24] M. F. R. Lee and S. H. Yusuf, "Mobile Robot Navigation Using Deep Reinforcement Learning," Process. 2022, Vol. 10, Page 2748, vol. 10, no. 12, p. 2748, Dec. 2022, doi: 10.3390/PR10122748.

[25] A. Iskandar and B. Kovács, "Investigating the Impact of Curriculum Learning on Reinforcement Learning for Improved Navigational Capabilities in Mobile Robots," Intel. Artif., vol. 27, no. 73, pp. 163–176, Mar. 2024, doi: 10.4114/INTARTIF.VOL27ISS73PP163-176.

[26] C. Trararak, T.-T. Hoang, and P. Cong-Kha, "Pedestrian Avoidance Simulation by Deep Reinforcement Learning Using Webots," pp. 0734–0739, Mar. 2025, doi: 10.1109/ICAIIC64266.2025.10920794.

[27] A. Šareiko, D. Mažeika, and A. Laukaitis, "Framework for deep reinforcement learning in Webots virtual environments," New Trends Comput. Sci., vol. 3, no. 1, pp. 49–63, Jun. 2025, doi: 10.3846/NTCS.2025.23668.

[28] I. Alaa and K. Béla, "Curriculum learning for deep reinforcement learning in swarm robotic navigation task," Multidiszcip. Tudományok, vol. 13, no. 3, pp. 175–187, Dec. 2023, doi: 10.35925/J.MULTI.2023.3.18.

[29] K. Levrone Rodrigues Machado Silva and R. Calvo, "Mobile Robot Navigation Strategies Through Behavioral Cloning and Generative Adversarial Imitation Learning", doi: 10.5220/0011856700003467.

[30] D. K. Sahoo, "Adaptive TD3: Robust Mobile Robot Navigation in Dynamic Environments with Mixed Obstacles," Recent Trends Autom. Automob. Eng., vol. 6, no. 2, pp. 4–18, 2023, doi: 10.5281/ZENODO.8004578.

[31] J. M. Fajardo, F. G. Roldan, S. Realpe, J. D. Hernández, Z. Ji, and P.-F. Cardenas, "FRobs RL: A Flexible Robotics Reinforcement Learning Library", [Online]. Available: https://github.com/jmfajardod/frobs

[32] X. Hu et al., "Impact of Static Friction on Sim2Real in Robotic Reinforcement Learning," Mar. 2025, [Online]. Available: https://www.arxiv.org/pdf/2503.01255

[33] H. Xue, B. Hein, M. Bakr, G. Schildbach, B. Abel, and E. Rueckert, "Using Deep Reinforcement Learning with Automatic Curriculum Learning for Mapless Navigation in Intralogistics," Appl. Sci. 2022, Vol. 12, Page 3153, vol. 12, no. 6, p. 3153, Mar. 2022, doi: 10.3390/APP12063153.

[34] N. Oskolkov, H. Zhang, D. Makarov, D. Yudin, and A. Panov, "SGN-CIRL: Scene Graph-based Navigation with Curriculum, Imitation, and Reinforcement Learning," Jun. 2025, [Online]. Available: https://arxiv.org/pdf/2506.04505v1

[35] W. Liu et al., "X-MOBILITY: End-To-End Generalizable Navigation via World Modeling," Jul. 2025, [Online]. Available: https://arxiv.org/pdf/2410.17491v2

[36] S. Zhu, L. Mou, D. Li, B. Ye, R. Huang, and H. Zhao, "VR-Robo: A Real-to-Sim-to-Real Framework for Visual Robot Navigation and Locomotion," p. 2025, Jun. 2025, doi: 10.1109/LRA.2025.3575648.

[37] N. Botteghi, B. Sirmacek, J. Ai, K. A. A. Mustafa, M. Poel, and S. Stramigioli, "On Reward Shaping for Mobile Robot Navigation: A Reinforcement Learning and SLAM Based Approach," Feb. 2020, [Online]. Available: https://arxiv.org/pdf/2002.04109

[38] L. D. de Moraes et al., "Double Deep Reinforcement Learning Techniques for Low Dimensional Sensing Mapless Navigation of Terrestrial Mobile Robots," Lect. Notes Networks Syst., vol. 715 LNNS, pp. 156–165, 2023, doi: 10.1007/978-3-031-35507-3_16.

[39] L. Zhang, Z. Hou, J. Wang, Z. Liu, and W. Li, "Robot Navigation With Reinforcement Learned Path Generation and Fine-Tuned Motion Control," IEEE Robot. Autom. Lett., vol. 8, no. 8, pp. 4489–4496, Aug. 2023, doi: 10.1109/LRA.2023.3284354.

[40] S. Fischer, S. Hyeon Hong, Y. Wang, M. Aljamal, S. Patel, and A. Mahmood, "Comprehensive Review of Robotics Operating System-Based Reinforcement Learning in Robotics," Appl. Sci. 2025, Vol. 15, Page 1840, vol. 15, no. 4, p. 1840, Feb. 2025, doi: 10.3390/APP15041840.

[41] T. Zhang and H. Mo, "Reinforcement learning for robot research: A comprehensive review and open issues," Int. J. Adv. Robot. Syst., vol. 18, no. 3, 2021, doi: 10.1177/17298814211007305.

[42] W. Lik Hang Kenny, K. Bai, A. Robots, and G. Jianwei Zhang, "A Survey of Robotic Navigation and Manipulation with Physics Simulators in the Era of Embodied AI," May 2025, [Online]. Available: https://arxiv.org/pdf/2505.01458v1

[43] H. Khan et al., "Neuro-Symbolic Reinforcement Learning for Context-Aware Decision Making in Safe Autonomous Vehicles," Int. J. Adv. Comput. Sci. Appl., vol. 16, no. 5, pp. 599–609, May 2025, doi: 10.14569/IJACSA.2025.0160558.

Deep Learning Approach for Solar Radiation Forecasting in a Tropical Region Using LSTM Networks

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***Abstract*—Solar radiation forecasting is a key task for energy planning, grid management, and photovoltaic deployment, especially in tropical regions where weather variability reduces operational reliability. This work applies deep learning techniques to forecast hourly solar radiation in Mompox, Colombia, using Long Short-Term Memory (LSTM) neural networks. Three temporal windows were studied (5, 24, and 720 hours) to examine how sequence length affects prediction accuracy and model behavior. Hourly radiation data from 2021 to 2022 were used for training, and independent datasets from 2023 to 2024 were used for external validation to ensure long-term assessment and reproducibility. Most existing studies use short input windows designed for mid-latitude environments (5–24 hours), which do not capture multi-day tropical cloud persistence or sub-seasonal radiation variability. This gap limits forecasting accuracy and restricts practical use in tropical energy planning. To address this issue, this study introduces a long temporal input design that allows the model to learn month-scale variability more effectively. The three network configurations were trained under the same settings, allowing a direct comparison between short, daily, and long input memories. The LSTM-720 model performed best, achieving the lowest RMSE and the most stable predictions across all validation years, showing its ability to reconstruct both diurnal cycles and broader seasonal dynamics. Unlike most solar forecasting work, which treats window size as a tuning parameter, this study introduces a long-context LSTM design based on a 720-hour sequence. This allowed the model to learn intra-month atmospheric persistence—an essential tropical feature that short windows cannot represent—positioning the approach as a methodological contribution that expands the temporal learning paradigm rather than a configuration adjustment. Time-series comparisons revealed close agreement between measured and predicted radiation, particularly during stable climate periods. The proposed framework can support practical applications in solar plant design, renewable energy scheduling, and operational grid strategies in tropical regions. Future work will integrate satellite information and hybrid deep learning architectures to enhance spatial transferability and long-term forecasting accuracy.**

***Keywords*—Deep learning; LSTM networks; renewable energy; solar radiation forecasting; time series prediction**

This study is considered a product within the framework of the project: "Desarrollo Sostenible Mediante la Implementación de Energía Solar Fotovoltaica en Zonas Rurales no Conectadas a la Red Eléctrica Nacional en Mompox, Colombia (022-2024)", which is part of an internal research initiative at the University of Cartagena, Cartagena, Colombia.

I. Introduction

Given the growing constraints on fossil fuel generation [1], integrating clean energy systems (such as solar) with conventional power generation [2], [3] has become a key strategy to enhance efficiency and reduce emissions [4], [5]. At the solar energy level, solar radiation is a fundamental variable for energy management, particularly in the planning and design of photovoltaic (PV) systems [6], [7], agricultural applications [8], [9], and environmental modelling [10]–[12].

The use of solar energy significantly reduces greenhouse gas emissions [13], as its generation produces no CO_2 or other pollutants [14], thereby lowering dependence on non-renewable resources and promoting ecosystem conservation as a clean and sustainable electricity source [15]–[17]. In tropical regions, accurate forecasting is even more crucial for the effective planning, construction, and operation of PV power plants because sunlight availability changes rapidly with cloud cover and seasonal variation [18], [19].

The town of Mompox, located in northern Colombia, offers an interesting setting for solar radiation prediction. It combines a humid tropical climate with high solar potential, but has limited meteorological monitoring infrastructure. Although Colombia's Caribbean region receives abundant solar energy, few predictive models have been developed specifically for this area. This lack of localized modeling limits the efficient deployment of solar technologies and constrains opportunities for grid optimization and energy independence.

Traditional statistical approaches, such as ARIMA and Support Vector Machines (SVM), often fall short when modeling the nonlinear and time-dependent behavior typical of solar radiation [20], [21]. Recent progress in artificial intelligence has changed this landscape [22]–[25]. Recurrent Neural Networks (RNNs) [26], and particularly Long Short-Term Memory (LSTM) architectures [27], can capture long-term dependencies and nonlinear trends in meteorological time series [4], [28]. Several studies have demonstrated their effectiveness in predicting solar irradiance across different regions [29]–[31], however, few have explored their use in small tropical towns like Mompox, where climatic variability and data scarcity pose additional challenges.

In this context, the research evaluates the ability of LSTM models to forecast solar radiation at multiple temporal resolutions (5, 24, and 720 hours) using real measurements from

Mompox. The model was trained with data from 2021 to 2022 and validated with independent datasets from 2023 to 2024, ensuring reproducibility and robustness. This approach can be adapted to other data-limited regions seeking to improve renewable energy forecasting. Predicting solar radiation in tropical climates remains a challenging task. In these environments, cloud systems can evolve within minutes, humidity levels fluctuate abruptly, and short-lived storms frequently interrupt solar exposure [32]. Such variability introduces nonlinear and nonstationary behavior that traditional statistical models struggle to capture effectively [33].

Deep learning methods, particularly Long Short-Term Memory (LSTM) networks, offer a promising alternative because they can learn how these rapid changes in cloud cover and humidity interact over time. By retaining information from previous states, LSTMs can represent the temporal continuity and sudden transitions that characterize tropical weather, resulting in more accurate and resilient radiation forecasts [34]. Yet, few studies have examined their effectiveness in humid equatorial zones like Mompox, where diurnal and seasonal cycles interact in distinctive ways.

Solar radiation forecasting in tropical regions is strategically important for national energy planning, particularly in areas where rural electrification, PV expansion, and microgrid deployment depend on accurate generation forecasting. Improving prediction stability in data-limited locations, such as Mompox, supports lower operational uncertainty, reduces reserve margin dependence, enables more reliable agricultural scheduling, and improves climate adaptation strategies. This context shows that the research is not only a methodological exercise, but also responds to a regional need for energy autonomy and system planning, making the development of long-memory forecasting approaches an urgent technical requirement for tropical countries.

Tropical solar radiation dynamics differ fundamentally from conditions addressed in most LSTM-based forecasting studies. Prior works overwhelmingly employ short input memories ranging from several hours to one day, an assumption that aligns with mid-latitude irradiance behavior but not with tropical environments. In the tropics, radiation variability is governed by persistent multi-day cloud systems, moisture accumulation cycles, and sub-seasonal atmospheric structures that extend far beyond diurnal periodicity. These characteristics produce long temporal dependencies that short window LSTMs cannot capture, resulting in phase shift errors, amplitude smoothing, and loss of climatic context. This gap in the literature motivated the exploration of long-memory recurrent models. By incorporating a 720-hour input window, equivalent to a full intra-month sequence, we aimed to enable the network to learn climatic persistence patterns rather than only daily oscillations, addressing a structural limitation of existing approaches and positioning this work beyond parameter tuning studies.

The novelty of this study lies in its methodological approach rather than parameter scaling. While previous LSTM works overwhelmingly rely on short input windows (5–24 hours), we demonstrate that tropical radiation dynamics demand long-context modelling to reconstruct sub-seasonal variability. By implementing a 720-hour sequence, the model learns persistent atmospheric structures that cannot be captured by traditional diurnal frameworks, establishing long-memory LSTM forecasting as a required paradigm for tropical environments rather than a configuration variant.

The main contributions of this research are summarized as follows: 1) a long-context LSTM architecture was introduced that uses a 720-hour input sequence tailored to represent seasonal tropical radiation dynamics, a configuration not previously explored in related forecasting literature. 2) The model's robustness was evaluated through a multi-year external validation over unseen 2023 and 2024 datasets, demonstrating long-term predictive stability rarely addressed in prior deep learning work for tropical environments. 3) It was shown that long-context learning improves forecasting accuracy over traditional short-window and daily configurations, providing evidence that tropical radiation behavior requires long-memory modelling rather than parameter scaling, and 4) a reproducible and scalable modelling framework was constructed based on raw ground solar radiation measurements, which can be transferred to other tropical locations with limited climatological infrastructure.

To address this gap, this study proposes an LSTM-based approach optimized for tropical solar radiation forecasting using high-resolution ground data. It systematically analyzes how different window sizes (from 5 to 720 hours) influence prediction accuracy and identifies the most suitable configuration for practical energy management in tropical environments.

II. Related Works

Forecasting solar irradiance has evolved rapidly in recent years with the introduction of deep learning models, especially Long Short-Term Memory (LSTM) networks and their hybrid variants. Several studies have shown that LSTM architectures consistently outperform classical methods such as ARIMA, Artificial Neural Networks (ANN), and Support Vector Machines (SVM) when handling the nonlinear dynamics of solar radiation. For instance, [35] employed an LSTM network for short-term irradiance forecasting and found that combining multiple input sequences helped the model generalize better while reducing both variance and bias. In a similar vein, [23] compared ARIMA, feed-forward neural networks, and LSTM using Colombian datasets and reported that the LSTM model delivered the highest accuracy under cloudy conditions, one of the most challenging scenarios for solar prediction.

Hybrid models have also gained attention for their enhanced representational power. A review by [36] noted that CNN–LSTM architectures, which merge spatial and temporal learning, consistently outperform single-model approaches in irradiance forecasting, albeit with higher computational requirements. Recent developments even include BiLSTM–Transformer hybrids that achieved the lowest RMSE in seven-day forecast experiments, outperforming both standalone LSTM and GRU networks [24]. Comprehensive literature reviews further confirm that deep learning techniques, including LSTM, GRU, CNN–LSTM, and attention-based networks, yield significant accuracy improvements over traditional approaches, though at the expense of longer training times [37]. For example, [19] compared LightGBM, LSTM, and GRU using hourly radiation

data. While LSTM achieved an RMSE of about 59 W/m², LightGBM provided slightly better accuracy (≈54.8 W/m²) and faster computation, suggesting that tree-based ensembles can still compete when computational resources are constrained.

The field has also begun shifting toward probabilistic and multivariate forecasting. Hybrid frameworks that integrate BiLSTM and GRU layers, combined with Bayesian hyperparameter optimization and dropout regularization, have achieved strong performance in multivariate irradiance prediction [25]. Additionally, several studies that merge global climate models with ground-based measurements through hybrid deep learning and machine learning pipelines have produced reliable daily radiation forecasts [22]. Despite these advancements, certain research gaps remain clear. Few studies have focused on tropical towns such as Mompox, where meteorological data are scarce, and climate variability is high. Equally uncommon are works that compare multiple forecasting horizons (short-term, daily, and monthly) within a unified framework, or that evaluate pure LSTM configurations at extended horizons of up to 720 hours. The present study directly addresses these gaps by developing an LSTM model tailored to solar radiation forecasting in Mompox, Colombia. Using datasets from 2021 to 2022 for training and from 2023 to 2024 for validation, this work provides a comprehensive, horizon-sensitive modeling framework specifically designed for tropical regions with limited historical observations.

III. METHODOLOGY

This section presents the methodological framework designed to forecast solar radiation in Mompox using Long Short-Term Memory (LSTM) neural networks. It describes the dataset collected from IDEAM [38], the preprocessing steps applied, the configuration of the neural architectures, and the training and validation strategy adopted. Together, these components ensure transparency, reproducibility, and methodological rigor for the subsequent analyses.

Hourly solar radiation data were collected for Mompox (9°14'N, 74°26'W; elevation 10 m a.s.l.), a town located in the tropical Magdalena River basin of northern Colombia. The dataset covers the period from January 2021 to December 2022 and corresponds to global horizontal irradiance (Wh/m²). The information was provided in CSV format by the Instituto de Hidrología, Meteorología y Estudios Ambientales (IDEAM), Colombia's national meteorological authority [38].

The original file also included ancillary variables such as air temperature and wind speed. However, these were excluded to focus the analysis exclusively on solar radiation prediction. Additional datasets spanning January–December 2023 and January–July 2024 were used solely for external validation. In total, the dataset contains about 17,500 hourly records. Missing values, representing less than 1 % of the data, were interpolated linearly to maintain the temporal continuity of the series. Extreme outliers, defined as values exceeding ±3 standard deviations from the mean, were replaced using a rolling median filter. A summary of the dataset, including temporal coverage and partitioning strategy, is shown in Table I.

The time series of global horizontal irradiance (Wh/m²) was used directly, without normalization or scaling, in order to preserve the physical meaning of the radiation values. Input–output pairs were created using a sliding window method, in which a sequence of past radiation observations was used to predict the next value. Three different input window sizes were evaluated to capture varying temporal behaviors: 5 hours: short-term fluctuations, 24 hours: daily cycles, and 720 hours: monthly or intra-seasonal patterns. For each configuration, the data were chronologically divided into training (67 %), testing (22 %), and validation (11 %) subsets (see Table I). This temporal split preserved the natural sequence of the observations and avoided data leakage between model phases.

TABLE I. SUMMARY OF THE DATASET

Dataset	Data Features		
	Period	*Frequency*	*Samples*
Training	2021-2022	Hourly	11,910
Testing	2021-2022	Hourly	3,853
Validation	2021-2022	Hourly	1,752
External validation	2023	Hourly	8,760
External validation	Jan-Jul 2024	Hourly	5,040

All forecasting models were implemented in Python 3.10 using TensorFlow 2.15 with the Keras API. Three LSTM architectures were designed, each corresponding to one of the input window sizes.

- LSTM-5: Input (5 × 1), one LSTM layer with 64 units, followed by a dense layer with 8 neurons (ReLU activation) and a linear output layer.
- LSTM-24: Input (24 × 1), one LSTM layer with 64 units, followed by a dense layer with 8 neurons (ReLU activation) and a linear output layer.
- LSTM-720: Input (720 × 1), one LSTM layer with 720 units, two dense layers with 16 and 8 neurons (both ReLU activation), and a final linear output layer.

The increase in the number of LSTM units for the 720-hour configuration was intentional and proportional to the longer input sequence length. A higher number of recurrent units provides the model with greater representational capacity to retain and process extended temporal dependencies across a full monthly cycle. Preliminary tests indicated that using fewer than 720 units led to underfitting, particularly in reproducing smooth transitions between consecutive days, while the chosen configuration achieved lower RMSE and faster convergence without overfitting. Thus, the increase in hidden units was empirically justified as it improved the model's ability to capture long-term patterns inherent to tropical solar radiation.

The choice of the 720-hour input configuration was not defined as a tuning exercise but as a methodological decision derived from climatic characteristics of the study region. The thirty-day temporal span was selected to encode full intra-month variability related to cloud persistence, humidity accumulation, and low-frequency atmospheric patterns typical of tropical environments. Unlike short window configurations (5, 24 hours), the 720 hour structure enables the model to learn sub-seasonal energy dynamics and long term irradiance memory,

which are not recoverable through repeated diurnal cycles. This design transforms the LSTM into a long context recurrent learner, allowing it to internalize radiation persistence behavior and avoid phase misalignment effects commonly reported in tropical solar forecasting. Therefore, the 720-hour model represents a conceptual modelling framework rooted in regional climate physics rather than a parametric extension of existing approaches.

All networks used the Adam optimizer (learning rate = 0.001) and the Mean Absolute Error (MAE) as the loss function. Model performance was tracked using the Root Mean Squared Error (RMSE) metric. Each model was trained for 30 epochs, with a ModelCheckpoint callback to save the best-performing weights according to validation loss, thus minimizing the risk of overfitting.

Fig. 1 illustrates the general LSTM configuration applied for solar radiation forecasting, showing the sequential structure from the input window to the output layer.

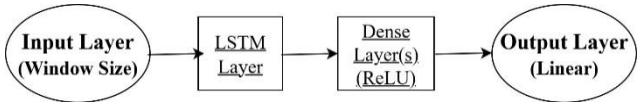


Fig. 1. General LSTM architecture for solar radiation forecasting.

Model training was performed in a Google Colab Pro environment equipped with an NVIDIA Tesla T4 GPU. The same optimizer, learning rate, and loss function were maintained for consistency across all experiments. Each training session lasted 30 epochs, and the ModelCheckpoint callback was again used to retain the best weights based on validation loss.

Data splitting followed a chronological order to preserve temporal dependencies: 67 % for training, 22 % for testing, and 11 % for validation, corresponding to 11,910, 3,853, and 1,752 hourly samples, respectively. Performance was evaluated using RMSE, MAE, and coefficient of determination (R2) for each subset. Additionally, the trained networks were tested on the external datasets from 2023 and 2024 to assess their ability to generalize to unseen data. Training progress was monitored through loss and validation-loss curves to detect possible underfitting or overfitting behaviors. The main parameters used during training are summarized in Table II.

TABLE II. TRAINING PARAMETERS

Parameter	Description
Framework / API	TensorFlow 2.15 / Keras
Programming language	Python 3.10
Environment	Google Colab (GPU: NVIDIA Tesla T4)
Optimizer	Adam
Learning rate	0.001
Loss function	Mean absolute Error (MAE)
Evaluation metric	Root Mean Squared Error (RMSE)
Epochs	30
Batch size	Default (TensorFlow)
Validation strategy	Chronological split (67% / 22% / 11%)

All procedures in this section were designed to ensure reproducibility and consistency across model configurations. Combining historical hourly radiation data with structured input windows and systematic model training established a solid foundation for evaluating forecast performance. This methodological design can be easily extended in future research by incorporating additional meteorological variables or developing hybrid architectures that combine LSTM with other deep learning models.

IV. RESULTS

This section presents and interprets the results obtained from the three LSTM configurations developed for solar radiation forecasting in Mompox, Colombia. The analysis integrates both quantitative and visual assessments of model performance, highlighting how different temporal window sizes influence prediction accuracy and generalization capacity. The following subsections examine, in detail, how each model performed in reproducing observed solar radiation patterns, comparing predicted and measured values across multiple time horizons.

A. Model Comparison by Input Window Size

To examine how the temporal context affects forecasting accuracy, three LSTM configurations were tested using input window sizes of 5, 24, and 720 hours. All models were trained under the same conditions (30 epochs, Adam optimizer, learning rate = 0.001) using hourly solar radiation data. The goal was to identify the sequence length that best balances short-term fluctuations with longer-term seasonal patterns.

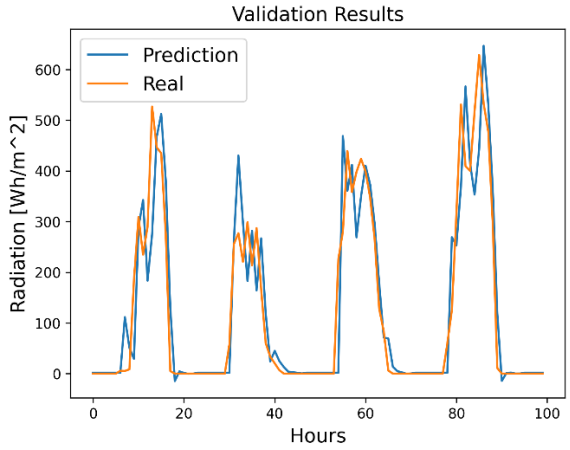


Fig. 2. Predicted vs. observed radiation using LSTM-5 (*window = 5 hours*).

The LSTM-5 model reproduced rapid fluctuations in solar radiation, particularly on clear days, but it struggled to represent complete diurnal transitions. As shown in Fig. 2, the predicted values follow the general pattern of observed radiation but show amplitude mismatches during peak irradiance hours. According to Fig. 2, this limitation is mainly due to the network's short memory window, which restricts its ability to capture the full daily energy cycle.

When the input window was expanded to 24 hours (Fig. 3), the model captured the daily periodicity of solar radiation. Fig. 3 shows that the predicted curves align more closely with observed diurnal patterns, reducing phase shifts and errors at

sunrise and sunset. However, the model still tended to underestimate radiation peaks on cloudy days, suggesting that a one-day context is insufficient to describe multi-day atmospheric variability.

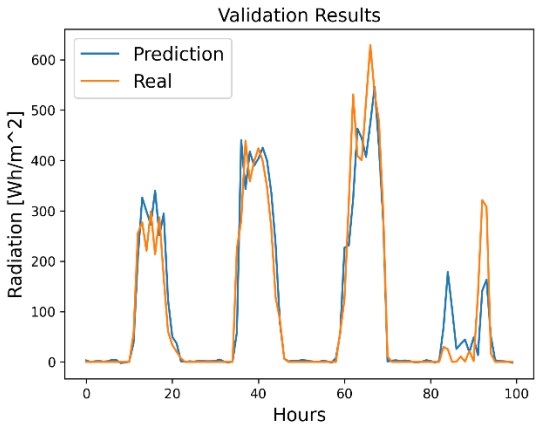


Fig. 3. Predicted vs. observed radiation using LSTM-24 (*window = 24 hours*).

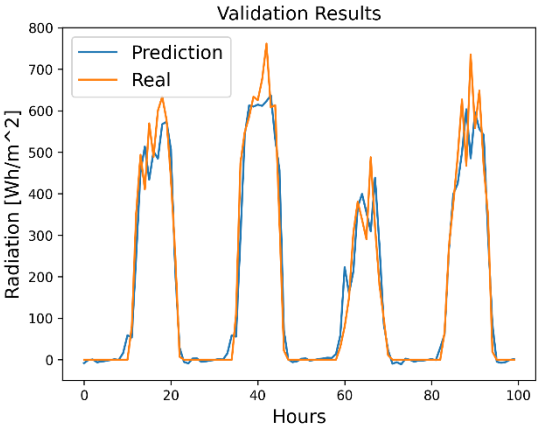


Fig. 4. Predicted vs. observed radiation using LSTM-720 (window = 720 hours).

The LSTM-720 model, trained on a monthly (30-day) input window, produced the most accurate and stable forecasts (Fig. 4). By learning over a broader temporal context, the network captured both daily and intra-monthly variations, resulting in smoother transitions and reduced noise. This improvement confirms that long-range dependencies are critical for reliable radiation prediction in tropical regions, where multi-day weather persistence is common.

In accordance with the above, extending the temporal window from 5 to 720 hours significantly enhanced model performance. Although computational cost increased with larger input sequences, the gains in accuracy justified using the LSTM-720 configuration for subsequent analyses. This setup successfully captures the natural temporal structure of solar radiation and provides the foundation for the evaluations presented in Section B and C.

B. Model Training Behavior

During training, the LSTM-720 model showed fast and stable convergence. Both training and validation losses decreased sharply within the first ten epochs and then plateaued, as illustrated in Fig. 5.

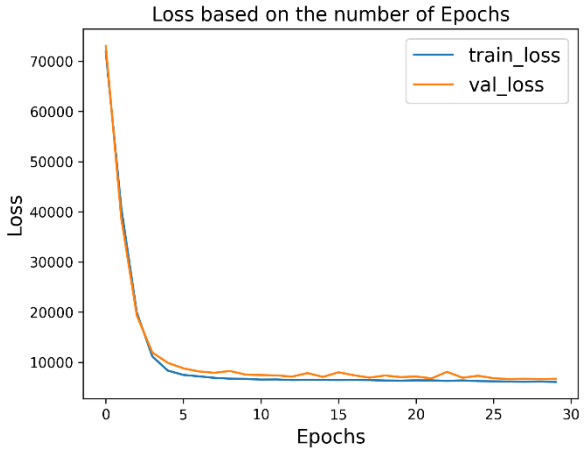


Fig. 5. Training and validation loss curves of LSTM-720 model.

The close alignment of the two curves indicates good generalization and minimal overfitting, confirming that the model effectively learned the underlying temporal dependencies. The smooth decline in loss values reflects the appropriate choice of hyperparameters, particularly the moderate learning rate (0.001) and batch size (32), which ensured stable gradient descent and reproducible convergence. Overall, these results demonstrate that the selected architecture and optimization settings are well suited for modeling the complexity of tropical solar radiation time series.

C. Validation and External Testing Performance

The predictive ability of the final LSTM-720 model was assessed in three validation stages: 1) internal validation using data from 2021 to 2022, 2) external validation with unseen data from 2023, and 3) an additional external validation using 2024 data. Each stage tested how well the model generalized under distinct climatic conditions.

Fig. 6 compares the observed and predicted hourly radiation during the internal validation period. The model accurately reproduced both clear and cloudy day dynamics, closely matching the amplitude and timing of daily cycles.

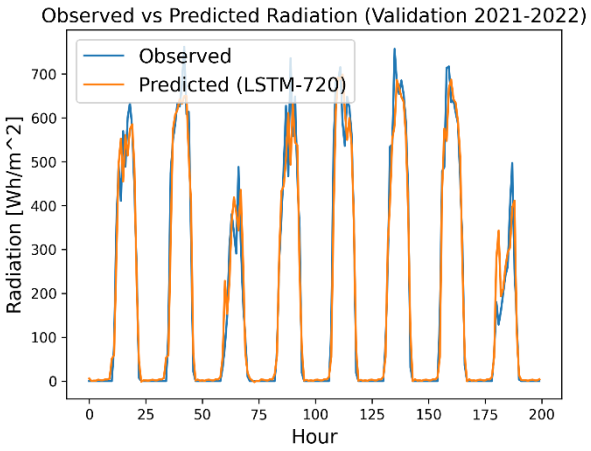


Fig. 6. Internal validation for the years 2021 to 2022 of LSTM-720 model.

Minor underestimations were observed at midday peaks, a common feature of networks trained without data normalization, but overall performance remained excellent, with RMSE = 63.88 Wh/m² and R^2 = 0.9535, explaining over 95 % of the observed variance. These metrics demonstrate strong calibration and confirm that the model learned the key temporal structures of solar radiation.

The first external test, shown in Fig. 7, evaluates the model on independent data from 2023. Predictions closely tracked the observed series throughout the year, with small amplitude differences during peak irradiance. Despite slightly higher RMSE (71.93 Wh/m²) and a marginally lower R^2 (0.913), the model maintained high accuracy, demonstrating robust generalization across years. This performance decay is modest and expected when forecasting beyond the training period. It also confirms that the temporal patterns learned from 2021 to 2022 remain valid under new atmospheric conditions.

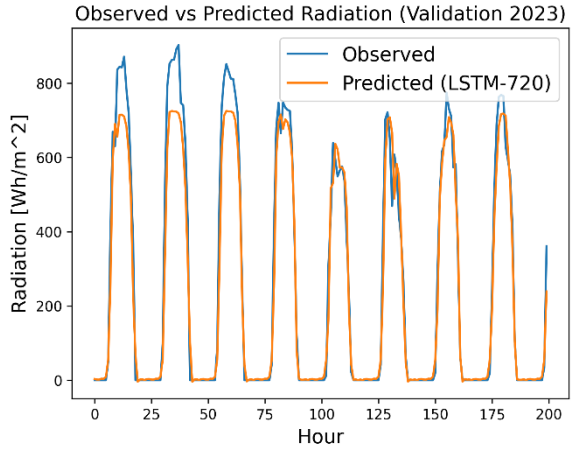


Fig. 7. External validation for the year 2023 of LSTM-720 model.

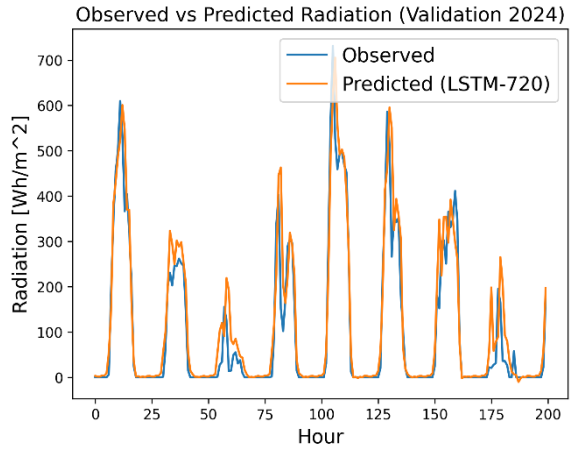


Fig. 8. External validation for the year 2024 of LSTM-720 model.

Fig. 8 presents the results for the 2024 dataset. The predicted time series aligned closely with the observed data, accurately reproducing diurnal cycles and the effects of intermittent cloud cover. Model metrics remained strong (RMSE = 65.53 Wh/m², MAE = 33.97 Wh/m², R^2 = 0.902), confirming stable performance and adaptability across consecutive years. The slightly narrower error range compared with 2023 suggests that weather patterns in 2024 were more similar to those seen during training.

A summary of all validation results is shown in Table III. R^2 values consistently above 0.90 confirm the model's ability to generalize well across different years and atmospheric conditions. The lowest RMSE corresponds to the internal validation, while external datasets remain within ±8 Wh/m² of that baseline, evidence of minimal performance decay. The MAE values (33–36 Wh/m²) indicate that average hourly errors are small relative to typical radiation levels in Mompox (> 600 Wh/m²). Altogether, these results emphasize the temporal stability and predictive robustness of the LSTM-720 architecture for operational solar radiation forecasting.

TABLE III. PERFORMANCE METRICS OF THE LSTM-720 MODEL ACROSS DATASETS

Dataset	Metrics		
	RMSE (Wh/m²)	*MAE (Wh/m²)*	*R^2*
2021–2022	63.88	35.66	0.954
2023	71.93	36.43	0.913
2024	65.53	33.97	0.902

To further evaluate model robustness, residual distributions were analyzed across the three validation periods (Fig. 9). Residuals were calculated as the difference between observed and predicted radiation, providing direct insight into systematic bias and variability. Across all years, residuals remained centered around zero with narrow interquartile ranges, indicating consistent performance and no major bias.

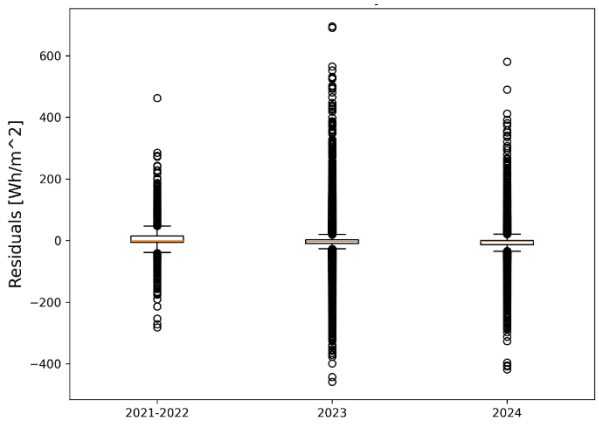


Fig. 9. Residual error distributions by year.

The statistical indicators summarized in Table IV show small negative mean values, suggesting a slight underestimation of peak irradiance.

Standard deviations stayed below 70 Wh/m², matching the RMSE magnitudes reported earlier. Skewness values near zero confirm symmetric error distributions, a desirable trait in predictive modeling. Slightly broader residual spreads in 2023 and 2024 correspond to stronger local variability, likely due to convective cloud formation and intermittent tropical rainfall. Even so, the overall bias remains low, confirming that the LSTM-720 model captures dominant radiation dynamics across changing weather conditions. Future research could enhance

accuracy further by incorporating auxiliary variables such as temperature, humidity, or cloud fraction, or by employing ensemble architectures to better capture transient atmospheric behaviors.

TABLE IV. STATISTICAL ANALYSIS OF MODEL RESIDUALS FOR THE VALIDATION DATASETS

Dataset	Metrics		
	Mean Residual (Wh/m²)	*Std. Deviation (Wh/m²)*	*Skewness*
2021–2022	-2.47	59.82	-0.06
2023	-3.85	67.49	0.12
2024	-1.91	63.07	-0.09

V. DISCUSSION AND IMPLICATIONS

The discussion of the broader implications of these findings in the context of previous research focused on three main aspects: 1) the effect of input window size on temporal learning, 2) the model's stability when applied to unseen years (2023–2024), and 3) the statistical characteristics of forecast residuals. Together, these analyses provide a comprehensive understanding of how LSTM networks can effectively model solar radiation dynamics under tropical climatic conditions and characteristics.

The findings confirm that deep recurrent neural networks, when trained on sufficiently long sequences, can model the nonlinear and seasonal variability of tropical solar radiation. Compared with conventional methods such as ARIMA or SVM [18], [20], [26], [28], LSTM models provide superior capacity to represent temporal dependencies without extensive feature engineering. This agrees with previous work on deep learning for solar forecasting [31], [35]–[37], further validating the effectiveness of recurrent architectures for meteorological time-series prediction.

Beyond outperforming traditional statistical baselines, the proposed 720-hour LSTM model offers a structural advantage over existing short-window and hybrid machine-learning approaches. Studies using ARIMA, LightGBM, CNN–RNN and BiLSTM–GRU configurations have shown accuracy improvements under standard mid-latitude conditions [19], [20], [24], [25], yet these models rely on short temporal dependencies and lose stability when climatic variability increases. In contrast, the long-context design used in this work was able to reconstruct multi-day and intra-month persistence patterns that those architectures cannot represent, demonstrating that forecasting improvement resulted from modelling strategy rather than parameter tuning. This positions the LSTM-720 framework as a distinct methodological alternative capable of recovering tropical atmospheric structure, rather than as another competing model variant. As such, the findings highlight a clear modelling advantage: long-memory recurrent networks enable tropical radiation learning behavior that existing methods structurally fail to reproduce.

Away from accuracy improvements, these findings translate into general modelling insights that apply to broader forecasting tasks. The results show that tropical radiation prediction requires architectures capable of learning sub-seasonal patterns rather than isolated diurnal signals, establishing a transferable design principle: input horizons must extend into the multi-day domain to reconstruct persistence dynamics. This principle aligns with recent studies reporting that deep recurrent models outperform statistical and short-window baselines when climatic variability increases [22], [23], [24], [25], [31]. In particular, works comparing ARIMA, LightGBM, hybrid CNN–RNN and BiLSTM–GRU approaches show that when atmospheric conditions are highly unstable, conventional models lose capacity to retain temporal structure [19], [20], [24], [25]. These links support the interpretation that forecasting improvements observed here are not dataset-dependent but reflect an underlying modelling requirement for tropical climates. Thus, the contribution extends beyond a single architecture: it provides guidance for window selection, long-context design, and application to other subtropical and equatorial solar forecasting problems.

A key strength of the LSTM-720 configuration is its durability over time. Beyond outperforming shorter input configurations, the results indicate that the 720 hour model delivers a fundamentally different learning behavior. Rather than improving accuracy through parameter scaling, the long-window architecture captured low frequency variability, radiation persistence, and intra month climatic structures that short-memory networks failed to represent. This shift reveals an underlying methodological implication: tropical radiation forecasting requires long context recurrent models to reconstruct non periodic atmospheric processes, not merely diurnal oscillations. The model's stability across 2021–2024 external validation years further demonstrates that this behavior is structural rather than dataset dependent. Consequently, this work contributes a conceptual advance to the field by demonstrating that long memory design is a necessary modelling component for tropical solar forecasting, positioning the approach as a generalizable framework rather than a sensitivity study.

In addition to demonstrating performance improvements, the findings from this study offer practical modelling guidance. The results show that tropical irradiance prediction benefits structurally from extended temporal contexts, establishing a clear design principle: forecasting windows must exceed diurnal or daily horizons to reconstruct persistence dynamics. Short-memory configurations captured rapid fluctuations but systematically failed to reproduce multi-day energy cycles, confirming that traditional daily window assumptions are unsuitable for humid tropical climates. Moreover, the stability of the 720-hour model across independent yearly datasets suggests that long-context LSTMs can retain climatic structure without retraining, providing a blueprint for robust tropical forecasting architectures. These elements sharpen the contribution of this work beyond experimentation results and translate into modelling guidelines applicable to future solar forecasting studies in similar environments.

Further to these findings, the results open several structured research directions. First, incorporating meteorological predictors such as cloud fraction, humidity or temperature may reveal whether tropical persistence originates from atmospheric drivers rather than radiation memory alone, helping to explain why monthly windows outperform daily horizons. Second,

evaluating GRU, BiLSTM–GRU and Transformer-based models could determine whether attention mechanisms improve multi-day pattern extraction beyond recurrent gating, clarifying if the benefit of long-context learning is architectural or temporal. Third, transferring and retraining the 720-hour framework in other tropical and subtropical climates would test whether the monthly memory requirement is a regional phenomenon or a general forecasting principle. Finally, integrating satellite imagery or reanalysis data may allow the model to learn cloud-system morphology, enabling spatial forecasting and operational deployment. Together, these directions illustrate how the present findings extend beyond model testing and establish a research pathway toward scalable tropical solar forecasting systems.

Even without retraining, the model retained high accuracy when applied to new years, confirming its potential for long-term operational use in solar energy management. Its consistent performance across varying atmospheric conditions demonstrates its adaptability to the complex climate patterns typical of tropical zones. The LSTM-720 model proved capable of capturing both rapid fluctuations and seasonal trends in solar radiation. Its ability to generalize with minimal degradation highlights the reliability of deep learning methods for renewable energy forecasting in tropical regions. Beyond Mompox, this approach offers a scalable framework adaptable to other data-limited locations that experience strong climatic variability.

Although the long-context design produced strong predictive performance, this study presents several limitations that should be acknowledged. First, the model was trained and evaluated using ground-based measurements from a single tropical location. This restricts the generalizability of the results to other geographic regions, where climatological dynamics and atmospheric behavior may differ significantly. Second, the network relied exclusively on previous radiation values, without integrating meteorological predictors such as cloud cover, humidity, temperature, or satellite observations. The absence of these external drivers may limit model sensitivity during extreme or rapidly changing weather conditions. Third, the hyperparameter configuration was not extensively optimized through large-scale search procedures because the objective of this study focused on evaluating temporal context rather than architecture tuning. Finally, the proposed LSTM-720 design was not benchmarked against other deep learning architectures such as GRU, transformer-based models, or hybrid CNN-RNN frameworks. These limitations highlight the need to expand the modelling scale, incorporate additional predictors, and conduct spatial transferability tests across different tropical regions.

VI. Conclusion

This study demonstrated the strong potential of deep recurrent neural networks, particularly the LSTM-720 architecture, for forecasting hourly global solar radiation in a tropical setting. Using data collected in Mompox, Colombia, from 2021 to 2024, the model accurately reproduced both short-term variations and long-term seasonal trends without requiring normalization or additional meteorological inputs. By employing a 720-hour input window, the network achieved consistently high predictive accuracy, with determination coefficients (R^2) exceeding 0.90 in all validation years. These results confirm the model's ability to generalize across distinct climatic conditions and emphasize the importance of selecting an appropriate temporal window to capture the intrinsic periodicity of solar radiation. Shorter input sequences (5–24 hours) were effective for representing diurnal behavior but fell short in modeling multi-day persistence and intra-monthly variability. In contrast, the 720-hour configuration provided a more complete view of atmospheric dynamics, allowing the LSTM to learn both daily and broader climatological dependencies relevant for solar energy forecasting. The model also demonstrated strong temporal stability when validated against independent datasets from 2023 and 2024, maintaining RMSE deviations within ±8 Wh/m² of the internal benchmark.

Residual analysis revealed minimal bias, near-symmetric error distributions, and stable variance across all years, evidence of the robustness and reliability of the proposed LSTM-720 approach. Beyond accuracy improvements, the results reveal a structural implication: forecasting in tropical environments requires long-memory recurrent modelling rather than short-window designs. The 720-hour context enabled the model to capture intra-month atmospheric persistence and sub-seasonal variability, which short sequences cannot represent. This positions the proposed framework as a methodological contribution that advances solar forecasting research beyond parameter optimization, providing a foundation for long-context modelling in other tropical regions.

From a practical standpoint, these findings underscore the suitability of recurrent neural networks for operational solar forecasting in tropical regions with limited meteorological infrastructure. The framework developed here can support photovoltaic energy management, grid planning, and hybrid renewable energy system design, offering a scalable and data-efficient tool for real-world applications. Future research should explore the integration of additional predictors, such as air temperature, humidity, and cloud fraction, and test hybrid deep learning architectures to enhance both predictive accuracy and spatial transferability. These results also provide modelling guidance for future tropical forecasting studies by confirming that long-context horizons are structurally required to recover sub-seasonal atmospheric behavior, a principle that may transfer to other equatorial locations and to different renewable forecasting tasks.

Declarations

The datasets analyzed in this research were provided by the Instituto de Hidrología, Meteorología y Estudios Ambientales (IDEAM), Colombia. They include hourly measurements of global solar radiation for the period 2021–2024, corresponding to the Mompox meteorological station. Due to institutional data-sharing restrictions, the original datasets are not publicly available but can be obtained upon reasonable request from the corresponding author or directly from IDEAM at https://www.ideam.gov.co/. All model training scripts and supplementary materials used in this study are also available from the corresponding author upon reasonable request to ensure full reproducibility of the results.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

M.O.: conceptualization, writing an original draft, investigation, data curation, reviewing and editing; G.C.: investigation, methodology, reviewing and editing; A.R.: research design, data analysis, funding acquisition and project administration. All authors have read and agreed to the published version of the manuscript.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work, the authors used Grammarly and ChatGPT to improve their writing. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the publication's content.

References

[1] H. Shahbeik et al., "Biomass to biofuels using hydrothermal liquefaction: A comprehensive review," Renew. Sustain. Energy Rev., vol. 189, p. 113976, Jan. 2024, doi: 10.1016/j.rser.2023.113976.

[2] F. A. Ahmad, J. Liu, F. Hashim, and K. Samsudin, "Short-Term Load Forecasting Utilizing a Combination Model: A Brief Review," Int. J. Technol., vol. 15, no. 1, p. 121, Jan. 2024, doi: 10.14716/ijtech.v15i1.5543.

[3] B. Tian, N. Wang, Y. Lin, and S. Shao, "Enhancing solar irradiance prediction precision: A stacked ensemble learning-based correction paradigm," Next Energy, vol. 8, p. 100306, Jul. 2025, doi: 10.1016/j.nxener.2025.100306.

[4] W. Dou, K. Wang, S. Shan, K. Zhang, H. Wei, and V. Sreeram, "A hybrid correction framework using disentangled seasonal-trend representations and MoE for NWP solar irradiance forecast," Appl. Energy, vol. 397, p. 126295, Nov. 2025, doi: 10.1016/j.apenergy.2025.126295.

[5] A. Kumar and S. Kerdsuwan, "Efficient Energy Conversion of Wastes and Fuels in Power Systems," KMUTNB Int. J. Appl. Sci. Technol., vol. 7, no. 2, pp. 1–26, Jun. 2014, doi: 10.14416/j.ijast.2014.02.001.

[6] F. J. L. de Lima et al., "Evaluation of the short and medium-term forecast quality of global solar irradiance from GFS-MOS and WRF-Solar models for the northeast region of Brazil," Energy Reports, vol. 13, pp. 2187–2203, Jun. 2025, doi: 10.1016/j.egyr.2025.01.073.

[7] M. Wild, D. Folini, C. Schär, N. Loeb, E. G. Dutton, and G. König-Langlo, "The global energy balance from a surface perspective," Clim. Dyn., vol. 40, no. 11–12, pp. 3107–3134, Jun. 2013, doi: 10.1007/s00382-012-1569-8.

[8] H. Mokhtarzadeh, S. Gorjian, and S. Minaei, "Design, development, and evaluation of a low-cost smart solar-powered weather station for use in agricultural environments," Results Eng., vol. 26, p. 104848, Jun. 2025, doi: 10.1016/j.rineng.2025.104848.

[9] U. H. Ramadhani, L. N. Ramdhania, H. Iskandar, A. Fudholi, and H. Abimanyu, "Review of solar thermal technologies in sustainable animal agriculture farms: Current and potential uses," Sol. Energy, vol. 291, p. 113374, May 2025, doi: 10.1016/j.solener.2025.113374.

[10] A. O. Adelakun and F. M. Adelakun, "Mathematical modeling and seasonal solar radiation variability in Nigeria's geo-political zones: A recurrence and multifractal analysis," J. Atmos. Solar-Terrestrial Phys., vol. 261, p. 106290, Aug. 2024, doi: 10.1016/j.jastp.2024.106290.

[11] X. Wang, P. Xie, Y. Xie, and H. Jiang, "Localized solar radiation zoning by combining spatially continuous estimates and Gaussian mixture models," J. Atmos. Solar-Terrestrial Phys., vol. 268, p. 106432, Mar. 2025, doi: 10.1016/j.jastp.2025.106432.

[12] J. Polo et al., "Preliminary survey on site-adaptation techniques for satellite-derived and reanalysis solar radiation datasets," Sol. Energy, vol. 132, pp. 25–37, Jul. 2016, doi: 10.1016/j.solener.2016.03.001.

[13] E. Piña Henríquez and C. Millán Aguilar, "Propuesta para incrementar el uso de energía solar fotovoltaica en Ámsterdam. = Strategic guidelines to increase the use of photovoltaic solar energy in Amsterdam," Cuad. Investig. Urbanística, no. 153, pp. 01–66, Apr. 2024, doi: 10.20868/ciur.2024.153.5251.

[14] O. F. Al-Rawi, Y. Bicer, and S. G. Al-Ghamdi, "Sustainable solutions for healthcare facilities: examining the viability of solar energy systems," Front. Energy Res., vol. 11, Jul. 2023, doi: 10.3389/fenrg.2023.1220293.

[15] I. Akhtar, S. Kirmani, M. Jameel, and F. Alam, "Feasibility Analysis of Solar Technology Implementation in Restructured Power Sector With Reduced Carbon Footprints," IEEE Access, vol. 9, pp. 30306–30320, 2021, doi: 10.1109/ACCESS.2021.3059297.

[16] S. Keeratianant, S. Chirarattananon, A. Nathakaranakule, and P. Rakkwamsuk, "Cost-effectiveness of Solar Cooling for Office and Hypermarket," Appl. Sci. Eng. Prog., Sep. 2019, doi: 10.14416/j.asep.2019.09.004.

[17] M. M. de Souza Grilo, A. F. C. Fortes, R. P. G. de Souza, J. A. M. Silva, and M. Carvalho, "Carbon footprints for the supply of electricity to a heat pump: Solar energy vs. electric grid," J. Renew. Sustain. Energy, vol. 10, no. 2, Mar. 2018, doi: 10.1063/1.4997306.

[18] W. Dou et al., "A multi-modal deep clustering method for day-ahead solar irradiance forecasting using ground-based cloud imagery and time series data," Energy, vol. 321, p. 135285, Apr. 2025, doi: 10.1016/j.energy.2025.135285.

[19] N. T. Anh et al., "Evaluation Of Solar Radiation Forecast Models: Lightgbm, Lstm And Gru," J. Sci. Technol. - HaUI, vol. 60, no. 8, pp. 3–10, Aug. 2024, doi: 10.57001/huih5804.2024.256.

[20] E. Gulay, M. Sen, and O. B. Akgun, "Forecasting electricity production from various energy sources in Türkiye: A predictive analysis of time series, deep learning, and hybrid models," Energy, vol. 286, p. 129566, Jan. 2024, doi: 10.1016/j.energy.2023.129566.

[21] A. Verdone, M. Panella, E. De Santis, and A. Rizzi, "A review of solar and wind energy forecasting: From single-site to multi-site paradigm," Appl. Energy, vol. 392, p. 126016, Aug. 2025, doi: 10.1016/j.apenergy.2025.126016.

[22] S. Ghimire, R. C. Deo, D. Casillas-Pérez, and S. Salcedo-Sanz, "Boosting solar radiation predictions with global climate models, observational predictors and hybrid deep-machine learning algorithms," Appl. Energy, vol. 316, p. 119063, Jun. 2022, doi: 10.1016/j.apenergy.2022.119063.

[23] L. S. Hoyos-Gómez, J. F. Ruiz-Muñoz, and B. J. Ruiz-Mendoza, "Short-term forecasting of global solar irradiance in tropical environments with incomplete data," Appl. Energy, vol. 307, p. 118192, Feb. 2022, doi: 10.1016/j.apenergy.2021.118192.

[24] Z. He, X. Zhang, M. Li, S. Wang, and G. Xiao, "A novel solar radiation forecasting model based on time series imaging and bidirectional long short-term memory network," Energy Sci. Eng., vol. 12, no. 11, pp. 4876–4893, Nov. 2024, doi: 10.1002/ese3.1875.

[25] N. E. Michael, R. C. Bansal, A. A. A. Ismail, A. Elnady, and S. Hasan, "A cohesive structure of Bi-directional long-short-term memory (BiLSTM) -GRU for predicting hourly solar radiation," Renew. Energy, vol. 222, p. 119943, Feb. 2024, doi: 10.1016/j.renene.2024.119943.

[26] A. Sebastianelli, F. Serva, A. Ceschini, Q. Paletta, M. Panella, and B. Le Saux, "Machine learning forecast of surface solar irradiance from meteo satellite data," Remote Sens. Environ., vol. 315, p. 114431, Dec. 2024, doi: 10.1016/j.rse.2024.114431.

[27] M. Mohammadi, S. Jamshidi, A. Rezvanian, M. Gheisari, and A. Kumar, "Advanced fusion of MTM-LSTM and MLP models for time series forecasting: An application for forecasting the solar radiation," Meas. Sensors, vol. 33, p. 101179, Jun. 2024, doi: 10.1016/j.measen.2024.101179.

[28] S. C. Nwokolo et al., "Machine learning and physics-based model hybridization to assess the impact of climate change on single- and dual-axis tracking solar-concentrated photovoltaic systems," Phys. Chem. Earth, Parts A/B/C, vol. 138, p. 103881, Jun. 2025, doi: 10.1016/j.pce.2025.103881.

[29] L. Barancsuk, V. Groma, and B. Kocziha, "Hybrid ultra-short term solar irradiation forecasting using resource-efficient multi-step long-short term memory," Renew. Energy, vol. 247, p. 122962, Jul. 2025, doi: 10.1016/j.renene.2025.122962.

[30] S. Al-Dahidi et al., "Techno-economic implications and cost of forecasting errors in solar PV power production using optimized deep learning models," Energy, vol. 323, p. 135877, May 2025, doi: 10.1016/j.energy.2025.135877.

[31] G. Jerse and A. Marcucci, "Deep Learning LSTM-based approaches for 10.7 cm solar radio flux forecasting up to 45-days," Astron. Comput., vol. 46, p. 100786, Jan. 2024, doi: 10.1016/j.ascom.2024.100786.

[32] J. Kapica et al., "The potential impact of climate change on European renewable energy droughts," Renew. Sustain. Energy Rev., vol. 189, p. 114011, Jan. 2024, doi: 10.1016/j.rser.2023.114011.

[33] Y. Fan et al., "Assessing the potential and complementary characteristics of China's solar and wind energy under climate change," Renew. Energy, vol. 249, p. 123213, Aug. 2025, doi: 10.1016/j.renene.2025.123213.

[34] A. Rathore, P. Gupta, R. Sharma, and R. Singh, "Day ahead solar forecast using long short term memory network augmented with Fast Fourier transform-assisted decomposition technique," Renew. Energy, vol. 247, p. 123021, Jul. 2025, doi: 10.1016/j.renene.2025.123021.

[35] M. Madhiarasan and M. Louzazni, "Combined Long Short-Term Memory Network-Based Short-Term Prediction of Solar Irradiance," Int. J. Photoenergy, vol. 2022, pp. 1–19, Aug. 2022, doi: 10.1155/2022/1004051.

[36] A. M. Assaf, H. Haron, H. N. Abdull Hamed, F. A. Ghaleb, S. N. Qasem, and A. M. Albarrak, "A Review on Neural Network Based Models for Short Term Solar Irradiance Forecasting," Appl. Sci., vol. 13, no. 14, p. 8332, Jul. 2023, doi: 10.3390/app13148332.

[37] R. A. Rajagukguk, R. A. A. Ramadhan, and H.-J. Lee, "A Review on Deep Learning Models for Forecasting Time Series Data of Solar Irradiance and Photovoltaic Power," Energies, vol. 13, no. 24, p. 6623, Dec. 2020, doi: 10.3390/en13246623.

[38] IDEAM, "Banco de Datos Meteorológicos," 2024. https://www.ideam.gov.co

A Hybrid Spherical Fuzzy–Machine Learning Model for Multi-Criteria Decision-Making in Sustainable Water Resource Management

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***Abstract*—The aim of this study is to develop an innovative, multi-dimensional, and uncertain decision-making model that can identify the most appropriate alternative irrigation method for the efficient use of water resources in agriculture. In this context, the proposed model is based on the integrated use of spherical fuzzy sets, machine learning, MEREC, and WASPAS methods. The evaluations obtained from ten experts were converted into spherical fuzzy numbers, and the experts' importance weights were objectively calculated using machine learning. Criteria weights were determined using the MEREC method, and alternatives were ranked using the WASPAS method. This hybrid approach both reduces expert subjectivity and objectively reflects the relationships between criteria. According to the findings, feasibility/technological suitability (0.152) emerged as the most important criterion, followed by environmental impacts (0.144). Among the alternatives, drip irrigation (2.226) was identified as the most suitable option for efficient use of water resources. This result demonstrates that modern, technology-based irrigation systems should be a priority in sustainable agricultural policies. This study's contribution to the literature is its ability to bring objectivity, transparency, and the ability to manage high uncertainty to decision-making processes in agricultural water management. The model offers both methodological innovation and a practical decision-support tool at the application level.**

Keywords*—Irrigation activities; water use; decision-making model; machine learning; MEREC; WASPAS

I. Introduction

Identifying the most appropriate alternative irrigation methods for sustainable water management in agriculture is crucial because each region's climate, soil structure, plant species, and economic capacity vary. Therefore, the same method cannot be expected to yield the most efficient results in every situation. Choosing the best irrigation method both conserves limited water resources and increases production efficiency [1]. Furthermore, determining the right method is critical for the efficient use of limited budgets and the rapid implementation of implementation strategies. Decision-making in this process is influenced by many different factors. Water efficiency refers to the extent to which water is delivered to the plant root zone without wasting water and is a key indicator of sustainable agriculture. Cost determines the economic viability of the system's installation, operation, and maintenance. Energy consumption is particularly important due to the pumps and pressure lines used in modern systems, as energy costs directly impact production costs. Applicability and technological compatibility indicate the compatibility of the selected method with existing infrastructure and technical capacity. Plant yield and quality directly reflect the impact of the irrigation method on agricultural output and are the most tangible measures of success for farmers [2]. Environmental impacts include soil salinity, erosion, and changes in groundwater levels that may be caused by excessive or inappropriate water use. Ease of maintenance and operation is a factor that determines the long-term sustainability of a method, as complex systems may not be managed effectively, especially by producers with limited technical knowledge. However, the number of studies in the literature that evaluate these criteria holistically is quite limited. Most studies focus on a single factor or are limited to a specific geographical context. This creates a significant gap in the literature, as there is insufficient comparative data to determine which irrigation method is most effective under which conditions. This gap creates uncertainty in decision-making processes and makes it difficult for practitioners to select the most appropriate system. Furthermore, the varying weights of criteria depending on the situation highlight the need for multi-criteria analyses. Therefore, this gap in the existing literature represents a research problem that needs to be addressed from both theoretical and practical perspectives. New studies on this topic will significantly contribute to identifying strategies to increase water efficiency and support sustainable agricultural production.

This study aims to identify the most effective alternative irrigation methods for the efficient use of water resources in agriculture. The primary motivation for the study is increasing water scarcity, the impacts of climate change, and the need for sustainability in agricultural production. The lack of systematic multi-criteria comparisons of irrigation methods in the existing literature creates a significant research gap. Therefore, this study aims to fill this gap at both the theoretical and practical levels. A holistic decision-making model for selecting alternative irrigation methods was developed. The model is based on a hybrid approach that integrates expert opinions with fuzzy logic. In this context, seven criteria were identified for use in the evaluation following a comprehensive literature review. These criteria are water efficiency, cost, energy consumption, applicability, plant yield and quality, environmental impacts,

and ease of maintenance and operation. The alternatives comprise sprinkler irrigation, drip irrigation, surface irrigation, subsurface irrigation, and microsprinkler irrigation. Expert assessments were collected from ten different experts and converted into spherical fuzzy numbers. Expert importance weights were calculated using a machine learning-based method, thus reducing the influence of subjective evaluations. The importance levels of the criteria were determined using the MEREC method, allowing the contribution of each criterion to the model to be objectively measured. The resulting weights were used to rank the performance of the alternatives using the WASPAS method. This integrated approach provides a decision support framework that takes both uncertainties into account and is computationally efficient. The study seeks to answer the following research questions: 1) Which alternative irrigation method is the most effective for the sustainable management of water resources in agriculture? 2) What are the most decisive factors in the decision-making process among the seven criteria determined? 3) How does the diversity of expert opinions affect the ranking of alternatives? 4) To what extent is the spherical fuzzy-based approach effective in reducing uncertainty compared to traditional fuzzy methods? 5) What advantages does the integrated use of the MEREC and WASPAS methods provide in multi-criteria decision-making processes? By addressing these research questions, the study proposes an innovative decision-making model that will increase water efficiency in the agricultural sector and provide a strategic reference framework for policy developers and practitioners.

This study addresses a clear methodological and practical gap in the literature by proposing a hybrid decision-making framework that goes beyond existing fuzzy-based MCDM applications in agricultural water management. Unlike prior studies that typically rely on static expert-driven fuzzy weighting and conventional ranking techniques, the proposed model uniquely combines spherical fuzzy sets with machine learning–assisted data structuring, the objective weighting capability of the MEREC method, and the compensatory–noncompensatory evaluation mechanism of WASPAS within a single integrated framework. This specific configuration is fundamentally novel in that spherical fuzzy sets are employed not merely as a linguistic extension, but as a means to capture hesitation and uncertainty in irrigation-related expert judgments, while machine learning is used to enhance data consistency and reduce subjectivity prior to weighting and ranking. To the best of our knowledge, no existing study in the irrigation method selection literature has systematically integrated these four components to jointly address uncertainty modeling, objective criterion weighting, and robust alternative ranking. Consequently, the proposed approach offers a structurally distinct and methodologically advanced decision-support tool for the efficient use of water resources in agriculture.

The proposed model developed in this study has several advantages over previously presented decision-making models in the literature: 1) First, the model utilizes machine learning techniques to calculate the importance weights of experts. This approach allows for objective weighting based not only on the opinions of experts but also on their demographic characteristics, areas of expertise, experience levels, and academic backgrounds. The vast majority of existing models in the literature treat experts as equal or base weights on subjective assessments. This increases the risk of subjectivity and inconsistency in the decision-making process. However, the machine learning-based approach used in this study systematically evaluates differences among experts, providing more objective, reliable, and data-driven weightings. This increases the accuracy and confidence levels of the model and enhances the scientific validity of decision-making results. 2) The second advantage of the model is the use of spherical fuzzy sets in the decision-making process. These new-generation fuzzy sets have a higher uncertainty representation capacity compared to classical, intuitionistic, and Pythagorean fuzzy sets. By defining membership, non-membership, and degrees of uncertainty independently, the spherical fuzzy structure models the uncertainties and knowledge gaps in expert opinions in a much more realistic and flexible manner. This allows for more effective management of uncertainty in the decision-making environment and increased consistency of results. Furthermore, the spherical fuzzy approach offers advantages over other sets in terms of both ease of calculation and interpretability. This contributes to the model's robustness both theoretically and practically. 3) The MEREC (Method Based on the Removal Effects of Criteria) technique used in the study is another significant advantage of the model. Entropy, CRITIC, or standard statistical methods are frequently used in the literature for criterion weighting; however, these methods generally fail to adequately reflect the mutual influences between criteria. The MEREC method analyzes the change in overall performance when each criterion is removed from the system, revealing the true impact of each criterion. This feature allows the model to better capture inter-criterion sensitivity and ensure more objective, reliable, and data-driven decision-making outcomes. The MEREC method offers higher accuracy and significance than other techniques, particularly in areas such as water management, where multidimensional environmental and technical factors are evaluated simultaneously. Considering all these advantages together, the proposed model offers a holistic approach that is both methodologically innovative and provides high accuracy, flexibility, and consistency in decision-making processes.

The remainder of the study is as follows: Section II includes the research gap in the literature. Section III focuses on the proposed model. The results are denoted in Section IV. Section V makes a comparative discussion. Section VI highlights the main conclusion.

II. Literature Review

Applicability, or technological suitability, is one of the key criteria when determining alternative irrigation methods for the efficient use of water resources in agriculture. Given the challenges of climate change, the use of technologies that can increase productivity and efficiency in agriculture, including precision agriculture, drones, and climate information systems, is crucial. In today's world, the development of systems such as remote sensing with artificial intelligence-based decision-making tools also promotes the efficient use of water resources in agriculture. These technologies include software applications, water management applications, nutrient management, temperature measurement, and soil health analysis tools. These technologies can also contribute to climate change-resilient crop

development, irrigation water management, fostering local knowledge, and increasing agricultural yields, ensuring food security. Vedovello et al. [3] provided an overview of hydrogel technologies as adaptable solutions to address challenges such as water scarcity and soil degradation in agriculture. Indeed, hydrogels offer agricultural innovations that address challenges associated with traditional agricultural practices and technologies while also providing some answers for the future of these technologies. Singh and Singh [4] examined the impact of UAV use in Indian agriculture on precision agriculture, crop monitoring, and pesticide application. They assess technological advancements, infrastructure, regulatory frameworks, farmer perceptions, and financial accessibility of UAV technology.

Environmental impacts are another effective criterion in determining alternative irrigation methods for the efficient use of water resources in agriculture. Ultimately, water efficiency in agriculture is a critical element of sustainable water management, particularly in rural areas, and is vital for ensuring environmental sustainability in rural areas where water resources are limited [5]. While traditional surface irrigation has been reported to cause environmental consequences such as water loss, advanced alternatives such as drip and sprinkler systems have been observed to improve irrigation infrastructure and promote climate-smart agricultural practices [6]. Saini et al. [7] investigated the behaviors and perspectives of rural and regional urban water consumers regarding water consumption. They develop a conceptual model of the factors affecting the amount of water consumed, including the barriers that hinder water conservation. Yasmeen et al. [8] examined the synergy of water use efficiency between 2006 and 2020 between the aggregation of water resources at the provincial and regional levels in China and the integration of innovative conservation technologies.

Cost is another important criterion when determining alternative irrigation methods for the efficient use of water resources in agriculture. The initial investment cost of irrigation systems designed for efficient water use can be high. This is because sprinkler and drip irrigation systems, while achieving efficiency by using less water, require operator control, operation, and monitoring [9]. Furthermore, while external factors such as regulations, national water policies, financial incentives, government subsidies, and technology provide solutions for efficient water supply in agriculture, they can also be considered among the factors affecting costs [10]. Chaudhary et al. [11] summarized the fundamental aspects of sprinkler and precision irrigation, their development and prospects, particularly in Asian countries. This approach leverages significant advances in sprinkler systems for precision applications to increase net crop production, conserve irrigation water, maximize irrigation uniformity, and improve fertilizer management with minimal leakage loss. On the other hand, Bhavsar et al. [12] comprehensively examined numerous IoT-enabled smart micro-irrigation systems, including smart sprinkler systems and smart drip irrigation, to reduce water and energy waste. The aim is to find the most appropriate irrigation strategy.

Energy consumption is another important criterion in determining alternative irrigation methods for the efficient use of water resources in agriculture. The agricultural sector consumes large amounts of water and energy through irrigation, collection, pumping, water treatment, land preparation, fertilizer production, agricultural machinery, processing, and storage [13]. In other words, energy is used both directly and indirectly for the efficient use of water resources in agriculture, while the energy provided to modern and sustainable agricultural production systems and processing is one of the main factors in the growth of agricultural production [14]. Yang et al. [15] established a framework for examining water and energy consumption at every stage of the crop growth process, including growth, planting, germination, ripening, and harvesting. Pomoni et al. [16] aimed to reveal the environmental, water, and energy impacts of traditional agriculture and a new soilless cultivation technology, namely hydroponic agriculture.

The results of the literature review indicate that certain criteria are important in determining alternative irrigation methods for the efficient use of water resources in agriculture. These criteria include applicability (technological suitability), environmental impacts, cost, and energy consumption. Since it is not possible to improve all criteria simultaneously, the study aims to identify the most important criterion. This aims to address a gap in the literature on this topic. This study accomplishes this by analyzing a new decision-making model.

III. METHODOLOGY

This section relates to the formulations of spherical fuzzy sets (SFSs), dimensionality reduction, MEREC, and WASPAS. Using these formulations, the methodology of the manuscript is constructed. The methodology includes SFSs to minimize uncertainty, while dimensionality reduction is used to determine the level of experts. Additionally, after calculating the criterion priority value from MEREC, comparative results of WASPAS and RAWEC are obtained in ranking the alternatives. The diagram of the methodology is presented in Fig. 1.

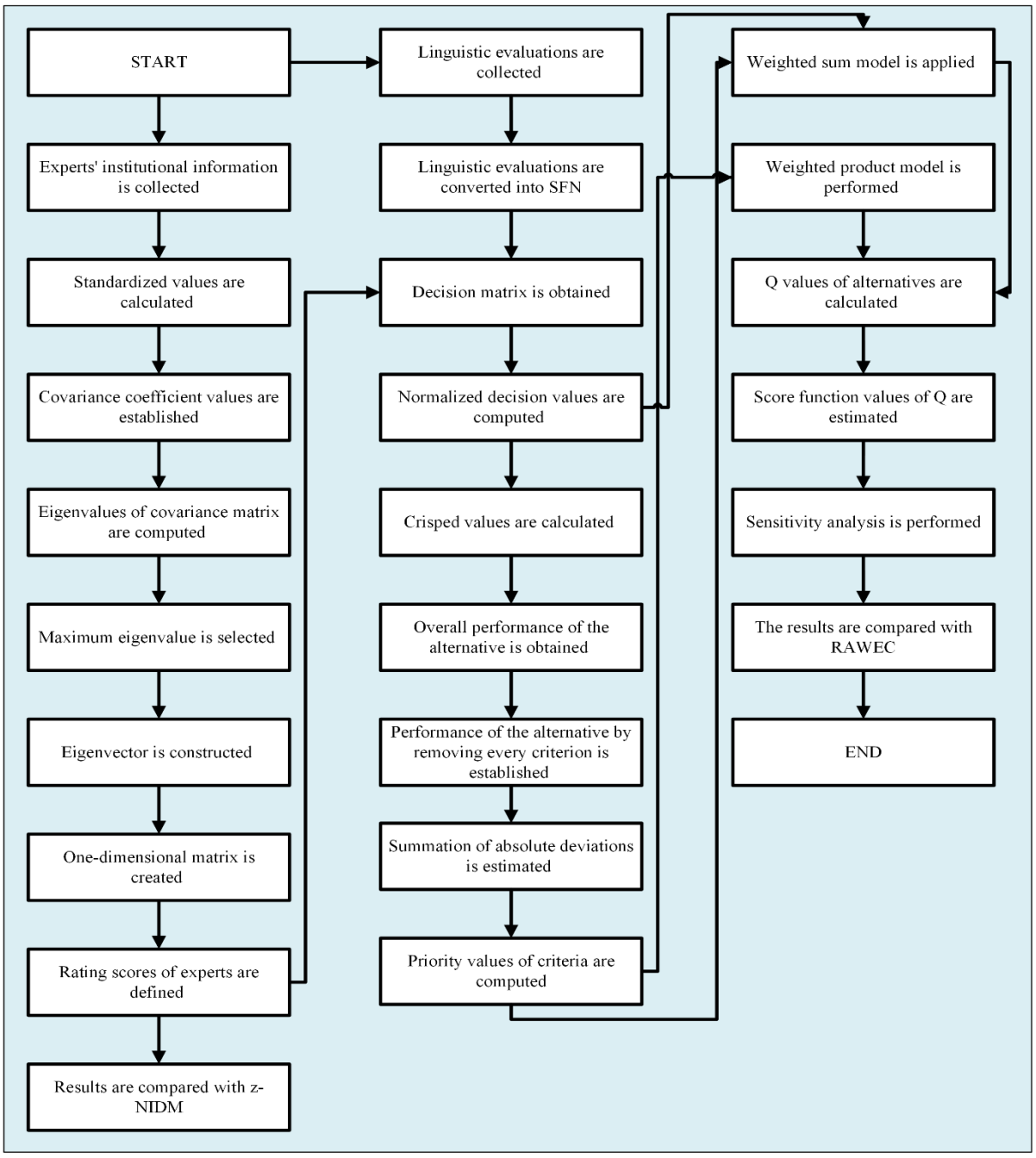


Fig. 1. Diagram of the methodology.

A. Dimensionality Reduction

Creating a decision matrix by calculating the unweighted average of expert evaluations has been criticized. Due to this criticism, different approaches have been developed in the literature. While dimensionality reduction is primarily used to reduce the number of variables in machine learning, it is preferred in MCDM due to its objectivity in calculating the experts' ratings. This approach aims to obtain rating scores for experts using information provided by the experts on the websites of their affiliated institutions. The assumption here is that if an institution's knowledge is high, the institution is of high quality; if the institution is good, the expert working there is also qualified. Under this assumption, the calculation steps can be summarized as follows [17].

The websites of k institutions, where k experts work, are examined. The f numerical information about the institutions is collected. This information includes the number of business partners the institutions have collaborated with and the years they have been in operation. Based on these variables, an institution is considered high-quality if it has been operating for a long time. Similarly, the more business partners it has, the better the institution. In other words, the matrix (B) in Eq. (1) is created using the data from the relevant variables indicating the institution's qualification.

$$B = \begin{bmatrix} b_{11} & \cdots & b_{1f} \\ \vdots & \ddots & \vdots \\ b_{k1} & \cdots & b_{kf} \end{bmatrix} \quad (1)$$

When the value range and unit sizes of the variables differ from each other, standardized values (r) are calculated with the help of Eq. (2) to Eq. (4) using arithmetic mean $(\bar{b})$ and centred values (c).

$$\bar{b}_j = \frac{\sum_{i=1}^{k} b_{ij}}{k} \quad (2)$$

$$c_{ij} = b_{ij} - \bar{b}_j \quad (3)$$

$$r_{ij} = \frac{c_{ij}}{\sqrt{\sum_{i=1}^{k} c_{ij}^2}} \quad (4)$$

Afterwards, covariance coefficient values (cov) between standardized variables are established via Eq. (5). Thus, the covariance matrix (A) formed in Eq. (6) is obtained.

$$cov_{jt} = \frac{1}{k}\left(\sum_{i=1}^{k}(r_{ij} - \bar{r}_j)(r_{it} - \bar{r}_t)\right) \quad (5)$$

$$A = \begin{bmatrix} cov_{11} & \cdots & cov_{1f} \\ \vdots & \ddots & \vdots \\ cov_{f1} & \cdots & cov_{ff} \end{bmatrix} \quad (6)$$

where, $\bar{r}$ is the average value of the standardized variable and is estimated using Eq. (2). Next, f eigenvalues of the covariance matrix (ξ) are computed by Eq. (7). Then, the maximum eigenvalue (ξ^*) is selected with Eq. (8) for saving the maximum variance.

$$\det(A - \xi_i \mathrm{I}) = 0 \quad (7)$$

$$\xi^* = \max \xi_i \quad (8)$$

where, I is the identity matrix with dimensions *fxf*. Later, the eigenvector (Y) is constructed with the help of Eq. (9):

$$(A - \xi^* \mathrm{I})Y = 0 \quad (9)$$

Finally, a one-dimensional matrix (H) is created via Eq. (10), then the rating scores of experts (rs) are defined as Eq. (11):

$$H = BY \quad (10)$$

$$rs_i = \frac{h_i}{\sum_{i=1}^{k} h_i} \quad (11)$$

where, h is the items of one-dimensional matrix. The multiplication operation in Eq. (10) is matrix multiplication.

B. SFSs

Fuzzy sets define different degrees to measure uncertainty. From the set family formed by the degrees of membership (α), non-membership (β), and hesitancy (γ), SFSs are defined by the sum of the squares of these degrees. In other words, an SFS $(\tilde{F})$ of the universe of discourse $(\mathcal{S})$ is described as in Eq. (12) [18].

$$\tilde{F} = \left\{x, \left(\alpha_{\tilde{F}}(x), \beta_{\tilde{F}}(x), \gamma_{\tilde{F}}(x)\right) | x \in \mathcal{S}\right\} \quad (12)$$

where, these degrees are between zero and one. These degrees are the satisfied conditions in Eq. (13):

$$0 \le \alpha_{\tilde{F}}^2(x) + \beta_{\tilde{F}}^2(x) + \gamma_{\tilde{F}}^2(x) \le 1;\ \forall x \in \mathcal{S} \quad (13)$$

The refusal degree is computed with Eq. (14):

$$\varsigma_{\tilde{F}}(x) = \sqrt{1 - \alpha_{\tilde{F}}^2(x) - \beta_{\tilde{F}}^2(x) - \gamma_{\tilde{F}}^2(x)} \quad (14)$$

Consider that $\tilde{F}$ and $\tilde{G}$ are two SFNs. Then, basic operators are identified with Eq. (15) to Eq. (18):

$$\tilde{F} + \tilde{G} = \left\{ \begin{matrix} \sqrt{\alpha_{\tilde{F}}^2 + \alpha_{\tilde{G}}^2 - \alpha_{\tilde{F}}^2\alpha_{\tilde{G}}^2}, \beta_{\tilde{F}}\beta_{\tilde{G}}, \\ \sqrt{\left(1-\alpha_{\tilde{G}}^2\right)\gamma_{\tilde{F}}^2 + \left(1-\alpha_{\tilde{F}}^2\right)\gamma_{\tilde{G}}^2 - \gamma_{\tilde{F}}^2\gamma_{\tilde{G}}^2} \end{matrix} \right\} \quad (15)$$

$$\tilde{F} \times \tilde{G} = \left\{ \begin{matrix} \alpha_{\tilde{F}}\alpha_{\tilde{G}}, \sqrt{\beta_{\tilde{F}}^2 + \beta_{\tilde{G}}^2 - \beta_{\tilde{F}}^2\beta_{\tilde{G}}^2}, \\ \sqrt{\left(1-\beta_{\tilde{G}}^2\right)\gamma_{\tilde{F}}^2 + \left(1-\beta_{\tilde{F}}^2\right)\gamma_{\tilde{G}}^2 - \gamma_{\tilde{F}}^2\gamma_{\tilde{G}}^2} \end{matrix} \right\} \quad (16)$$

$$\lambda\tilde{F} = \left\{ \begin{matrix} \sqrt{1 - \left(1-\alpha_{\tilde{F}}^2\right)^{\lambda}}, \beta_{\tilde{F}}^{\lambda}, \\ \sqrt{\left(1-\alpha_{\tilde{F}}^2\right)^{\lambda} - \left(1-\alpha_{\tilde{F}}^2-\gamma_{\tilde{F}}^2\right)^{\lambda}} \end{matrix} \right\} \quad (17)$$

$$\tilde{F}^{\lambda} = \left\{ \begin{matrix} \alpha_{\tilde{F}}^{\lambda}, \sqrt{1 - \left(1-\beta_{\tilde{F}}^2\right)^{\lambda}}, \\ \sqrt{\left(1-\beta_{\tilde{F}}^2\right)^{\lambda} - \left(1-\beta_{\tilde{F}}^2-\gamma_{\tilde{F}}^2\right)^{\lambda}} \end{matrix} \right\} \quad (18)$$

Assume that $\tilde{F}_i$ be the sequence of SFNs and $\sum_{i=1}^{n} w_i = 1$. Then, weighted arithmetic mean $(\tilde{\mathcal{A}})$ is calculated using Eq. (19):

$$\tilde{\mathcal{A}}_{\tilde{F}_i} = \left\{ \begin{matrix} \sqrt{1 - \prod_{i=1}^{n}\left(1-\alpha_{\tilde{F}_i}^2\right)^{w_i}}, \\ \prod_{i=1}^{n}\beta_{\tilde{F}_i}^{w_i}, \\ \sqrt{\prod_{i=1}^{n}\left(1-\alpha_{\tilde{F}_i}^2\right)^{w_i} - \prod_{i=1}^{n}\left(1-\alpha_{\tilde{F}_i}^2-\gamma_{\tilde{F}_i}^2\right)^{w_i}} \end{matrix} \right\} \quad (19)$$

Similarly, weighted geometric mean $(\tilde{\mathcal{G}})$ is computed with Eq. (20):

$$\tilde{\mathcal{G}}_{\tilde{F}_i} = \left\{ \begin{matrix} \prod_{i=1}^{n}\alpha_{\tilde{F}_i}^{w_i}, \\ \sqrt{1 - \prod_{i=1}^{n}\left(1-\beta_{\tilde{F}_i}^2\right)^{w_i}}, \\ \sqrt{\prod_{i=1}^{n}\left(1-\beta_{\tilde{F}_i}^2\right)^{w_i} - \prod_{i=1}^{n}\left(1-\beta_{\tilde{F}_i}^2-\gamma_{\tilde{F}_i}^2\right)^{w_i}} \end{matrix} \right\} \quad (20)$$

Score (SF) and accuracy (AF) functions are identified by Eq. (21) and Eq. (22), respectively.

$$SF\left(\tilde{F}\right) = \left(2\alpha_{\tilde{F}} - \frac{\gamma_{\tilde{F}}}{2}\right)^2 - \left(\beta_{\tilde{F}} - \frac{\gamma_{\tilde{F}}}{2}\right)^2 \quad (21)$$

$$AF\left(\tilde{F}\right) = \alpha_{\tilde{F}}^2 + \beta_{\tilde{F}}^2 + \gamma_{\tilde{F}}^2 \quad (22)$$

C. SF-MEREC-Based SF-WASPAS

MEREC-based WASPAS is a hybrid approach that ranks alternatives by combining two models after determining objective criteria priorities. This hybrid approach aims to

minimize uncertainty by integrating SFSs. This manuscript analysis process is described below [19].

For the decision model in which n criteria are considered to rank m alternatives, evaluations from k experts are collected with a linguistic scale. These linguistic evaluations are converted into SFNs, and their weighted averages are calculated by Eq. (23):

$$\tilde{d}_{ij} = \left\{\alpha_{\tilde{d}_{ij}}, \beta_{\tilde{d}_{ij}}, \gamma_{\tilde{d}_{ij}}\right\} = \tilde{\mathcal{A}}_{\tilde{E}^t{}_{ij}} \quad (23)$$

where, $\tilde{E}^t{}_{ij}$ refers to SFN of the linguistic evaluation of jth criterion of ith alternative for t^{th} expert. $\tilde{\mathcal{A}}$ is the weighted arithmetic mean defined in Equation (19) using the rating scores of experts as weights. Next, normalized decision values $(\tilde{\mathfrak{y}})$ are computed with Eq. (24) and Eq. (25):

$$\tilde{\mathfrak{y}}_{ij} = \left\{\alpha_{\tilde{d}_{ij}}, \beta_{\tilde{d}_{ij}}, \gamma_{\tilde{d}_{ij}}\right\}; for\ benefical\ criterion \quad (24)$$

$$\tilde{\mathfrak{y}}_{ij} = \left\{\gamma_{\tilde{d}_{ij}}, \beta_{\tilde{d}_{ij}}, \alpha_{\tilde{d}_{ij}}\right\}; for\ cost\ criterion \quad (25)$$

Afterwards, crisped values $(\mathfrak{h})$ are calculated by Eq. (26):

$$\mathfrak{h}_{ij} = \frac{1}{2}\begin{pmatrix} 1 + \left(\alpha_{\tilde{\mathfrak{y}}_{ij}}\right)^2 \\ -\left(\beta_{\tilde{\mathfrak{y}}_{ij}}\right)^2 - \left(\gamma_{\tilde{\mathfrak{y}}_{ij}}\right)^2 - \ln\left(1 + \left(\varsigma_{\tilde{\mathfrak{y}}_{ij}}\right)^2\right) \end{pmatrix} \quad (26)$$

The overall performance of the alternative (G) is obtained with the help of Eq. (27):

$$G_i = \ln\left(1 + \left(\frac{1}{n}\sum_j \left|\mathfrak{h}_{ij}\right|\right)\right) \quad (27)$$

The performance of the alternative by removing every criterion (G') is established using Eq. (28):

$$G'_{ij} = \ln\left(1 + \left(\frac{1}{n}\sum_{f\, f\neq j} \left|\mathfrak{h}_{if}\right|\right)\right) \quad (28)$$

Next, the summation of absolute deviations (K) is estimated by Eq. (29):

$$K_j = \sum_i \left|G'_{ij} - G_i\right| \quad (29)$$

The last step of MEREC is about the computation of priority values (pv) of criteria with Eq. (30):

$$pv_j = \frac{K_j}{\sum_{j=1}^{n} K_j} \quad (30)$$

Afterwards, the weighted sum model $\left(\tilde{Q}^{(1)}\right)$ is applied using Eq. (31).

$$\tilde{Q}_i^{(1)} = \sum_{j=1}^{n} pv_j \tilde{\mathfrak{y}}_{ij} \quad (31)$$

Similarly, the weighted product model $\left(\tilde{Q}^{(2)}\right)$ is performed via Eq. (32):

$$\tilde{Q}_i^{(2)} = \prod_{j=1}^{n} \left(\tilde{\mathfrak{y}}_{ij}\right)^{pv_j} \quad (32)$$

Next, the $\tilde{Q}$ values of alternatives are calculated by Eq. (33) [20].

$$\tilde{Q}_i = \varphi\tilde{Q}_i^{(1)} + (1-\varphi)\tilde{Q}_i^{(2)} \quad (33)$$

Finally, score function values of $\tilde{Q}$ are estimated with the help of Eq. (34) for ranking of alternatives.

$$Q_i = SF\left(\tilde{Q}_i\right) \quad (34)$$

IV. Analysis

This section relates to the results of the methodology in Fig. 1.

A. Obtaining the Rating Scores of Experts

Experts with at least ten years of work experience are selected. Data from the website is analyzed using the experts' institutional information. The institutions' business partners, period of activity, and number of countries they operate in are obtained. This information is used to create the matrix in Eq. (1). The matrix is shown in Table I.

TABLE I. Information About the Institutional Business Partners

	Business Partners	**Activity Period**	**Operation Country**
Expert.1	16	16	6
Expert.2	21	16	5
Expert.3	23	21	5
Expert.4	32	26	4
Expert.5	33	33	6
Expert.6	24	22	4
Expert.7	25	18	3
Expert.8	35	35	6
Expert.9	29	15	4
Expert.10	34	24	6

According to the variables in Table I, the average business partner is 27.2 with a standard deviation of 6.03. Similarly, the minimum activity period is 15. The range of operation country is between 3 and 6. The descriptive statistics are shared in Table II.

TABLE II. Descriptive Statistics

	Business Partners	**Activity Period**	**Operation Country**
Average	27.2	22.6	4.9
Deviation	6.030	6.666	1.044
Max	35	35	6
Min	16	15	3

Standardized values are calculated with the help of Eq. (2) to Eq. (4) using arithmetic mean and centered values in Table II. The standardized values are given in Table III.

TABLE III. STANDARDIZED VALUES

	Business Partners	Activity Period	Operation Country
Expert.1	-.587	-.313	.333
Expert.2	-.325	-.313	.030
Expert.3	-.220	-.076	.030
Expert.4	.252	.161	-.273
Expert.5	.304	.493	.333
Expert.6	-.168	-.028	-.273
Expert.7	-.115	-.218	-.575
Expert.8	.409	.588	.333
Expert.9	.094	-.361	-.273
Expert.10	.357	.066	.333

Covariance coefficient values between standardized variables in Table III are established via Eq. (5). Thus, the covariance matrix formed in Eq. (6) is summarized in Table IV.

TABLE IV. COVARIANCE MATRIX

	Business Partners	Activity Period	Operation Country
Business Partners	.100	.075	.016
Activity Period	.075	.100	.045
Operation Country	.016	.045	.100

Next, the 3 eigenvalues of the covariance matrix are computed by Eq. (7). These eigenvalues are illustrated in Table V with explained variances. Then, the maximum eigenvalue is selected with Eq. (8) for saving the maximum variance. The maximum eigenvalue is .19569.

TABLE V. EIGENVALUES WITH EXPLAINED VARIANCES

	Value	Explained Variance
Eigenvalue.1	.19569	65.23%
Eigenvalue.2	.018526	6.18%
Eigenvalue.3	.085784	28.59%

The first eigenvalue contains 65.23% of the variance, which is considered a relatively high rate. Later, eigenvector is constructed with the help of Eq. (9). The results are displayed in Table VI.

TABLE VI. ITEMS OF EIGENVECTOR

	Vector
1	.603644
2	.675852
3	.422891

A one-dimensional matrix is created via Eq. (10). This matrix is exhibited in Table VII.

TABLE VII. ONE-DIMENSIONAL MATRIX

	First-dimension
Expert.1	23.009
Expert.2	25.605
Expert.3	3.191
Expert.4	38.580
Expert.5	44.761
Expert.6	31.048
Expert.7	28.525
Expert.8	47.320
Expert.9	29.335
Expert.10	39.282

Finally, the items in Table VII are normalized. Thus, the rating scores of experts are defined as Eq. (11). The rating scores of experts are presented in Fig. 2.

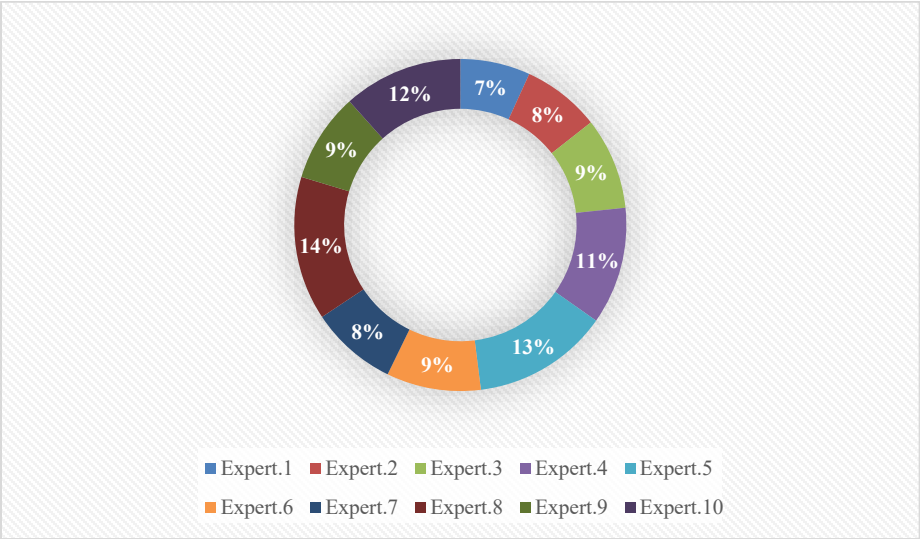


Fig. 2. Rating scores of experts.

As can be seen from rating scores in Fig. 2, the most important evaluation is Expert.8 with .140. This expert's institution has the maximum business partners, operation county and activity period. Moreover, as a second method to compare the results, the z-NIDM method is applied. The comparative results are visualized in Fig. 3.

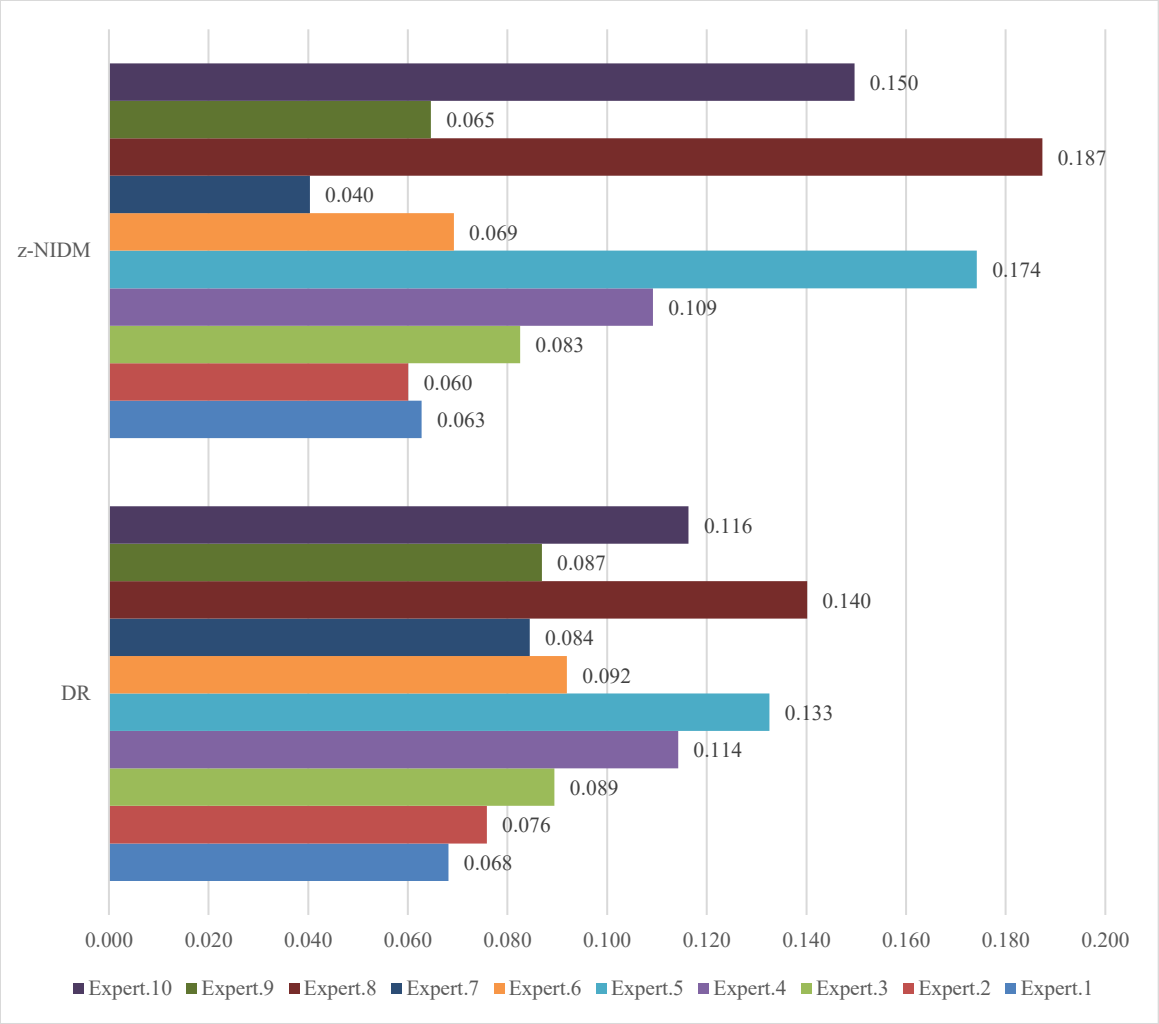


Fig. 3. Comparative results for experts.

Pearson and Spearman correlation coefficients between two approaches are obtained for results. Pearson coefficient is .939 and Spearman coefficient is .944. These coefficients are very high. In other words, the results are consistent and reliable.

B. *Weighting of Criteria and Ranking of Alternatives*

Alternative irrigation methods for efficient use of water resources in agriculture are sprinkler irrigation (SPR), drip irrigation (DRP), surface irrigation (channel or flood) (SRF), subsurface irrigation (SBS), and micro sprinkler irrigation (MCR). The criteria effective in the selection of these alternatives are presented with their short codes in Table VIII.

Linguistic evaluations from 10 experts are collected with a linguistic scale shared in Fig. 4.

TABLE VIII. CRITERIA LIST WITH SHORT CODES

Definition	Short Code
Water Efficiency (Savings)	WEF
Cost	CST
Energy Consumption	ECN
Applicability/Technological Compatibility	APT
Plant Yield and Quality	PTQ
Environmental Impacts	EVI
Ease of Maintenance and Operation	EMO

Using the initials of the linguistic scale in Fig. 4, the experts' evaluations are summarized in Table IX. For example, VHI is of very high importance.

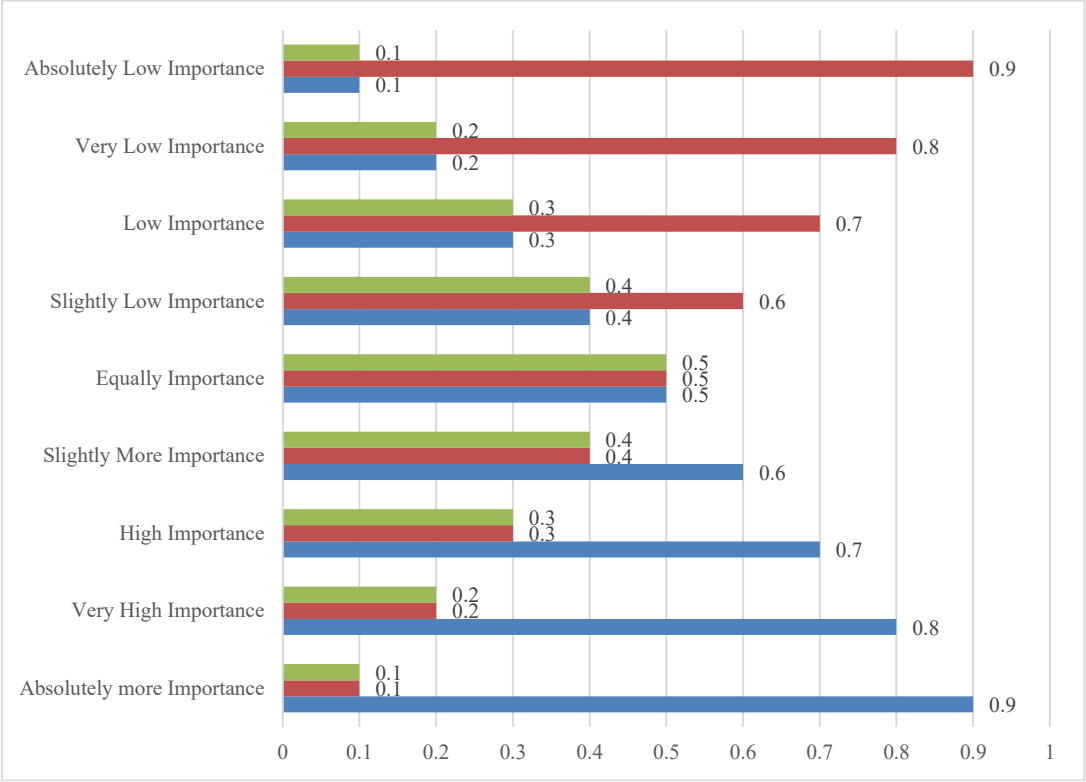


Fig. 4. Linguistic scales.

TABLE IX. LINGUISTIC EVALUATIONS

Expert.1	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	VLI	ALI	ALI	VLI	VLI	SLI	ALI
DRP	AI	VHI	HI	AI	AI	AI	SMI
SRF	SLI	SLI	SMI	EI	SMI	SLI	SLI
SBS	SMI	SMI	SMI	SMI	EI	EI	EI
MCR	LI	LI	SLI	LI	VLI	LI	VLI
Expert.2	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	LI	VLI	ALI	LI	ALI	SLI	LI
DRP	VHI	AI	VHI	AI	AI	VHI	VHI
SRF	EI	HI	SMI	HI	EI	HI	HI
SBS	EI	SMI	EI	EI	EI	EI	EI
MCR	SLI	VLI	VLI	VLI	SLI	LI	SLI
Expert.3	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	VLI	VLI	VLI	VLI	SLI	SLI	ALI
DRP	AI	AI	AI	AI	HI	VHI	AI
SRF	SMI	EI	SMI	SMI	SLI	HI	HI
SBS	SMI	EI	EI	SMI	SMI	EI	SMI
MCR	LI	LI	VLI	LI	VLI	SLI	VLI
Expert.4	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	LI	LI	ALI	ALI	VLI	SLI	VLI

DRP	SMI	HI	AI	HI	AI	VHI	AI
SRF	HI	EI	HI	HI	EI	SMI	SMI
SBS	SMI	EI	SMI	EI	SMI	EI	SMI
MCR	SLI	SLI	SLI	LI	SLI	VLI	SLI
Expert.5	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	ALI	SLI	VLI	SLI	SLI	ALI	VLI
DRP	AI	AI	SMI	SMI	SMI	SMI	VHI
SRF	EI	SMI	SLI	SMI	SMI	HI	SMI
SBS	SMI	EI	EI	SMI	SMI	EI	EI
MCR	VLI	LI	LI	VLI	VLI	SLI	VLI
Expert.6	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	LI	SLI	ALI	ALI	ALI	ALI	SLI
DRP	SMI	HI	HI	AI	HI	VHI	HI
SRF	SMI	HI	EI	SLI	SMI	EI	SLI
SBS	SMI	SMI	SMI	SMI	SMI	EI	EI
MCR	SLI	VLI	VLI	SLI	VLI	VLI	VLI
Expert.7	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	ALI	ALI	VLI	VLI	LI	SLI	ALI
DRP	SMI	HI	HI	HI	VHI	AI	VHI
SRF	EI	SLI	SMI	HI	HI	SMI	EI
SBS	EI	EI	SMI	SMI	SMI	EI	SMI
MCR	SLI	LI	LI	SLI	SLI	VLI	VLI
Expert.8	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	ALI	ALI	SLI	LI	ALI	ALI	ALI
DRP	HI	SMI	AI	SMI	VHI	SMI	SMI
SRF	SMI	SMI	EI	HI	SMI	EI	EI
SBS	SMI	EI	SMI	SMI	EI	EI	EI
MCR	VLI	LI	LI	SLI	SLI	SLI	VLI
Expert.9	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	VLI	SLI	ALI	VLI	ALI	SLI	ALI
DRP	SMI	SMI	VHI	SMI	VHI	SMI	AI
SRF	SMI	SMI	HI	EI	HI	SMI	HI
SBS	EI	SMI	SMI	EI	EI	SMI	SMI
MCR	VLI	SLI	VLI	SLI	LI	SLI	VLI
Expert.10	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	SLI	ALI	VLI	SLI	LI	ALI	SLI
DRP	HI	VHI	HI	VHI	HI	VHI	AI
SRF	SMI	SLI	SLI	HI	SMI	SMI	HI
SBS	SMI	SMI	SMI	SMI	SMI	SMI	EI
MCR	LI	LI	SLI	SLI	VLI	LI	LI

These linguistic evaluations in Table IX are converted into SFNs according to Fig. 4. Then, weighted averages are calculated by Eq. (23) using rating scores of experts in Fig. 2 as weights. Thus, the decision matrix that accepts the weighted average values as elements is obtained. This matrix is displayed in Table X.

TABLE X. DECISION MATRIX

	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	(.271,.777,.222)	(.316,.756,.248)	(.23,.809,.203)	(.301,.741,.261)	(.273,.765,.253)	(.342,.729,.285)	(.254,.788,.232)
DRP	(.781,.236,.243)	(.8,.214,.217)	(.815,.2,.201)	(.794,.222,.23)	(.808,.207,.205)	(.784,.231,.232)	(.833,.181,.192)
SRF	(.601,.425,.399)	(.585,.445,.385)	(.593,.44,.383)	(.652,.369,.347)	(.616,.412,.381)	(.627,.398,.374)	(.626,.404,.365)
SBS	(.598,.423,.409)	(.573,.453,.437)	(.597,.427,.411)	(.595,.426,.412)	(.587,.435,.422)	(.55,.478,.46)	(.567,.46,.443)
MCR	(.337,.694,.301)	(.35,.694,.286)	(.33,.7,.293)	(.378,.664,.322)	(.341,.702,.291)	(.366,.679,.309)	(.291,.746,.246)

Normalized decision values are computed with Eq. (24) and Eq. (25). All criteria are beneficial. For this reason, Eq. (24) is used. In other words, normalized decision values and the decision matrix's elements are the same. Next, crisped values are calculated by Equation (26). The crisped values are shown in Table XI.

The overall performance of the alternative is obtained with the help of Eq. (27). The overall performance values are visualized in Fig. 5.

TABLE XI. CRISPED VALUES

	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	.089	.115	.066	.109	.090	.133	.079
DRP	.626	.655	.678	.645	.667	.631	.706
SRF	.380	.363	.372	.446	.399	.413	.412
SBS	.376	.344	.374	.373	.362	.317	.337
MCR	.134	.143	.130	.163	.136	.154	.103

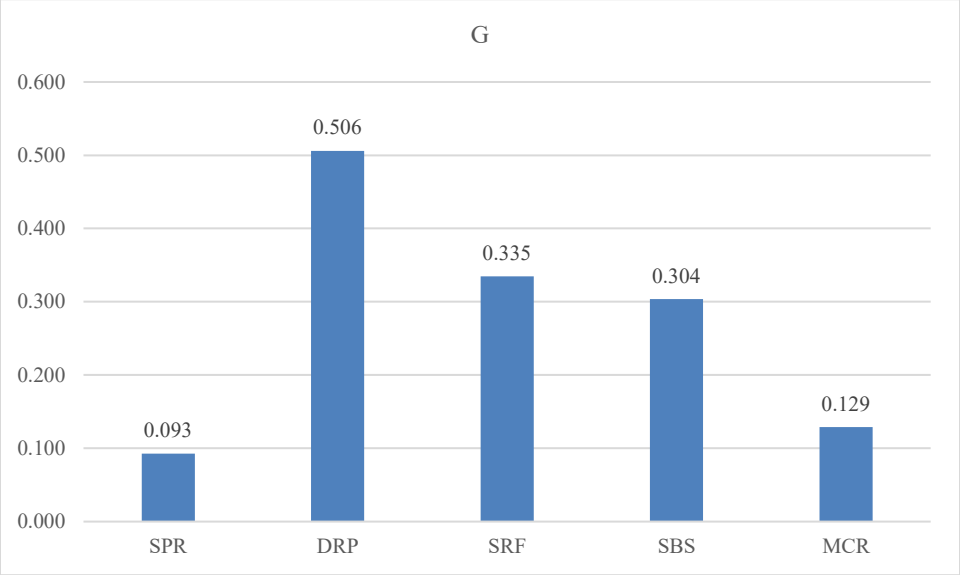


Fig. 5. Overall performance values.

The performance of the alternative by removing every criterion is established using Eq. (28). The results are illustrated in Table XII.

Next, the summation of absolute deviations is estimated by Eq. (29). The summation values are presented in Fig. 6.

The last step of MEREC is about the computation of priority values of criteria with Eq. (30). The results are shown in Fig. 7.

TABLE XII. G' VALUES

	WEF	CST	ECN	APT	PTQ	EVI	EMO
SPR	.081	.078	.084	.079	.081	.075	.083
DRP	.450	.448	.446	.449	.447	.450	.443
SRF	.295	.297	.296	.288	.293	.292	.292
SBS	.263	.267	.263	.264	.265	.270	.267
MCR	.112	.111	.112	.108	.112	.109	.116

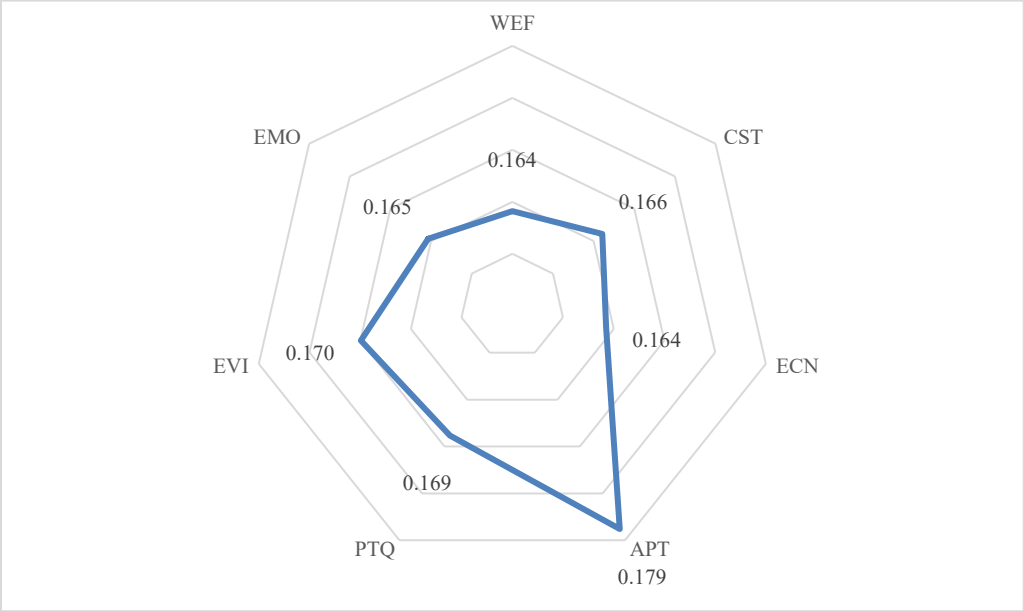


Fig. 6. Summation of absolute deviations.

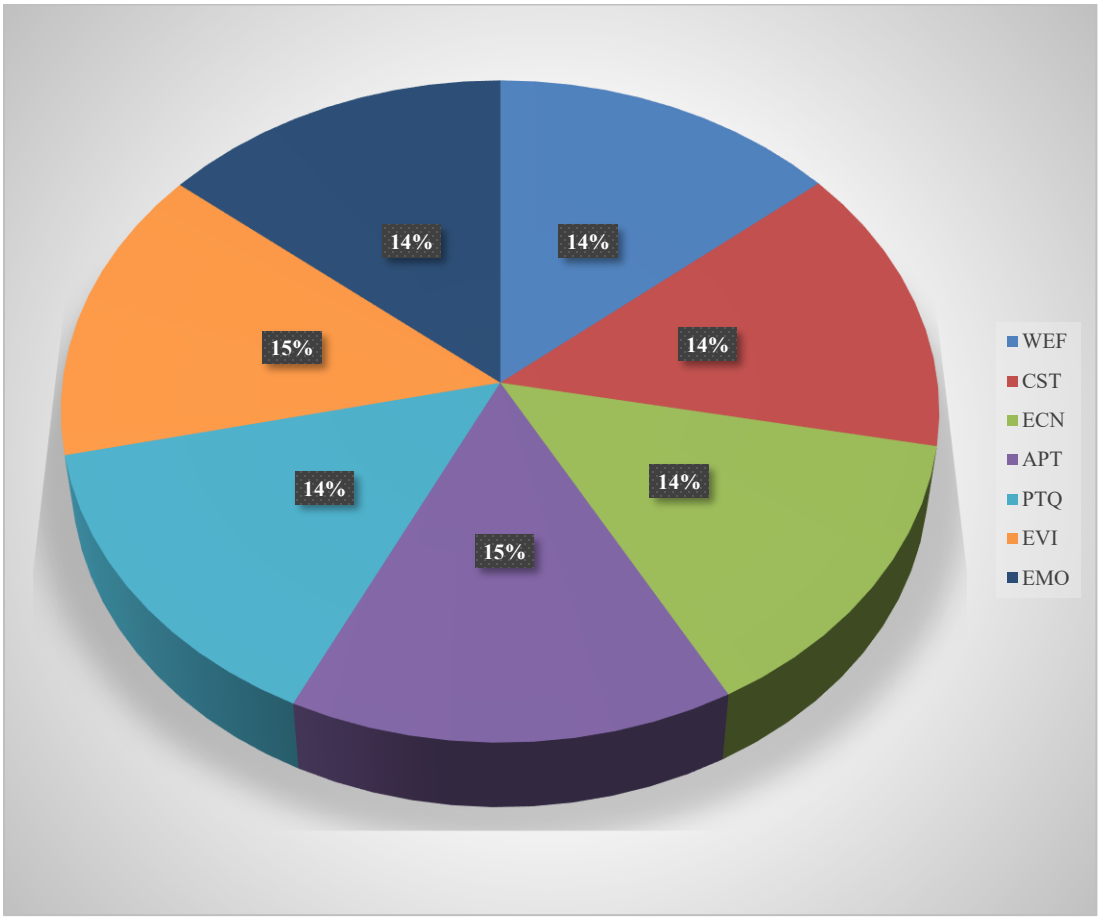


Fig. 7. Priority values of criteria.

When Fig. 7 is examined, the most important criterion effective in the selection of these alternative irrigation methods for efficient use of water resources in agriculture is applicability/technological compatibility with .152. The second important criterion is environmental impacts with .144. Afterwards, weighted sum model is applied using Eq. (31). The weighted sum model result is described in Table XIII.

TABLE XIII. WEIGHTED SUM MODEL

	$\tilde{Q}^{(1)}$
SPR	(.287,.766,.246)
DRP	(.803,.212,.217)
SRF	(.616,.412,.376)
SBS	(.582,.443,.428)
MCR	(.344,.696,.294)

Similarly, weighted product model is performed via Eq. (32). The weighted product model result is illustrated in Table XIV.

TABLE XIV. WEIGHTED PRODUCT MODEL

	$\tilde{Q}^{(2)}$
SPR	(.282,.768,.244)
DRP	(.802,.214,.218)
SRF	(.614,.413,.377)
SBS	(.581,.444,.429)
MCR	(.341,.698,.293)

Next, the $\tilde{Q}$ values of alternatives are calculated by Eq. (33). The results are summarized in Table XV with φ of .5.

TABLE XV. $\tilde{Q}$ VALUES ($\varphi = .5$)

	$\varphi\tilde{Q}^{(1)}$	$(1-\varphi)\tilde{Q}^{(2)}$	$\tilde{Q}$
SPR	(.205,.875,.179)	(.202,.876,.177)	(.285,.767,.245)
DRP	(.635,.461,.202)	(.634,.462,.203)	(.802,.213,.218)
SRF	(.46,.642,.309)	(.459,.643,.31)	(.615,.413,.377)
SBS	(.432,.665,.349)	(.431,.666,.35)	(.581,.443,.428)
MCR	(.247,.834,.218)	(.245,.835,.216)	(.342,.697,.294)

Finally, score function values of $\tilde{Q}$ are estimated with the help of Eq. (34) for the ranking of alternatives. The ranking values of alternative irrigation methods for efficient use of water resources are visualized in Fig. 8.

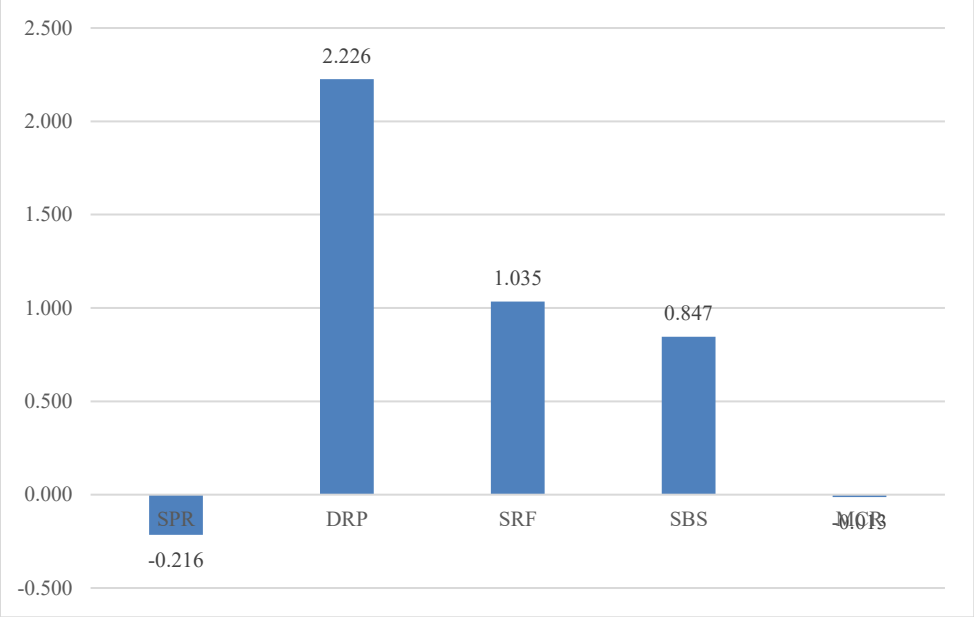


Fig. 8. Defuzzified Q values.

As can be seen, defuzzified Q values in Fig. 8, the most suitable alternative irrigation method for efficient use of water resources is drip irrigation with 2.226.

C. Sensitivity Analysis

Calculations are performed with different φ values and the results are compared. This tests the sensitivity of the results. The ranking values based on φ values are summarized in Table XVI.

TABLE XVI. RESULTS BY φ

	0	.1	.2	.3	.4	.5	.6	.7	.8	.9	1
SPR	-.221	-.220	-.219	-.218	-.217	-.216	-.214	-.213	-.212	-.211	-.210
DRP	2.222	2.223	2.224	2.225	2.225	2.226	2.227	2.228	2.229	2.229	2.230
SRF	1.032	1.032	1.033	1.033	1.034	1.035	1.035	1.036	1.037	1.037	1.038
SBS	.845	.845	.845	.846	.846	.847	.847	.847	.848	.848	.849
MCR	-.016	-.016	-.015	-.014	-.014	-.013	-.012	-.012	-.011	-.010	-.010

As can be understood from ranking scores of alternatives in Table XVI, the ranks of alternatives are the same. In other words, the results are reliable and consistent.

D. Comparative Analysis

To validate the results, a second method is used to compare them. The RAWEC method is preferred for this purpose. The crisp values in Table XI are used. The comparative results are presented in Fig. 9.

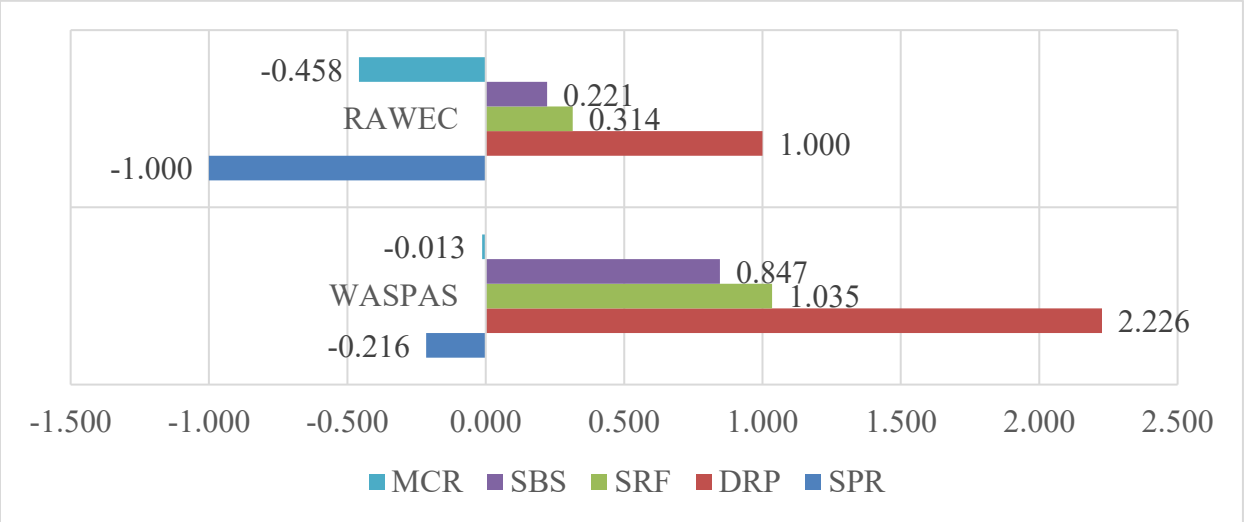


Fig. 9. Comparative analysis for ranking.

Pearson and Spearman correlation coefficients are calculated to determine the consistency between the results of the two methods. These coefficients are 0.972 and 1, respectively. High correlations indicate that the results are valid.

V. Discussion

Applicability, or technological suitability, is one of the key criteria when determining alternative irrigation methods for the efficient use of water resources in agriculture. This is because implementing innovative strategies and leveraging the power of technology can increase the efficient use of water resources in agriculture. This can be achieved through the combined use of artificial intelligence, automated water supply systems, and IoT-based precision irrigation systems in industrial wastewater treatment [21]. In other words, promoting modern and improved water use through irrigation practices and other smart approaches is crucial for sustainable water use [22]. In this context, Et-Taibi et al. [23] argued that IoT-based smart agriculture could be a promising solution. In their study, they introduce a cloud-based smart irrigation system to connect numerous small-scale smart farms and centralize the data they obtain. The system optimizes irrigation water use through comprehensive big data collection, storage, and analysis. Xing and Wang [24] summarized recent advances in molecular breeding, precision agriculture, and innovative water management techniques aimed at improving crop drought resilience, soil health, and overall agricultural productivity. This is because the increasing challenges of climate change and water scarcity make it imperative to increase agricultural productivity and sustainability, especially in arid regions.

Environmental impacts have been identified as another important criterion in determining alternative irrigation methods for the efficient use of water resources in agriculture. Indeed, while the use of water resources has a certain impact on the ecological conditions of a region, it is possible to address three dimensions of environmental impact: wastewater discharge, non-point pollution, and carbon emissions [25]. In addition, the effective application of computerization in the efficient use of water resources in agriculture ensures the improvement of environmental impacts and contributes to the environmentally conscious use of water resources [26]. Kalfas et al. [27] extensively evaluate the link between land use planning, water resources, and global climate change in their study. They state that proper land use planning can guide the establishment of waste management systems that minimize methane emissions and that land use planning affects agricultural practices. On the other hand, Keson et al. [28] aimed to evaluate the performance of land, water and climate relationship in his study using geographic information systems-based tools for optimized planning and management of sustainable production practices.

Drip irrigation [29] is one of the most important alternatives for determining alternative irrigation methods for the efficient use of water resources in agriculture. Drip irrigation is one of the most effective ways to integrate water and fertilizer for productivity in agriculture. Proper application of drip irrigation can reduce nutrient loss and emissions while maintaining nutrient balance in the soil (Yang et al., 2024). In drip irrigation, water, nutrients, and other essential growth substances are precisely delivered directly to the plant's root zone through a hole. This quickly restores plant moisture and nutrient levels, minimizes water stress, and improves overall quality, growth, and productivity [30]. In this context, Sanchis-Ibor et al. [31] focused on the process of switching to drip irrigation in Acequia Real del Júcar (Valencia, Spain). Their aim is to analyze how the estimation and distribution of expected water savings vary across different water planning tools and how they are perceived by the various actors involved in this process.

VI. CONCLUSION

The aim of this study is to develop a holistic and methodologically advanced decision-making model that enables the identification of the most appropriate alternative irrigation methods for the efficient use of water resources in agriculture. To this end, a novel hybrid framework integrating spherical fuzzy sets, machine learning, MEREC, and WASPAS methods is proposed. Evaluations obtained from ten domain experts were transformed into spherical fuzzy numbers to capture hesitation and uncertainty; expert importance weights were objectively derived using machine learning; criterion weights were determined through the MEREC method; and alternative irrigation methods were ranked using WASPAS.

Beyond its technical outcomes, the primary research contribution of this study lies in advancing the state of the art in AI-assisted multi-criteria decision-making for agricultural water management. Unlike existing studies that predominantly rely on static expert-based fuzzy weighting and conventional ranking schemes, the proposed framework introduces a structured human–AI collaborative mechanism that simultaneously addresses uncertainty modeling, objective expert differentiation, and compensatory–noncompensatory alternative evaluation within a unified architecture. In this sense, the study moves beyond incremental tool-level efficiency improvements and offers a conceptually distinct decision-support paradigm that enhances methodological robustness and interpretability in complex resource management problems. The empirical findings indicate that feasibility and technological suitability constitute the most influential criterion, followed by environmental impacts, while drip irrigation emerges as the most suitable alternative for efficient water use. These results not only corroborate prior empirical insights but also demonstrate how advanced hybrid AI–fuzzy frameworks can yield more nuanced and reliable decision outcomes under uncertainty.

Nevertheless, the study has certain theoretical and technical limitations. The relatively small number of experts, the focus on a specific regional or sectoral context, and the consideration of only seven criteria constrain the generalizability of the findings. From a technical perspective, the machine learning–based expert weighting process is sensitive to dataset size and diversity, which may lead to variability across different samples. In addition, while spherical fuzzy modeling provides a robust representation of uncertainty, it entails relatively high computational complexity. Future research is therefore encouraged to incorporate larger and more diverse expert panels, extend the model to different geographic and agricultural contexts, integrate additional criteria such as socioeconomic and climatic variables, and combine the proposed framework with other AI-driven decision-support systems. Such extensions would further strengthen the generalizability of the model and consolidate its contribution to both methodological research and practical decision-making in sustainable agricultural water management.

REFERENCES

[1] Ali, S., Zahid, A., Fatima, A., Ahmad, M., Chattha, M. B., Raza, A., ... & Anwar, S. (2025). Climate Resilient Agriculture for Ensuring Food Security. In Climate Resilient and Sustainable Agriculture: Volume 1: Adaptation and Mitigation Strategies (pp. 357-390). Cham: Springer Nature Switzerland.

[2] Srivastav, A. L., Dhyani, R., Ranjan, M., Madhav, S., & Sillanpää, M. (2021). Climate-resilient strategies for sustainable management of water resources and agriculture. Environmental Science and Pollution Research, 28(31), 41576-41595.

[3] Vedovello, P., Sanches, L. V., da Silva Teodoro, G., Majaron, V. F., Bortoletto-Santos, R., Ribeiro, C., & Putti, F. F. (2024). An overview of polymeric hydrogel applications for sustainable agriculture. Agriculture, 14(6), 840.

[4] Singh, R., & Singh, S. (2025). A review of Indian-based drones in the agriculture sector: Issues, challenges, and solutions. Sensors, 25(15), 4876.

[5] Yadav, M., Vashisht, B. B., Jalota, S. K., Jyolsna, T., Singh, S. P., Kumar, A., ... & Singh, G. (2024). Improving water efficiencies in rural agriculture for sustainability of water resources: a review. Water Resources Management, 38(10), 3505-3526.

[6] Tariq, S., Mubeen, M., & Ali, M. (2025). Ongoing Programs in On-Farm Water Management. In Innovations in Agricultural Water Management: Risks and Solutions (pp. 263-276). Cham: Springer Nature Switzerland.

[7] Saini, L., Sharma, K., & Kumar, P. (2024). Water efficiency in agriculture as a vital approach toward water management in rural areas. In Water Resources Management for Rural Development (pp. 127-138). Elsevier.

[8] Yasmeen, R., Hao, G., Ye, Y., Shah, W. U. H., & Tang, C. (2023). The synergy of water resource agglomeration and innovative conservation technologies on provincial and regional water usage efficiency in China: A super SBM-DEA approach. Water, 15(19), 3524.

[9] Ali, A., Hussain, T., & Zahid, A. (2025). Smart irrigation technologies and prospects for enhancing water use efficiency for sustainable agriculture. AgriEngineering, 7(4), 106.

[10] Raimondi, A., Quinn, R., Abhijith, G. R., Becciu, G., & Ostfeld, A. (2023). Rainwater harvesting and treatment: State of the art and perspectives. Water, 15(8), 1518.

[11] Chauhdary, J. N., Li, H., Jiang, Y., Pan, X., Hussain, Z., Javaid, M., & Rizwan, M. (2023). Advances in sprinkler irrigation: a review in the context of precision irrigation for crop production. Agronomy, 14(1), 47.

[12] Bhavsar, D., Limbasia, B., Mori, Y., Aglodiya, M. I., & Shah, M. (2023). A comprehensive and systematic study in smart drip and sprinkler irrigation systems. Smart Agricultural Technology, 5, 100303.

[13] Karamian, F., Mirakzadeh, A. A., & Azari, A. (2021). The water-energy-food nexus in farming: Managerial insights for a more efficient consumption of agricultural inputs. Sustainable Production and Consumption, 27, 1357-1371.

[14] Rokicki, T., Perkowska, A., Klepacki, B., Bórawski, P., Bełdycka-Bórawska, A., & Michalski, K. (2021). Changes in energy consumption in agriculture in the EU countries. Energies, 14(6), 1570.

[15] Yang, M., Zhu, Y., Zhao, Y., Li, C., Zhang, Y., Fan, Y., ... & Kang, M. (2024). Life cycle water and energy consumption and efficiency analysis of major crops in China. Journal of Cleaner Production, 467, 142899.

[16] Pomoni, D. I., Koukou, M. K., Vrachopoulos, M. G., & Vasiliadis, L. (2023). A review of hydroponics and conventional agriculture based on energy and water consumption, environmental impact, and land use. Energies, 16(4), 1690.

[17] Orlov, A. A., Akhmetshin, T. N., Horvath, D., Marcou, G., & Varnek, A. (2025). From high dimensions to human insight: exploring dimensionality reduction for chemical space visualization. Molecular Informatics, 44(1), e202400265.

[18] Tarafdar, A., Shaikh, A., Bhowmik, D., Majumder, P., Pamucar, D., Simic, V., & Bera, U. K. (2025). Integration of data-driven T-spherical fuzzy mathematical models for evaluation of electric vehicles: Response to electric vehicle market demands. Renewable and Sustainable Energy Reviews, 223, 116008.

[19] Seikh, M. R., & Chatterjee, P. (2025). Sustainable strategies for electric vehicle adoption: A confidence level-based interval-valued spherical fuzzy MEREC-VIKOR approach. Information Sciences, 699, 121814.

[20] Yücenur, G. N., & Maden, A. (2025). Location selection for a photovoltaic agricultural with f-PIPRECIA and WASPAS methods: A case study. Energy, 314, 134179.

[21] Alharbi, S., Felemban, A., Abdelrahim, A., & Al-Dakhil, M. (2024). Agricultural and Technology-based strategies to improve water-use efficiency in Arid and Semiarid areas. Water, 16(13), 1842.

[22] Iyiola, A. O., Kolawole, A. S., Ajayi, F. O., Ogidi, O. I., & Ogwu, M. C. (2024). Sustainable water use and management for agricultural transformation in Africa. In Water resources management for rural development (pp. 287-300). Elsevier.

[23] Et-Taibi, B., Abid, M. R., Boufounas, E. M., Morchid, A., Bourhnane, S., Hamed, T. A., & Benhaddou, D. (2024). Enhancing water management in smart agriculture: A cloud and IoT-Based smart irrigation system. Results in Engineering, 22, 102283.

[24] Xing, Y., & Wang, X. (2024). Precision agriculture and water conservation strategies for sustainable crop production in arid regions. Plants, 13(22), 3184.

[25] Cao, X., Wang, H., Zhang, B., Liu, J., & Yang, J. (2024). Sustainable management of land use patterns and water allocation for coordinated multidimensional development. Journal of Cleaner Production, 457, 142412.

[26] Pattanaik, S., Mehta, A., Dhillon, S. S., & Vinciarelli, A. (2025). Case studies: Successful implementation of automation for water quality assessment. Computational Automation for Water Security, 325-336.

[27] Kalfas, D., Kalogiannidis, S., Papaevangelou, O., & Chatzitheodoridis, F. (2024). Assessing the connection between land use planning, water resources, and global climate change. Water, 16(2), 333.

[28] Keson, J., Silalertruksa, T., & Gheewala, S. H. (2024). Integrating the land–water–climate nexus approach with spatial-based sustainable agriculture production. Agricultural Systems, 219, 104059.

[29] Yang, X., Zhang, L., & Liu, X. (2024). Optimizing water-fertilizer integration with drip irrigation management to improve crop yield, water, and nitrogen use efficiency: A meta-analysis study. Scientia Horticulturae, 338, 113653.

[30] Rambabu, G. V., Bridjesh, P., Kishore, N. P., & Sai, N. S. (2023). Design and development of a drip irrigation system. Materials Today: Proceedings.

[31] Sanchis-Ibor, C., Manzano-Juárez, J., & García-Mollá, M. (2024). Towards a new efficiency paradigm for drip irrigation? Changes in water allocation and management in irrigation and wetland systems. Agricultural Systems, 216, 103910.

Balancing Privacy and Acceptance: The Role of Anthropomorphism and Information Sensitivity in Autonomous Taxis

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***Abstract*—This study investigates how anthropomorphic interface design and information sensitivity influence users' acceptance of autonomous vehicles (AVS), and examines the underlying role of privacy concern and its boundary conditions in a commercial autonomous taxi context. Addressing prior research that has predominantly examined anthropomorphism or privacy concerns in isolation, this study employs a 2 × 2 experimental design to test the main interaction effects of anthropomorphism and information sensitivity on technology acceptance. The results demonstrate that both anthropomorphism and information sensitivity significantly affect users' acceptance of AV technology, with a significant interaction effect between the two. Specifically, when information sensitivity is high, lower levels of anthropomorphism lead to higher acceptance, whereas under low information sensitivity, anthropomorphic design enhances acceptance. Further analysis reveals that privacy concern mediates the relationship between anthropomorphism, information sensitivity, and technology acceptance. Moreover, cultural value orientation and technical familiarity moderate the effect of privacy concern on technology acceptance, such that the negative impact of privacy concern is attenuated among users with stronger collectivist orientations and higher levels of technical familiarity. By clarifying the sequential roles of design cues, privacy concern, and individual differences, this study reveals a dynamic balance mechanism between emotional engagement and perceived privacy risk in data-intensive mobility services. These findings advance understanding of privacy–acceptance dynamics and provide practical implications for the design and deployment of autonomous taxi interfaces.**

Keywords*—Anthropomorphism; information sensitivity; privacy concern; technology acceptance; individual cultural value; technical familiarity; autonomous taxis

I. Introduction

With the rapid development of smart cities, domains such as healthcare, smart parking, transportation, and public safety are becoming increasingly interconnected, allowing physical objects to provide intelligent services to citizens [1]. Among them, unmanned driving technology has become a vital part of modern transportation. Driverless taxis, exemplified by pilot projects in cities like Wuhan, China, are gaining global attention. Unlike traditional driving that relies on human control, autonomous driving depends on artificial intelligence and machine learning. For example, in Wuhan's "Radish Kuaipao" autonomous taxi service, safety officers monitor vehicles and intervene if necessary. Although such systems promise fewer accidents and higher efficiency, they raise concerns about privacy, security, and public acceptance [2].

Privacy is a particularly critical issue. As noted in [2], smart technologies often require large-scale personal data collection. In driverless taxis, this may involve continuous tracking and biometric data such as facial recognition.

Improper handling of such data can lead to misuse and privacy breaches. Moreover, users' perception of privacy risk strongly affects their acceptance. In [3], the authors found that greater privacy sensitivity reduces trust in autonomous vehicles, thereby lowering adoption willingness. Hence, balancing service efficiency and privacy protection remains a key challenge. Another important factor is anthropomorphism in driving behavior, which shapes user comfort and perception. In [4], the authors highlighted that vehicle behavior influences passengers' familiarity and perceived safety. In [5], the authors showed that intelligent in-vehicle voice agents using natural language processing can simulate human-like interaction, enhancing user experience. Similarly, [6] demonstrated that anthropomorphic driving increases trust and social acceptance. Technically, anthropomorphism does not involve data collection but rather evokes emotional and cognitive responses through perceived human-likeness. Thus, integrating anthropomorphic features effectively is essential for the broader acceptance of autonomous taxis. However, existing studies have largely examined privacy-related risks and anthropomorphic design cues as separate determinants of user acceptance, leaving their joint and potentially interactive effects insufficiently understood.

Despite the growing importance of autonomous taxis, most studies emphasize technical feasibility [7] rather than the socio-psychological mechanisms driving acceptance. Unlike privately owned autonomous vehicles, commercial autonomous taxi services involve transient usage, platform-based data governance, and limited user control, making privacy perceptions more salient and context-dependent. In particular, prior research has predominantly focused on privately owned autonomous vehicles, whereas commercial autonomous taxi services involve short-term use, platform-mediated data collection, and heightened information sensitivity, which may fundamentally alter users' privacy perceptions and acceptance mechanisms. While trust is central to understanding technology adoption [8], it cannot fully explain interactions involving privacy and anthropomorphism. Therefore, it is necessary to

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explore how these two dimensions jointly influence user acceptance.

This study proposes an integrative framework examining how anthropomorphism and information sensitivity influence technology acceptance, and investigates privacy concern as a mediating mechanism underlying this relationship. It further investigates whether anthropomorphic design can reduce perceived privacy risks and enhance willingness to use driverless taxis. Individual cultural value and technical familiarity are included as moderators to capture personal differences. These moderators are theoretically relevant because cultural orientation shapes how individuals weigh collective benefits against personal privacy risks, while technical familiarity influences users' perceived control and tolerance toward data-driven systems. To test these relationships, a 2×2 between-subjects experiment was conducted, manipulating anthropomorphism (high vs. low) and information sensitivity (high vs. low). Participants evaluated privacy concern and technology acceptance, and the moderating roles of culture and technical familiarity were analyzed using ANOVA and PROCESS procedures. This experimental approach enables a clear examination of both causal effects and interaction mechanisms between design cues and information characteristics, which are difficult to disentangle using survey-based or observational methods. By systematically manipulating anthropomorphism and information sensitivity, the study provides stronger internal validity in explaining users' acceptance of autonomous taxi services. Drawing upon the Privacy Calculus Framework, anthropomorphism theory, and the Technology Acceptance Model (TAM), this study bridges research on privacy protection and human-like design within autonomous mobility. It provides both theoretical insight and practical guidance for balancing efficiency, ethics, and psychological acceptance in the design and governance of driverless taxis in smart cities. While prior research has primarily addressed either privacy or anthropomorphism separately, little is known about their combined effect on user acceptance, especially in commercial AV contexts.

The remainder of this study is organized as follows: Section II reviews the relevant literature and develops the research questions. Section III shows the theoretical background of the research, research models and hypotheses. Section IV describes the experimental design, data collection procedures, measurement instruments, empirical results and hypothesis testing. Finally, Section V discusses the conclusions of the findings, acknowledges the limitations of the study, and outlines directions for future research.

II. Literature Review

A. Autonomous Driving Technology

AVs have evolved from early 20th-century visions into operational systems through decades of interdisciplinary research [9]. Early AVs operated in controlled environments, relying on infrastructure support, while advances in sensors, algorithms, and computation have enabled navigation in complex urban settings [10]. Pioneering projects, including Carnegie Mellon's Navlab and Germany's EUREKA initiative, laid the groundwork for partial automation, and Google's 2010 public-road tests accelerated global investment and research.

AV applications now span passenger transport and logistics, with companies such as Tesla and Waymo integrating automated driving assistance systems (ADAS) and partial self-driving features, while autonomous delivery vehicles undergo trials [11]. AV integration into intelligent transportation systems (ITS) leverages real-time data sharing and smart traffic infrastructure to improve efficiency and reduce congestion, prompting new considerations of human–machine interaction, privacy, and data governance [12].

Future AV development aims for full autonomy (SAE Level 5), yet technical challenges, including unpredictable traffic, adverse weather, and public trust, constrain adoption [13]. Progress relies on AI, deep learning, sensor fusion, and high-speed communication networks [14, 15, 16], alongside emerging ride-hailing platforms that may reshape transportation norms [17].

Privacy concerns are central, as AVs collect sensitive user data such as location, biometrics, and behavioral patterns [18]. Anthropomorphic AV interfaces—ranging from visual avatars to human-like behavioral cues—affect trust, emotional engagement, and privacy perception [19, 20]. User responses are moderated by individual cultural values (e.g., collectivism vs. individualism) and technical familiarity, influencing both privacy concern and technology acceptance.

In sum, successful AV adoption depends not only on technological advancement but also on human factors, including privacy perception, interface design, and cultural context. Integrating these considerations is essential for designing ethically responsible, user-centered autonomous mobility systems.

B. Information Sensitivity in Autonomous Vehicle Systems

Information sensitivity has become a critical concern in digital ecosystems, particularly in ITS and AVs, which rely on continuous data collection through sensors, GPS, and vehicle-to-infrastructure communications [21, 22]. Data ranges from geolocation and routing information to more sensitive types such as biometric identifiers and real-time behavioral patterns, elevating privacy risks beyond traditional transportation. Perceived sensitivity directly influences users' privacy concern and willingness to adopt AVs [23]. Regulatory and policy interventions, including GDPR and AV-specific strategies, emphasize user rights, informed consent, and data minimization [24, 25, 26].

Technological mechanisms, such as encryption, anonymization, and limited data collection, complement regulatory measures to mitigate privacy risks [27]. Transparency and user control—allowing data access, correction, or deletion—further enhance perceived safety [28]. Nonetheless, AV innovations continue to outpace existing protections, making perceived information sensitivity a key determinant of privacy concern and technology acceptance. User responses are also shaped by interface design, particularly anthropomorphic cues, which can mediate how sensitive data is perceived.

C. Anthropomorphism in Human-AV Interaction

Anthropomorphism involves attributing human-like traits to non-human agents, including AVs, via visual cues, language, or behavioral feedback, aiming to enhance user engagement, trust,

and comprehension [29, 30]. Such designs can reduce psychological distance and influence perceptions of data practices, though effects are context-dependent [31]. Emotional connection, transparency, and human-like responsiveness can increase perceived trust, safety, and enjoyment, fostering user acceptance [32, 33].

Privacy Concern (PC) reflects perceived vulnerability from personal data collection, which is crucial in AVs due to pervasive data capture [34]. Factors influencing PC include individual characteristics (age, education), socio-cultural background, prior privacy experiences, information sensitivity, perceived transparency, and technical familiarity [35, 36]. Elevated PC can reduce trust and perceived usefulness, thereby limiting Technology Acceptance (TA) [37].

Empirical evidence indicates that information sensitivity increases PC, which lowers TA [2, 18]. Anthropomorphic design can enhance trust and acceptance, but may also raise privacy concerns when systems appear highly human-like [19, 20]. Interaction effects show that high anthropomorphism combined with sensitive data amplifies privacy concerns, whereas low-sensitivity contexts allow anthropomorphism to primarily boost user satisfaction and adoption [38, 19]. This underscores the importance of balancing interface design with data sensitivity to optimize AV acceptance.

D. Moderating Effects of Individual Cultural Value and Technical Familiarity

The effects of information sensitivity and anthropomorphic design on PC and TA are moderated by Individual Cultural Value (ICV) and Technical Familiarity (TF). ICV dimensions, such as individualism–collectivism, influence privacy norms and risk tolerance: sensitivity to data is higher in individualistic cultures, while anthropomorphic cues may be perceived differently across cultures [39, 40]. TF shapes user evaluation of privacy and system functionality: higher TF can reduce PC by improving understanding of mitigation mechanisms, whereas low TF users rely more on human-like signals to assess unfamiliar systems [23]. Evidence suggests that these moderators interact, with cultural norms and technical knowledge jointly shaping trust, privacy perception, and acceptance [41, 42].

Despite progress, research gaps remain, particularly in commercial AV contexts such as autonomous taxis. Most studies focus on private vehicles, neglecting transactional, short-term interactions where data sensitivity and anthropomorphic design may fluctuate across service stages—from navigation to payment. The dynamic interplay of anthropomorphism and information sensitivity, and their amplification of PC, is underexplored. Additionally, the moderating roles of ICV and TF in such service-based environments require empirical validation to inform culturally adaptive and user-specific design principles [39] [40].

Future research should adopt integrated, mediated-moderated frameworks that examine combined effects of anthropomorphism and information sensitivity in commercial AV adoption, ensuring that system design balances usability, trust, and ethical data practices.

Basic the privacy theory and anthropomorphism theory, aiming to clarify the psychological processes through which human-like design cues and varying levels of sensitive data shape user perceptions in data-intensive AV systems. Three research questions guide this investigation:

RQ1: How do anthropomorphic design and information sensitivity, individually and interactively, affect users' privacy concerns?

RQ2: Does privacy concern mediate the relationship between anthropomorphism, information sensitivity, and technology acceptance?

RQ3: Do individual cultural value and technical familiarity moderate the effect of privacy concern on technology acceptance?

III. Methodology

A. Theoretical Background

Privacy has long been central to understanding individuals' decisions about data disclosure and technology use. In [43], the authors defined privacy as control over one's personal information—deciding when, how, and to what extent data are shared. In digital contexts such as autonomous driving, this control becomes complex and psychologically salient. Users weigh perceived risks and benefits of sharing data, consistent with the Privacy Calculus Framework. In this study, information sensitivity represents varying privacy costs, allowing examination of how perceived data risk influences emotional responses (privacy concern) and behavioral intentions (technology acceptance).

Anthropomorphism theory provides a complementary perspective. In [44], the authors suggest that human-like cues enhance engagement and trust by evoking social connection. In autonomous vehicles, anthropomorphic interfaces may improve approachability and trustworthiness, thereby increasing perceived usefulness and lowering adoption barriers. However, from a privacy calculus viewpoint, heightened human-likeness can also increase perceived monitoring or judgment, amplifying privacy concern under high information sensitivity. Thus, anthropomorphism may simultaneously increase trust and privacy risk, creating a psychological trade-off that shapes user acceptance.

To integrate these mechanisms, this study extends the Technology Acceptance Model [45] by incorporating privacy concern as a mediating variable derived from the privacy calculus. Privacy concern reflects the outcome of users' cost–benefit evaluations and connects design characteristics (anthropomorphism, information sensitivity) to behavioral intentions. Furthermore, consistent with extended TAM frameworks, individual factors—cultural value orientation and technical familiarity—are introduced as moderators. Together, these theories form a comprehensive model explaining how emotional engagement and privacy risk jointly determine users' adoption of autonomous driving technologies.

B. Research Model and Hypotheses

Most prior studies on autonomous driving have focused on private self-driving vehicles. This study instead situates its

research in the commercial driverless taxi context, emphasizing differences between private ownership and service-based use. This perspective aligns with real-world shared mobility applications while retaining theoretical generalizability across contexts.

The model of this study is constructed based on the relationship between autonomous driving and privacy, anthropomorphism and technology acceptance. However, unlike most studies that focus on "private self-driving vehicles" and ordinary human-machine interaction, this study clearly sets the research scenario as "unmanned taxis for business use". This setting not only highlights the differences from previous literature but also ensures that the research conclusions are closer to the context of shared mobility and commercial applications. Therefore, the research model proposed in this study should be understood as its applicability in the scenario of driverless taxis. Meanwhile, since the core variables and relationship mechanisms of this study have cross-scenario applicability, it is only necessary to emphasize the limitations of the research context (autonomous taxi) on the basis of the existing research framework, rather than introducing brand-new variables separately.

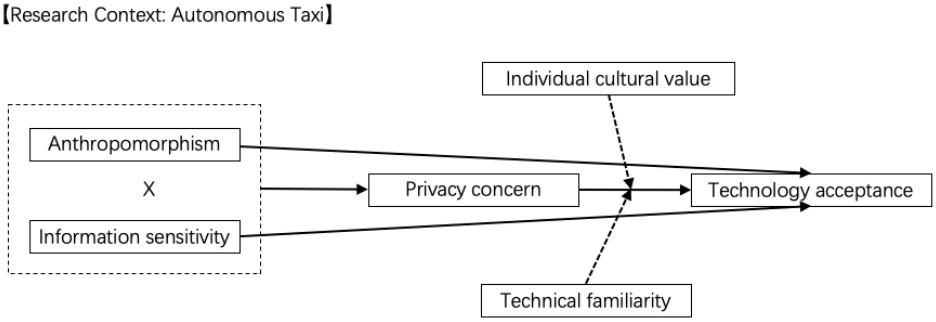


Fig. 1. Research framework.

The proposed research model (Fig. 1) employs a 2×2 experimental design manipulating Anthropomorphism (high vs. low) and Information Sensitivity (high vs. low). These factors jointly influence privacy concern, which mediates their effect on technology acceptance. Two moderators—Individual Cultural Value and Technical Familiarity—are included to test individual differences in this relationship. The model extends the Privacy Calculus Framework by linking design and data characteristics to perceived risk, and reconceptualizes anthropomorphism within privacy-sensitive environments, testing whether human-likeness enhances or hinders trust.

Prior studies indicate that anthropomorphism affects responses to sensitive information [46], while information sensitivity directly influences privacy concern [47, 48]. Accordingly, this study examines how these two factors shape users' privacy perception and acceptance.

H1: Anthropomorphic design positively influences technology acceptance when information sensitivity is low.

H2: High information sensitivity significantly reduces technology acceptance.

In addition, anthropomorphism and information sensitivity are expected to interact. High anthropomorphism under high sensitivity conditions may elicit the highest privacy concern [46, 49], with privacy concern mediating this relationship [50].

H3: Anthropomorphism and information sensitivity interact such that the positive effect of anthropomorphism on technology acceptance weakens under high information sensitivity.

H4: Privacy concern mediates the relationship among anthropomorphism, information sensitivity, and technology acceptance.

Cross-cultural studies suggest that cultural orientation moderates the effect of privacy concern on acceptance [51, 52]. Technical familiarity also moderates users' evaluation of privacy and system reliability [53, 54].

H5: Individual cultural value moderates the relationship between privacy concern and technology acceptance, such that under a high collectivist orientation, the negative effect of privacy concern is weaker.

H6: Technical familiarity moderates the relationship between privacy concern and technology acceptance, such that at high familiarity levels, the negative effect of privacy concern is weaker.

IV. Experiments and Results

Previous research has consistently demonstrated that anthropomorphic design shapes user experience and trust in human–computer interaction (HCI). For example, [55] showed that human-like facial expressions combined with anthropomorphic language elicited more positive user responses than mechanical dialogue, while [56] confirmed that anthropomorphic visual design enhances user perception and engagement. Extending this line of inquiry, [29] found that augmented reality (AR) agents equipped with environmental sensing (e.g., motion tracking) may implicitly signal sensitive data collection, yet users' privacy perceptions remain insufficiently examined. Similarly, [6] demonstrated, respectively, that physically anthropomorphic vehicle features and virtual agents can shape privacy-related responses in AV contexts.

Building on these findings, the present research conducted experiments to empirically test the proposed model. Firstly, examined the main and interaction effects of anthropomorphism and information sensitivity on privacy concern and technology

acceptance, whereas it further explored the moderating roles of individual cultural value and technical familiarity. Both studies adopted a 2 × 2 between-subjects design manipulating anthropomorphism (high vs. low) and information sensitivity (high vs. low).

A. Experiments

Participants were randomly assigned to one of four simulated AV interfaces (Fig. 2). Anthropomorphism manipulation: The high-anthropomorphism condition featured a human-like avatar with expressive facial features and conversational dialogue, while the low condition used a minimalistic, non-human-like interface [57, 58]. Information sensitivity manipulation: High-sensitivity interfaces indicated the collection of biometric and emotional data, whereas low-sensitivity interfaces collected only basic trip information [59, 60]. Data-use prompts clarified scope and storage—for example, "Facial information verified for risk control" versus "Only current location obtained; data stored locally" [61].



Fig. 2. Screenshot of the experimental video.

After exposure to an AV scenario like Fig. 2, participants completed 7-point Likert questionnaires measuring perceived anthropomorphism, information sensitivity, privacy concern, and technology acceptance. In addition, the study also included an Individual Cultural Value Scale adapted from Hofstede's cultural dimensions (e.g., [62]) and a Technical Familiarity Scale, which assessed participants' self-reported familiarity and experience with digital technologies. Data were collected via Wenjuanxing with attention checks for quality.

B. Results

To examine the proposed mediation and moderated mediation relationships, this study employed the PROCESS macro for SPSS [63]. The PROCESS procedure is a regression-based analytical approach that allows for direct estimation of mediation, moderation, and conditional process (moderated mediation) effects using bootstrapping. Unlike structural equation modeling (SEM), which requires a relatively large sample size and focuses on latent constructs and overall model fit, PROCESS is particularly suitable for experimental data with observed variables and clear causal directions. Its main advantage lies in its ability to test indirect and conditional effects efficiently without imposing stringent distributional assumptions. Previous studies have employed the PROCESS macro to examine mediation and moderation effects in the context of privacy concern and technology acceptance. For instance, [64] examined the relationships between attitude, privacy concern, and behavioral intention using PROCESS to estimate mediation and moderation effects. Similarly, [65] applied PROCESS to test the moderating role of personality traits in technology acceptance. In this research, PROCESS Model 4 was used to test the mediation of privacy concern, and Model 14 was applied to examine the moderated mediation effects of individual cultural value and technical familiarity. This analytical strategy ensured a robust and transparent examination of the hypothesized causal mechanisms.

TABLE I. DESCRIPTIVE STATISTICS AND CORRELATION ANALYSIS

Variable	M	SD	PC	TA	ICV	TF
PC	3.284	1.466	—	-.237**	-.001	-.024
TA	4.576	1.640	-.237**	—	.775**	.764**
ICV	4.469	1.743	-.001	.775**	—	.894**
TF	4.670	1.946	-.024	.764**	.894**	—

Note: M and SD are used to represent mean and standard deviation, respectively. Values in parentheses are Pearson correlation coefficients. *p < .05, **p< .01.

Before hypothesis testing, preliminary analysis were conducted to ensure the validity of the manipulations and reliability of the measures. Table I presents the descriptive statistics and Pearson correlation coefficients among the main variables. PC showed a significant negative correlation with TA ($r = –.237$, $p < .01$), indicating that higher PC is associated with lower acceptance of autonomous taxis. ICV and TF were both strongly and positively correlated with TA ($r = .775$, $p < .01$; $r = .764$, $p < .01$, respectively), suggesting that individuals with higher collectivist tendencies and greater technical familiarity tend to show higher levels of acceptance. Moreover, ICV and TF were highly correlated with each other ($r = .894$, $p < .01$), implying potential conceptual overlap or shared variance between these two moderators. No significant correlations were found between Privacy Concern and either ICV or TF.

TABLE II. MANIPULATION TEST RESULTS (INDEPENDENT SAMPLE T-TEST)

Manipulate variable	Condition	M	SD	t	df	p
Anthropomorphism	Low (n=100)	2.415	1.062	-19.713	198	< .001
	High (n=100)	5.435	1.105			
Information Sensitivity	Low (n=100)	2.540	1.259	-15.231	198	< .001
	High (n=100)	5.390	1.385			

Note: M and SD are used to represent mean and standard deviation, respectively.

Table II presents the results of the manipulation checks for anthropomorphism and information sensitivity. An independent-sample t-test confirmed that the manipulation of anthropomorphism was successful. Participants in the high-anthropomorphism condition ($M = 5.435$, $SD = 1.105$) perceived significantly higher levels of anthropomorphism than those in the low-anthropomorphism condition ($M = 2.415$, $SD = 1.062$), $t(198) = –19.713$, $p < .001$.

Similarly, the manipulation of information sensitivity was effective. Participants in the high-sensitivity condition ($M = 5.390$, $SD = 1.385$) perceived significantly higher information sensitivity than those in the low-sensitivity condition ($M = 2.540$, $SD = 1.259$), $t(198) = –15.231$, $p < .001$. These results indicate that both experimental manipulations were successful, validating the subsequent hypothesis testing.

TABLE III. ANALYSIS OF VARIANCE RESULTS OF ANTHROPOMORPHISM AND INFORMATION SENSITIVITY ON TECHNOLOGY ACCEPTANCE

Source	Sum of Squares	df	Mean Square	F	p
Anthro (A)	16.965	1	16.965	7.255	.008
InfoSens (B)	41.633	1	41.633	17.803	< .001
A × B	18.453	1	18.453	7.891	.005
Error	458.349	196	2.339		
Total	4723.813	200			

Note: Anthro = Anthropomorphism, InfoSens = Information Sensitivity.

A two-way ANOVA (Table III) was conducted to examine the effects of anthropomorphism and information sensitivity on technology acceptance. Results indicated that anthropomorphism had a significant main effect [$F(1,196) = 7.255$, $p = .008$], and information sensitivity also had a significant main effect [$F(1,196) = 17.803$, $p < .001$]. Moreover, the interaction effect between anthropomorphism and information sensitivity was significant [$F(1,196) = 7.891$, $p = .005$].

As illustrated in Fig. 3, when information sensitivity was low (blue line), the level of technology acceptance remained relatively high regardless of anthropomorphism. However, under high information sensitivity (red line), technology acceptance decreased sharply as anthropomorphism increased. This suggests that the positive influence of anthropomorphic design is dampened under conditions of high information sensitivity, supporting the hypothesized interaction effect.

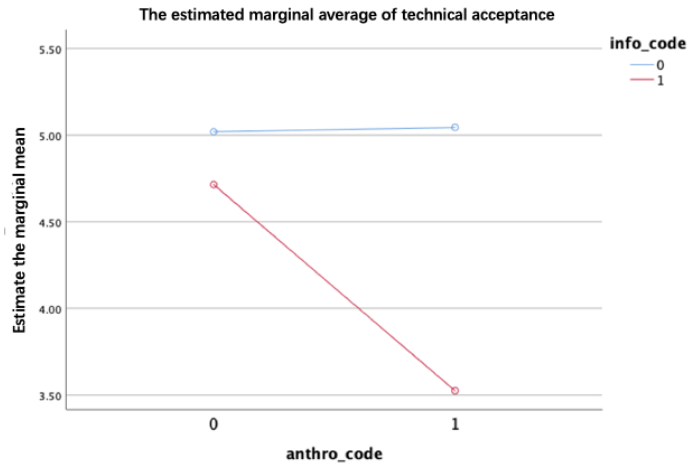


Fig. 3. The interaction graph of anthropomorphism and information sensitivity on technology acceptance.

TABLE IV. SIMPLE MEDIATION ANALYSIS (PROCESS MODEL 4)

Path	Coefficient	SE	t	p	95%CI
Interaction → PC	2.8617	0.1273	22.4757	< .0001	[2.6106, 3.1127]
PC → TA	0.3066	0.1378	2.2244	.0273	[0.0348, 0.5784]
Direct Effect					
Interaction → TA	-2.2790	0.4653	-4.8977	< .0001	[-3.1966, -1.3613]
Indirect Effect					
Interaction → PC → TA	0.8773	0.3709	-	-	[0.1053, 1.5707]

Note: N = [200]. Bootstrapping sample size = 5000. CI = confidence interval. Interaction = Anthropomorphism × Information Sensitivity interaction.

To further examine whether privacy concern mediates the effect of the interaction between anthropomorphism and information sensitivity on technology acceptance, a simple mediation analysis was conducted using PROCESS Model 4 [63]. As shown in Table IV, the interaction between anthropomorphism and information sensitivity had a significant positive effect on privacy concern ($\beta = 2.8617$, $t = 22.4757$, $p < .001$, 95% CI [2.6106, 3.1127]). In turn, privacy concern had a significant negative effect on technology acceptance ($\beta = 0.3066$, $t = 2.2244$, $p = .0273$, 95% CI [0.0348, 0.5784]). The direct effect of the interaction on technology acceptance remained significant ($\beta = -2.2790$, $t = -4.8977$, $p < .001$, 95% CI [–3.1966, –1.3613]), indicating a partial mediation effect. Moreover, the bootstrapped indirect effect through privacy concern was significant ($\beta = 0.8773$, 95% CI [0.1053, 1.5707]), as the confidence interval did not include zero. This finding suggests that the interaction between anthropomorphism and information sensitivity influences technology acceptance partly via increased privacy concern, supporting H4.

TABLE V. MODERATED MEDIATION ANALYSIS (PROCESS MODEL 14)

Moderator	Effect	Coeff.	SE	t	p	95%CI
ICV	Interaction → PC	2.8617	0.1273	22.48	< .001	[2.6106, 3.1127]
	PC → TA	0.3425	0.1419	2.41	.0167	[0.0627, 0.6224]
	ICV → TA	0.9729	0.0893	10.89	< .001	[0.7967, 1.1491]
	PC × ICV	-0.0857	0.0251	-3.42	.0008	[-0.1351, -0.0363]
	Direct Effect					
	Interaction → TA	-0.9985	0.2965	-3.37	.0009	[-1.5832, -0.4137]
		Effect	BootSE			BootCI
	Index of Moderated Mediation	-0.2452	0.0747			[-0.3948, -0.1053]
TF	Interaction → PC	2.8617	0.1273	22.48	< .001	[2.6106, 3.1127]
	PC → TA	0.4426	0.1403	3.16	.0019	[0.1660, 0.7192]
	TF → TA	0.8865	0.0836	10.61	< .001	[0.7217, 1.0514]
	PC × TF	-0.0852	0.0234	-3.64	.0003	[-0.1313, -0.0391]
	Direct Effect					
	Interaction → TA	-1.2785	0.2986	-4.28	< .001	[-1.8674, -0.6897]
		Effect	BootSE			BootCI
	Index of Moderated Mediation	-0.2437	0.0744			[-0.3979, -0.1032]

Note: N = [200]. Bootstrapping sample size = 5000.

To further test whether ICV and TF moderate the indirect effect of the interaction between anthropomorphism and information sensitivity on technology acceptance through privacy concern, two moderated mediation analyses were conducted using PROCESS Model 14 [63].

As shown in Table V, for ICV, the interaction between anthropomorphism and information sensitivity significantly predicted privacy concern ($\beta = 2.8617$, $t = 22.48$, $p < .001$, 95% CI [2.6106, 3.1127]). Privacy concern had a significant negative effect on technology acceptance ($\beta = 0.3425$, $t = 2.41$, $p = .0167$, 95% CI [0.0627, 0.6224]), and the interaction between privacy concern and ICV was also significant ($\beta = -0.0857$, $t = -3.42$, $p = .0008$, 95% CI [–0.1351, –0.0363]). The index of moderated mediation was significant ($\beta = -0.2452$, BootSE = 0.0747, 95% CI [–0.3948, –0.1053]), indicating that the indirect effect of the interaction on technology acceptance through privacy concern was contingent on individual cultural value. Specifically, the negative impact of privacy concern on technology acceptance was weaker among individuals with higher collectivist cultural values, supporting H5.

Similarly, for TF, the interaction term significantly predicted privacy concern ($\beta = 2.8617$, $t = 22.48$, $p < .001$), and the effect of privacy concern on technology acceptance was significant ($\beta = 0.4426$, $t = 3.16$, $p = .0019$, 95% CI [0.1660, 0.7192]). The interaction between privacy concern and TF was significant ($\beta = -0.0852$, $t = -3.64$, $p = .0003$, 95% CI [–0.1313, –0.0391]), and the index of moderated mediation was also significant ($\beta = -0.2437$, BootSE = 0.0744, 95% CI [–0.3979, –0.1032]). This pattern indicates that the negative influence of privacy concern on technology acceptance diminishes as users' technical familiarity increases, supporting H6.

C. Discussion

This study examined how anthropomorphic interface design and information sensitivity jointly shape users' acceptance of AVs, emphasizing the mediating role of privacy concern and the moderating effects of individual cultural value and technical familiarity. Drawing upon the Privacy Calculus Framework and the TAM, the findings reveal that user acceptance of AVs results from a dynamic balance between emotional engagement and perceived data risk.

Consistent with expectations, both anthropomorphism and information sensitivity significantly influenced technology acceptance. High anthropomorphism enhanced acceptance only when information sensitivity was low, whereas under high information sensitivity, anthropomorphic designs reduced acceptance by intensifying privacy concerns. This interaction indicates that anthropomorphism does not universally promote positive user attitudes but instead functions as a context-dependent cue that can either facilitate or hinder acceptance depending on the perceived privacy risk. The results highlight a privacy–affect trade-off: while human-like design enhances social connection and trust, it simultaneously heightens users' sense of vulnerability when sensitive data is involved.

The mediation analysis further supports that privacy concern partially explains the relationship between design cues and acceptance, confirming its central role in the privacy calculus process. Users weigh the benefits of engaging in human-like interaction against the risks of personal data exposure. This partial mediation also suggests that other factors, such as trust and perceived control, may concurrently influence acceptance decisions. Together, these results extend the TAM by positioning privacy concern as a critical antecedent in data-intensive technologies, aligning with the growing recognition that emotional design and risk perception jointly determine user behavior in autonomous systems.

Moreover, the moderated mediation analyses indicate that both individual cultural value and technical familiarity significantly weaken the negative impact of privacy concern on acceptance. Users with stronger collectivist orientations or higher technical familiarity were less deterred by privacy concerns, suggesting that cultural and experiential differences shape how individuals interpret and manage perceived risks. Notably, although these moderators were not directly correlated with privacy concern, they effectively altered the strength of its influence on behavioral intention, reinforcing the idea that user characteristics operate as boundary conditions rather than independent predictors. This finding advances current understanding of cross-cultural and experiential effects in human–technology interaction by demonstrating that acceptance dynamics are not uniform across user groups.

Theoretically, these findings contribute to the refinement of both the Privacy Calculus Framework and TAM by integrating emotional, cognitive, and cultural dimensions into a unified model of technology acceptance. The results reveal that anthropomorphism's benefits depend on contextual and personal factors, and that privacy concern serves as a psychological bridge connecting interface design and user adoption. Practically, the study suggests that designers and policymakers should exercise caution in applying anthropomorphic features in high-sensitivity contexts, as such designs may inadvertently increase users' privacy anxiety. Privacy-sensitive interface strategies—such as adaptive disclosure, transparent data communication, and culturally attuned messaging—can help balance emotional engagement and perceived security. Moreover, enhancing users' technical literacy and offering customization options for privacy settings may mitigate negative perceptions without compromising usability.

In summary, this study underscores that acceptance of autonomous vehicles is governed by a dynamic tension between human-like engagement and data privacy concerns. Anthropomorphism enhances acceptance only under low perceived risk, while privacy concern mediates and individual differences moderate this relationship. These findings enrich theoretical perspectives on human–AI interaction and provide actionable guidance for developing human-centered, context-aware, and privacy-responsible autonomous vehicle systems.

V. Conclusion and Implications

A. Conclusion

This research investigated how anthropomorphic design, information sensitivity, and individual differences influence privacy concern and technology acceptance in AVs. The findings reveal that when anthropomorphic features are combined with highly sensitive information, users experience greater privacy concern, which subsequently lowers technology acceptance. Conversely, under low information sensitivity, anthropomorphic elements enhance trust without significantly increasing privacy concern. Moreover, individual characteristics—particularly individual cultural values and technical familiarity—moderate these relationships. Users with stronger individualistic orientations or lower levels of technical familiarity exhibit heightened privacy concern in response to anthropomorphic cues. These results highlight the importance of context-aware design and the need to tailor AV interfaces to user characteristics.

Theoretically, this study extends privacy research into the autonomous mobility domain and identifies a dynamic balance mechanism in interface design. It underscores the dual role of anthropomorphism—serving as both a trust-enhancing and a privacy-threatening factor. Practically, the findings emphasize the necessity for adaptive AV interfaces, transparent data communication, and culturally and technically sensitive design strategies that foster acceptance while safeguarding user privacy.

B. Limitations and Future Research

Despite its contributions, this study has several limitations. First, the experimental stimuli, though carefully controlled, may not fully capture the complexity of real-world autonomous vehicle interactions. Participants' reactions in a laboratory setting may differ from those in immersive, on-road contexts. Future research could employ field experiments or longitudinal designs to enhance ecological validity. Second, the sample composition may constrain the generalizability of the findings. Extending the study to participants from diverse cultural backgrounds, age groups, and levels of digital literacy would strengthen external validity and allow cross-cultural comparisons. Third, this study captured users' responses at a single point in time, without accounting for how privacy concerns, trust, and acceptance evolve through repeated use. Longitudinal approaches could reveal how familiarity or habituation influences these dynamics over time. Finally, while this research focused on key predictors—anthropomorphism, information sensitivity, individual cultural value, and technical familiarity—other psychological constructs such as perceived control, algorithm transparency, and social influence may also

shape users' acceptance of AVs. Future studies could integrate these factors to develop a more comprehensive framework for understanding how interface design and data characteristics jointly influence privacy perceptions and technology adoption.

REFERENCES

[1] Majid A. Security and Privacy Concerns Over IoT Devices Attacks in Smart Cities (2022). Journal of Computer and Communications. 2023;11(1):26-42.

[2] Choi DD, Lowry PB. Balancing the Commitment to the Common Good and the Protection of Personal Privacy: Consumer Adoption of Sustainable, Smart Connected Cars. Information & Management. 2024;61(1):103876.

[3] Pozharliev R, De Angelis M, Donato C, Rossi D. Do Not Put the Blame on Me: Asymmetric Responses to Service Outcome with Autonomous Vehicles Versus Human Agents. Journal of Consumer Behaviour. 2023;22(2):455-467.

[4] Yu W, Zhao C, Wang H, Liu J, Ma X, Yang Y, et al. Online Legal Driving Behavior Monitoring for Self-Driving Vehicles. Nature Communications. 2024;15(1):408.

[5] Park D, Lee Y, Kim YM. Effects of Autonomous Driving Context and Anthropomorphism of In-Vehicle Voice Agents on Intimacy, Trust, and Intention to Use. International Journal of Human–Computer Interaction. 2023;1-14.

[6] Large DR, Hallewell M, Li X, Harvey C, Burnett G. I, AV: A Ghost Driver Field Study Exploring the Application of Anthropomorphism in AV-Pedestrian Communication. In: Adjunct Proceedings of the 15th International Conference on Automotive User Interfaces and Interactive Vehicular Applications. 2023. p. 127-132. ACM.

[7] Van Brummelen J, O'Brien M, Gruyer D, Najjaran H. Autonomous Vehicle Perception: The Technology of Today and Tomorrow. Transportation Research Part C: Emerging Technologies. 2018; 89:384-406.

[8] Raats K, Fors V, Pink S. Trusting Autonomous Vehicles: An Interdisciplinary Approach. Transportation Research Interdisciplinary Perspectives. 2020; 7:100201.

[9] Okamoto S, Sano S. Anthropomorphic AI agent mediated multimodal interactions in vehicles. In: Proceedings of the 9th International Conference on Automotive User Interfaces and Interactive Vehicular Applications Adjunct. 2017. p. 110-114.

[10] Pangbourne K, Stead D, Mladenović M, Milakis D. The case of mobility as a service: A critical reflection on challenges for urban transport and mobility governance. Governance of the Smart Mobility Transition. 2018. p. 33-48.

[11] Teoh ER, Kidd DG. Rage against the machine? Google's self-driving cars versus human drivers. Journal of Safety Research. 2017; 63:57-60.

[12] Akca A, Kara I, Aydos M. Privacy, Security and Legal Aspects of Autonomous Vehicles. International Conference on Materials Science, Mechanical and Automotive Engineerings and Technology (IMSMATEC'20). 2020.

[13] Hewitt C, Politis I, Amanatidis T, Sarkar A. Assessing public perception of self-driving cars: The autonomous vehicle acceptance model. In: Proceedings of the 24th International Conference on Intelligent User Interfaces. 2019. p. 518-527.

[14] Detjen H, Faltaous S, Pfleging B, Geisler S, Schneegass S. How to increase automated vehicles' acceptance through in-vehicle interaction design: A review. International Journal of Human–Computer Interaction. 2021;37(4):308-330.

[15] Lobinger K, Brantner C. Picture-sorting techniques: Card sorting and Q-sort as alternative and complementary approaches in visual social research. The Sage Handbook of Visual Research Methods. 2nd Revised and Expanded Edition. 2020. p. 309-321.

[16] Tian Y, Wang X. A study on psychological determinants of users' autonomous vehicles adoption from anthropomorphism and UTAUT perspectives. Frontiers in Psychology. 2022; 13:986800.

[17] Luo C, He M, Xing C. Public acceptance of autonomous vehicles in China. International Journal of Human–Computer Interaction. 2024;40(2):315-326.

[18] Kyriakidis M, Happee R, De Winter JC. Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. Transportation Research Part F: Traffic Psychology and Behaviour. 2015; 32:127-140.

[19] Wu M, Wang N, Yuen KF. Can autonomy level and anthropomorphic characteristics affect public acceptance and trust towards shared autonomous vehicles? Technological Forecasting and Social Change. 2023; 189:122384.

[20] Bartneck C, Kulić D, Croft E, Zoghbi S. Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots. International Journal of Social Robotics. 2009; 1:71-81.

[21] Darwazeh NS, Al-Qassas RS, AlDosari F. A secure cloud computing model based on data classification. Procedia Computer Science. 2015; 52:1153-1158.

[22] Glancy DJ. Privacy in autonomous vehicles. Santa Clara Law Review. 2012; 52:1171.

[23] Kaur K, Rampersad G. Trust in driverless cars: Investigating key factors influencing the adoption of driverless cars. Journal of Engineering and Technology Management. 2018; 48:87-96.

[24] Lim HSM, Taeihagh A. Autonomous vehicles for smart and sustainable cities: an in-depth exploration of privacy and cybersecurity implications. Energies. 2018;11(5):1062.

[25] Hataba M, Sherif A, Mahmoud M, Abdallah M, Alasmary W. Security and privacy issues in autonomous vehicles: A layer-based survey. IEEE Open Journal of the Communications Society. 2022; 3:811-829.

[26] Hoofnagle CJ, Van Der Sloot B, Borgesius FZ. The European Union general data protection regulation: what it is and what it means. Information & Communications Technology Law. 2019;28(1):65-98.

[27] Nelson GS. Practical implications of sharing data: a primer on data privacy, anonymization, and de-identification. In: SAS Global Forum Proceedings. 2015. p. 1-23.

[28] Nishihori Y, Kimura K, Taniguchi A, Morikawa T. What affects social acceptance and use intention for autonomous vehicles--benefits, risk perception, or experience? -meta-analysis in Japan. International Journal of Intelligent Transportation Systems Research. 2020; 18:22-34.

[29] Kang Y, Choi SE, An J, Hwang S, Kim S. Designing virtual agent human–machine interfaces depending on the communication and anthropomorphism levels in augmented reality. In: Proceedings of the 15th International Conference on Automotive User Interfaces and Interactive Vehicular Applications. 2023. p. 191-201. ACM.

[30] Weitz K, Schiller D, Schlagowski R, Huber T, André E. Let me explain! Exploring the potential of virtual agents in explainable AI interaction design. Journal on Multimodal User Interfaces. 2021;15(2):87-98.

[31] Bazilinskyy P, Sakuma T, de Winter J. What driving style makes pedestrians think a passing vehicle is driving automatically? Applied Ergonomics. 2021; 95:103428.

[32] Dey D, Martens M, Eggen B, Terken J. The impact of vehicle appearance and vehicle behavior on pedestrian interaction with autonomous vehicles. In: Proceedings of the 9th International Conference on Automotive User Interfaces and Interactive Vehicular Applications Adjunct. 2017. p. 158-162.

[33] Rödel C, Stadler S, Meschtscherjakov A, Tscheligi M. Towards autonomous cars: The effect of autonomy levels on acceptance and user experience. In: Proceedings of the 6th International Conference on Automotive User Interfaces and Interactive Vehicular Applications. 2014 Sep. p. 1-8.

[34] Steijn WM, Vedder A. Privacy under construction: A developmental perspective on privacy perception. Science, Technology, & Human Values. 2015;40(4):615-637.

[35] Ruggeri K, Kácha O, Menezes IG, Kos M, Franklin M, Parma L, Miles J. In with the new? Generational differences shape population technology adoption patterns in the age of self-driving vehicles. Journal of Engineering and Technology Management. 2018; 50:39-44.

[36] Schoonmaker J. Proactive privacy for a driverless age. Information & Communications Technology Law. 2016;25(2):96-128.

[37] Zhang T, Tao D, Qu X, Zhang X, Zeng J, Zhu H, Zhu H. Automated vehicle acceptance in China: Social influence and initial trust are key

determinants. Transportation Research Part C: Emerging Technologies. 2020; 112:220-233.

[38] Abdi E, Tojib D, Seong AK, Pamarthi Y, Millington-Palmer G. A study on the influence of service robots' level of anthropomorphism on the willingness of users to follow their recommendations. Scientific Reports. 2022;12(1):15266.

[39] Li D, Rau PP, Li Y. A cross-cultural study: Effect of robot appearance and task. International Journal of Social Robotics. 2010; 2:175-186.

[40] De Graaf MM, Malle BF. How people explain action (and autonomous intelligent systems should too). In: AAAI Fall Symposium Series. 2017 Oct.

[41] Liu K, Tao D. The roles of trust, personalization, loss of privacy, and anthropomorphism in public acceptance of smart healthcare services. Computers in Human Behavior. 2022; 127:107026.

[42] Ljubi K, Groznik A. Role played by social factors and privacy concerns in autonomous vehicle adoption. Transport Policy. 2023; 132:1-15.

[43] Westin AF. Privacy and freedom. Washington and Lee Law Review. 1968;25(1):166.

[44] Epley N, Waytz A, Cacioppo JT. On seeing human: a three-factor theory of anthropomorphism. Psychological Review. 2007;114(4):864.

[45] Davis FD. Technology acceptance model: TAM. In: Al-Suqri MN, Al-Aufi AS, editors. Information Seeking Behavior and Technology Adoption. 1989. p. 205-219.

[46] Xie Y, Chen K, Guo X. Online anthropomorphism and consumers' privacy concern: Moderating roles of need for interaction and social exclusion. Journal of Retailing and Consumer Services. 2020; 55:102119.

[47] Tao S, Liu Y, Sun C. Understanding information sensitivity perceptions and its impact on information privacy concerns in e-commerce services: Insights from China. Computers & Security. 2024; 138:103646.

[48] Hong W, Chan FK, Thong JY. Drivers and inhibitors of internet privacy concern: a multidimensional development theory perspective. Journal of Business Ethics. 2021;168(3):539-564.

[49] Xie L, Lei S. The nonlinear effect of service robot anthropomorphism on customers' usage intention: A privacy calculus perspective. International Journal of Hospitality Management. 2022; 107:103312.

[50] Guo T, Wu Q, Cai F. When privacy concerns drive AI adoption: a psychological perspective. Journal of Research in Interactive Marketing. 2025;1-15.

[51] Li Y, Kobsa A, Knijnenburg BP, Nguyen MC. Cross-cultural privacy prediction. Proceedings on Privacy Enhancing Technologies. 2017.

[52] Viberg O, Kizilcec RF, Jivet I, Monés AM, Oh A, Mutimukwe C, Scheffel M. Cultural differences in students' privacy concerns in learning analytics across Germany, South Korea, Spain, Sweden, and the United States. Computers in Human Behavior Reports. 2024; 14:100416.

[53] Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: Toward a unified view. MIS Quarterly. 2003; 27:425-478.

[54] Sahari S. Measuring the familiarity, usability, and concern towards AI-integrated education of college teachers at the undergraduate level. Scholars Journal of Arts, Humanities and Social Sciences. 2024;12(5):166-176.

[55] Niu D, Terken J, Eggen B. Anthropomorphizing information to enhance trust in autonomous vehicles. Human Factors and Ergonomics in Manufacturing & Service Industries. 2018;28(6):352-359.

[56] Jörling M, Böhm R, Paluch S. Mechanisms and consequences of anthropomorphizing autonomous products: The role of schema congruity and prior experience. Schmalenbach Business Review. 2020; 72:485-510.

[57] Song Y, Luximon Y. Trust in AI agent: A systematic review of facial anthropomorphic trustworthiness for social robot design. Sensors. 2020;20(18):5087.

[58] Kim Y, Sundar SS. Anthropomorphism of computers: Is it mindful or mindless? Computers in Human Behavior. 2012;28(1):241-250.

[59] Smith HJ, Dinev T, Xu H. Information privacy research: an interdisciplinary review. MIS Quarterly. 2011; 35:989-1015.

[60] Dinev T, Hart P. An extended privacy calculus model for e-commerce transactions. Information Systems Research. 2006;17(1):61-80.

[61] Acquisti A, Brandimarte L, Loewenstein G. Privacy and human behavior in the age of information. Science. 2015;347(6221):509-514.

[62] Triandis HC. Vertical and horizontal individualism and collectivism: Theory and research implications for international comparative management. 1998.

[63] Hayes AF. Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach. 2nd ed. New York: Guilford Press; 2018.

[64] de Cosmo LM, Piper L, Di Vittorio A. The role of attitude toward chatbots and privacy concern on the relationship between attitude toward mobile advertising and behavioral intent to use chatbots. Italian Journal of Marketing. 2021:83-102.

[65] Barjaktarovic S, Kovacevic I, Pantelic O. Exploring the Moderating Role of Personality Traits in Technology Acceptance: A Study on SAP S/4 HANA Learning Among University Students. Computers. 2025;14(10):445.

Intelligent Systems, Machine Learning, and Deep Learning Algorithms for Detecting Banking Fraud: A Review

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***Abstract*—The increase in unauthorized remote banking fraud has intensified with the expansion of digital channels, creating new risks and highlighting the inadequacy of traditional methods based on fixed rules and manual audits. This review aims to synthesize recent scientific evidence on the use of machine learning and deep learning techniques for the early detection of fraudulent banking transactions, considering supervised and unsupervised models and deep architectures that allow the analysis of complex patterns present in financial transactions. A total of 357 original articles were identified in the Scopus and Web of Science databases, in addition to manual research, published up to 2025. Of these, 35 studies met the inclusion criteria established using the PICOT approach and the PRISMA protocol. The most widely implemented models in the selected studies were Random Forest, XGBoost, SVM, LSTM networks, and graph-based approaches. The combination of different algorithms improves fraud detection by integrating temporal, relational, and behavioral patterns. Advanced models show better metrics in accuracy, recall, and F1-score compared to traditional methods, expanding the possibilities for continuous monitoring and reducing false positives. There are consistent associations between the application of advanced models, the availability of quality data, and the ability to adapt to different transactional scenarios, which favor timely fraud detection if challenges such as class imbalance, the need for real-time decisions, and the heterogeneity of financial contexts are addressed. The integration of multiple approaches and the optimization of preprocessing and evaluation processes allow us to move toward more robust, scalable anti-fraud systems that are better suited to the current demands of the digital environment.**

***Keywords*—Deep learning; algorithms; machine learning; fraud detection; real-time methods**

I. Introduction

Today, unauthorized remote banking fraud is one of the main threats to the stability of the financial system, as fraudsters use digital channels such as online banking, mobile banking, and telephone banking to illegally access customer accounts and make unauthorized transfers. This situation is exacerbated by the increasing digitization of financial services and the rise in the volume of online transactions, which exposes banking institutions to increasingly complex vulnerabilities [1].

Faced with this problem, IT security in the banking sector has become extremely important. The use of machine learning (ML) and deep learning (DL) techniques has made it possible to overcome many of the limitations of traditional rule-based systems, which tend to be rigid and ineffective against rapidly evolving attacks [2]. Furthermore, these methodologies have been shown to be useful not only in the financial sector, but also in other areas where they have been successfully applied in systematic reviews to solve large-scale problems [3]. Several recent studies have analyzed advances in the use of ML and DL applied to financial fraud. Husnaningtyas and Dewayanto [4] , evaluated the performance of unsupervised learning algorithms in detecting fraud within financial transactions, highlighting their effectiveness in identifying hidden patterns and irregular behavior in large volumes of data. Similarly, Yanto, Lisah, and Tandra [5], examined different supervised learning models, concluding that approaches such as Random Forest, XGBoost, and short-term and long-term memory (LSTM) are the most accurate and widely used in fraud detection, although with a limitation in terms of their real-time response capacity. Despite their advances, these methods still face obstacles in practice. Although they have been proven to process large volumes of data and uncover hidden patterns, many models cannot detect operations in real time and have difficulty adapting to class imbalance. This highlights the need to create anti-fraud models that are adaptive, scalable, and capable of working online efficiently [6]. Traditional solutions, such as static rules or manual audits, have proven to be completely inadequate. Not only do they generate a large number of false positives, but they also lack flexibility and fail to adapt quickly to changes in fraudsters' tactics [7].

In contrast, ML and DL algorithms have transformed the way banking fraud is addressed. Supervised models can differentiate between legitimate and fraudulent transactions, while unsupervised models identify anomalies that had not been previously classified [8].

Deep architectures, such as recurrent neural networks (RNN), LSTM, and convolutional neural networks (CNN), have also made a difference. These networks capture temporal and multivariate patterns, improving the accuracy and scalability of systems. In addition, they enable the development of hybrid models capable of processing transactions more quickly and in real time [9]. Empirical results reinforce these contributions. Semi-supervised graph models have been applied to detect suspicious connections with incomplete data [10]. Furthermore, comparisons between classical algorithms and deep models have shown that the latter are better at capturing the temporal dynamics of fraud [11].

Likewise, it has been proven that classifier assembly techniques help improve robustness in contexts with highly unbalanced data [12]. In addition, graph-based models with

attention networks have made it possible to uncover hidden relationships between customers, businesses, and organized fraud [13]. Working with real data has also been key. Zioviris, Kolomvatsos, and Stamoulis [14] , at a Moroccan bank showed that applying oversampling to unbalanced data and combining it with supervised classifiers achieved more effective results in fraud detection. However, there are still gaps. Many studies focus on specific techniques or datasets, which limits their applicability. In addition, there is often little attention paid to metrics that are more useful in practice, such as recall, F1-score, AUC, and latency, which are crucial for measuring effectiveness in real time.

For these reasons, the objective of this systematic review is to identify, analyze, and classify intelligent systems and machine learning and deep learning algorithms applied to the early detection of banking fraud in real time. It also seeks to synthesize performance metrics, trends, and challenges in order to provide a frame of reference to guide both future research and practical implementation in the financial industry.

II. Methodology

In the systematic review, the PICOT method was used to search for scientific articles, as it allows questions to be formulated based on the problem addressed through its components: Problem (P), Intervention (I), Comparison (C), Outcomes (O), and Time (T). Its application allows for the clear establishment of inclusion and exclusion criteria, ensuring relevance and rigor in the selection of the articles analyzed.

A. PICOT Formulation

During the first phase of the methodological process, the PICOT components were identified, as summarized in Table I, and a complementary Context variable was also incorporated for a more precise search.

TABLE I. Identification of Picot Components

P	Financial transactions susceptible to bank fraud.
I	Application of intelligent systems and Machine Learning and Deep Learning algorithms.
C	Conventional methods of fraud detection.
O	Performance and efficiency in detecting bank fraud using algorithms.
T	Speed and timeliness of detection.

B. Question Formulation

Once the PICOT components had been identified, the general research question (RQ) for this systematic review was formulated:

"What Machine Learning (ML) and Deep Learning (DL) models have been developed for the early detection of banking fraud in real-time, and how have they performed in terms of accuracy, efficiency, and resource optimization compared to traditional methods?"

Subsequently, specific questions linked to each PICOT component were designed to guide the literature search and ensure the relevance of the selected studies. These questions are summarized in Table II.

TABLE II. Questions Linked to PICOT Components

RQ1	What are the main types of bank fraud (suspicious transactions, digital payments, card fraud) addressed in recent studies?
RQ2	What machine learning and deep learning models have been developed for the early detection of banking fraud in real time?
RQ3	What are the differences in performance between intelligent ML/DL models and traditional methods (static rules, manual monitoring, conventional audits)?
RQ4	What metrics of precision, accuracy, efficiency, early detection, and reliability have been reported by the applied models?
RQ5	Which models enable immediate fraud detection, either online or through continuous real-time monitoring?

C. Identification of Keywords

The keywords for each PICOT component were identified and are presented in Table III. Thesauri were used for this purpose, along with the Boolean operators "OR" and double quotation marks ("") to facilitate the search for exact terms in the Scopus and WOS databases.

TABLE III. Keywords

P	"Banking transactions" OR "Bank fraud" OR "Digital payment fraud" OR "Credit card fraud"
I	"Machine learning" OR "Deep learning" OR "Artificial intelligence" OR "Supervised learning" OR "Support vector machine (SVM)"
C	"Traditional methods" OR "Manual monitoring" OR "Classic statistical methods" OR "Conventional auditing"
O	"Precision" OR "Accuracy" OR "Efficiency" OR "Early detection" OR "Reliability" OR "Resource optimization"
T	"Real time" OR "Immediate" OR "Online detection" OR "Continuous monitoring" OR "Instant evaluation"

D. Syntax of the PICOT Formula

The PICOT method was completed by combining all the previously identified keywords using the Boolean operator "AND" to perform the correct search in the Scopus and Web of Science databases, finding the search equations shown in Table IV.

TABLE IV. Search Equation

	Scopus	Web of Science
Busqueda equidad	TITLE-ABS-KEY("Transacciones bancarias" O "Fraude bancario" O "Fraude en pagos digitales" O "Fraude con tarjetas de crédito") AND TITLE-ABS-KEY("Machine learning" OR "Deep learning" OR "Artificial intelligence" OR "Supervised learning" OR "Support vector machine (SVM)") AND TÍTULO-ABS-CLAVE("Métodos tradicionales" O "Monitoreo manual" O "Métodos estadísticos clásicos" O "Auditoría convencional") AND TÍTULO-ABS-CLAVE("Precisión" O "Exactitud" O "Eficiencia" O "Detección temprana" O "Fiabilidad" O "Optimización de recursos") AND TÍTULO-ABS-CLAVE("Tiempo real" O "Inmediato" O "Detección en línea" O "Monitoreo continuo" O	(((((((TS = banking transactions) OR (TS = bank fraud)) OR (TS = digital payment fraud)) OR (TS = credit card fraud)) AND (((((TS = machine learning) OR (TS = deep learning)) OR (TS = artificial intelligence)) OR (TS = supervised learning)) OR ((TS = support vector machine) AND (TS = svm)))) AND ((((TS = traditional methods) OR (TS = manual monitoring)) OR (TS = classic statistical methods)) OR (TS = conventional auditing))) AND ((((((TS = precision) OR (TS = accuracy)) OR (TS = efficiency)) OR (TS = early detection)) OR (TS = reliability)) OR ((SO_SMART = optimization) AND (TS = resource)))) AND (((((TS = real

	"Evaluación instantánea") Y (LÍMITE A (SUBJAREA,"COMP")) Y (LÍMITE A (DOCTYPE,"ar")) Y (LÍMITE A (OA,"all")) Y (LÍMITE A (IDIOMA,"Español")) Y AÑO PUBLICITARIO > 2020 Y AÑO PUBLICITARIO < 2025	time) OR (TS = immediate)) OR (TS = online detection)) OR (TS = continuous monitoring)) OR (TS = instant evaluation)))

Once the PICOT method was completed and the search strategies were executed in the database, a total of 357 articles were obtained: 290 from Scopus and 67 from the Web of Science (WOS) database.

E. Specifications of Inclusion and Exclusion Criteria

In order to ensure the validity, relevance, and quality of the selected studies, inclusion and exclusion criteria were defined. These criteria allowed the review to focus on research directly related to the application of Machine Learning (ML) and Deep Learning (DL) models in the detection of bank fraud, thus ensuring consistency in the results. In terms of inclusion criteria, studies published between 2021 and 2025 in indexed scientific journals and specialized conference proceedings were selected, whose subject matter was related to the use of Machine Learning (ML) and Deep Learning (DL) techniques applied to bank fraud, including both financial transactions and fraud associated with digital payments and credit card use. It was also considered essential that the research presented performance evaluation metrics, such as precision, accuracy, sensitivity, specificity, recall, F1-score, or area under the curve (AUC), and that it incorporated approaches aimed at real-time detection, either online or through continuous monitoring schemes. Finally, only articles published in English or Spanish that offered full access to the text were included. With regard to exclusion criteria, duplicate studies or those corresponding to preliminary versions already published in other sources were discarded, as were studies published prior to 2021. Research that did not directly address the issue of bank fraud, studies that lacked quantitative performance metrics, and documents that were not fully accessible were also excluded. The application of these parameters ensured the methodological consistency of the review, refined the database of articles collected, and ensured the quality and relevance of the evidence analyzed.

F. PRISMA Statement

The PRISMA statement enabled the selection and analysis of articles, as well as the establishment of a process for extracting the articles to be examined in the literature review, ensuring consistency between the objectives and the criteria established. This approach guarantees transparency and comprehensiveness in the identification, selection, and synthesis of the included studies, which strengthens the validity of the methodology [15].

Likewise, Moher et al. [16] emphasizes that the correct application of the 27 items in the PRISMA statement allows for the standardization of the processes of searching, analyzing, and evaluating articles, promoting comparability between studies. This standardization is essential to ensure the consistency and quality of systematic reviews, as it promotes transparency in the presentation of results.

G. PRISMA Processes

The development was carried out in five stages. First, 357 articles were identified (290 from Scopus and 67 from WOS) and 40 duplicates were removed using Mendeley. Subsequently, 272 studies were excluded after analyzing unrelated titles and abstracts. Ten additional records were discarded because they did not meet the PICOT criteria. Finally, 35 articles relevant to the review were selected. Fig. 1 shows the comprehensive article selection process, using the PRISMA diagram, where 35 articles were selected.

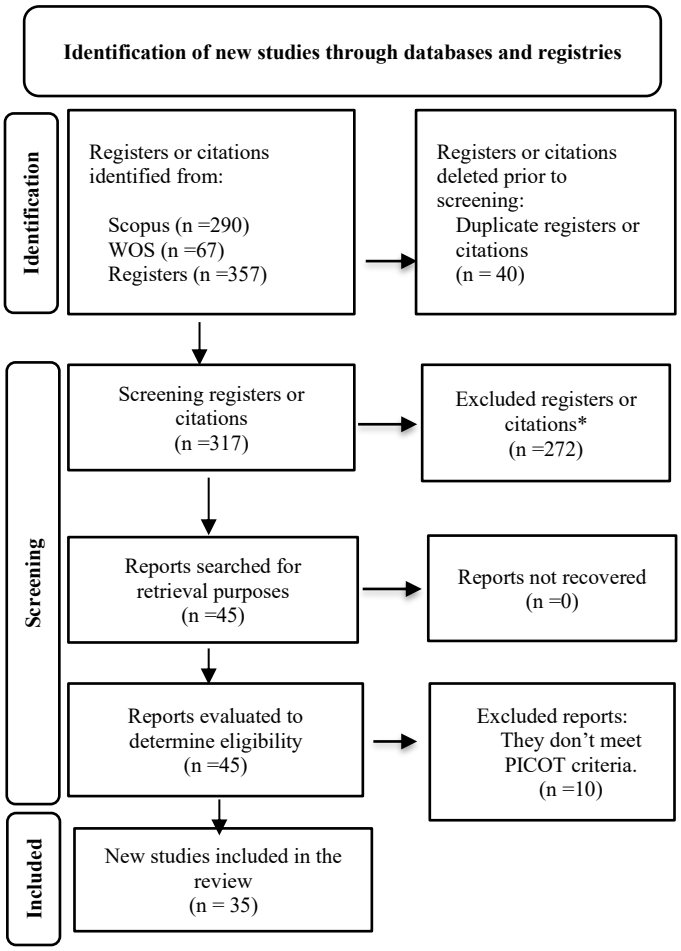


Fig. 1. Diagram of the PRISMA process.

H. Bibliometrix by R Studio

Bibliometric analysis has established itself as an essential tool for studying the evolution of knowledge about bank fraud. Using Bibliometrix in R, databases such as Scopus can be analyzed to identify trends, authors, and emerging topics in financial fraud detection. Shukla and Kashni demonstrated that scientific output on bank fraud has grown over the last decade, highlighting the use of machine learning models [17]. Recent studies show an increase in the use of artificial intelligence and machine learning to detect financial anomalies. Bibliometrix allows these advances to be visualized through co-occurrence and collaboration maps, showing an annual growth of 13.34% in research on AI applied to finance and highlighting gaps in transparency, ethics, and algorithmic biases in automated systems [18], [19].

According to Gangwar, the study of financial crimes, such as money laundering, has grown significantly over the last decade, driven by digitization and the increase in illicit flows. This approach provides an understanding of how technological tools, including artificial intelligence and predictive detection models, are integrated into fraud prevention processes [20].

III. RESULTS

In the results section, tables and graphs were created to visually represent the different categories of characteristics of the elements analyzed. Excel spreadsheets were used for the graphs. In addition, the results address the PICOT questions formulated during the writing of the research.

A. Developed Models

The results of the reviewed articles are shown in Table V, which indicates the reference, types of fraud, and Machine Learning (ML) and Deep Learning (DL) models applied.

B. Real-Time Detection Metrics and Techniques

The results of the reviewed articles are shown in Table VI, which indicates the reference, the metrics for each study result, and the models used for real-time detection.

TABLE V. RESULTS OF THE REVIEWED ARTICLES

Reference	Types of Fraud	ML and DL models
Adejoh, J. et al. (2024)[21]	CNP, skimming, unauthorized digital payments, account takeover, fake accounts, and money laundering using mule accounts.	Random Forest, XGBoost, Isolation Forest, Autoencoders, LSTM/GRU, CNN y Graph Neural Networks (GNN).
Ibrahim, Y. et al. (2025)[22]	Suspicious transactions, card fraud, and anomalous digital payments.	LSTM, CNN, AE, and hybrid ML/DL models enable online detection.
Hargreaves, C. A. (2025)[23]	Card, digital payments, account takeover/money laundering	ML: Logistic, RF, XGBoost/LightGBM/CatBoost. DL: LSTM/GRU, AE, 1D-CNN, GNN; hybrids: rules+ML.
Demirhan, H. (2024)[24]	Credit card fraud: fraudulent or legitimate transactions.	RF, XGBoost, SVM, DNN, LSTM, GNN, and fuzzy logistic regression.
Abd-Ellatif, L. et al. (2025)[25]	Suspicious transactions, digital payments, cards, and financial anomalies.	ML: RF, XGBoost, CatBoost; DL: CNN, RNN, LSTM, GNN
Theodorakopoulos, L. et al. (2025)[26]	credit cards, online payments, and suspicious transactions.	LR, DT, RF, XGBoost, CatBoost; PySpark for scalability and adaptive learning
El-Kenawy, E.-S. M. et al. (2024)[27]	Credit card fraud in electronic transactions.	DL: RNN, LSTM, and GRU applied to balanced Kaggle datasets
Rawashdeh, E. (2024)[28]	Card fraud: duplicates, unauthorized use, and anomalous online purchases.	HybridIG-CSO hybrid model with evolutionary selection and RWN.
Alarfaj, F. K. & Shahzadi, S. (2025)[29]	Fraud: credit cards, digital payments, and suspicious transactions.	Models: LSTM, CNN, AE, XGBoost, CatBoost, and ensembles.
Wang, H. (2024)[30]	Fraud: cards, digital payments, transfers, phishing, and identity theft.	ML: XGBoost, RF, LightGBM; DL: RNN/LSTM/GRU, CNN, AE, Transformers; Hybrids: GNN, CNN-LSTM, ensembles.
Saha, S. C. (2024)[31]	Fraud: cards, unusual transactions, digital payments, and account theft.	Online/lightweight models: Hoeffding Tree, Online RF, IF, incremental OCSVM, compact AEs, LSTM in short windows.
Baisholan, N. et al. (2025)[32]	Fraud: suspicious transactions, digital payments, and cards.	Models: RF, XGBoost, LSTM, CNN, AE, and ML+DL hybrids for real-time early detection.
Brown, J. (2022)[33]	Card fraud, digital payments, and identity theft.	ML/DL: RF, XGBoost, AE, LSTM, CNN, GNN, and streaming models (ARF, Hoeffding Tree).
Al-Maari, A. A. et al. (2025)[34]	Fraud: cards, digital payments, suspicious transactions, and account theft.	Hoeffding Tree, Isolation Forest, real-time LSTM.
Kcennedy, R. K. L. et al. (2024)[35]	Cloning and CNP fraud, transactions in apps/digital wallets, account hijacking, and money laundering.	ML: Logistic, RF, XGBoost/LightGBM/CatBoost; DL: RNN/LSTM/GRU, AE, 1D-CNN; Relational: GNN; Hybrids: rules + ML/DL.
Ibomoiye, D. M., et al. (2024)[36]	Credit card fraud (cloning, unauthorized transactions)	GAN + RNN/LSTM/GRU: GAN creates synthetic fraud, RNN/LSTM/GRU classifies.
Tayebi, M. et al. (2025)[37]	Fraud: cards, digital payments, and account takeover.	ML: Logistic, DT, RF, XGBoost/LightGBM/CatBoost; DL: RNN/LSTM/GRU, AE, 1D-CNN; Relational: GNN; Hybrids: rules + ML/DL.
Cascavilla, G. (2025)[38]	Suspicious transactions (payments, chargebacks, CNP) and atypical behavior, including anomalous digital payments.	Autoencoders, Isolation Forest, One-Class SVM
AbouGrad, H. (2025)[39]	Digital payment fraud and suspicious online banking transactions, with a focus on distributed data.	Decentralized Deep AutoEncoder
Liu, J. (2025)[40]	Main type: card fraud	DNN, CNN, RNN, GRU, LSTM, CCNN.
Ullah, H. (2022)[41]	Credit card fraud, including physical unauthorized use and online transactions (CNP).	Random Forest (RF), XGBoost Classifier, Convolutional Neural Network
Yu, J. (2024)[42]	Card fraud (CNP and unauthorized), suspicious transactions, and digital payments; focused on detecting anomalies in payment flows.	AutoEncoder, LightGBM, SMOTE
Sun, Y. (2023)[43]	It focuses on card fraud (CNP and unauthorized), suspicious transactions, and fraudulent digital payments.	Modelos ML: Random Forest, AdaBoost, XGBoost, LightGBM, CatBoost; DL: MLP, LSTM, GRU.
Al Balawi, S. (2023)[44]	It focuses on card fraud (in-person and CNP) and suspicious transactions.	ANN and CNN, with and without pooling layer.

Alsagri, H. S. (2025)[45]	It focuses on card fraud and fraudulent electronic transactions, concentrating on detecting anomalies in the CCF dataset.	ML: LR, SVM, RF, XGBoost, KNN; DL: DNN.
Akour, I. (2025)[46]	The main focus was on card fraud, especially unauthorized online transactions; the model analyzes sequences to distinguish normal behavior from anomalous patterns.	ML: LR, SVM, RF, ANN; DL: CNN, LSTM, CNN–LSTM, CNN–LSTM with Attention.
Benchaji, I. (2021)[47]	Card fraud, especially in digital transactions, was the most studied; the model identifies anomalies in sequential customer patterns.	The LSTM model outperforms other ML models by capturing temporal dependencies, improving early detection of irregular operations.
Owoh, N. (2024)[48]	Card fraud, especially in digital purchases, with anomalous patterns best detected by intelligent models.	RF, SVM, KNN, Bagging, Boosting, and an Ensemble model were applied.
Strelcenia, E. (2023)[49]	The main type of fraud analyzed is unauthorized use of credit cards in electronic transactions.	XGBoost, RF, KNN, MLP, and Logistic Regression were applied to balanced datasets using SMOTE, ADASYN, and GAN variants (CGAN, WSGAN, NSGAN, LSGAN, SDG-GAN, K-CGAN).
Ren, J. (2024)[50]	Types of fraud: credit/debit cards, digital payments and online banking, suspicious transactions, internal fraud.	DT, RF, GBDT, XGBoost, LightGBM, Stacking Ensemble.
Fedushko, S. (2023)[51]	It focuses on credit card fraud in online transactions.	ML models were developed and compared: LR, RF, DT, SVM, Naïve Bayes, KNN, and SGD Classifier.
Plakandaras, V. (2022)[52]	Primary fraud: credit card transactions in online environments.	Ridge LR (best performance), SVM, RF, DT
Alatawi, M. N. (2025)[53]	Credit card fraud, in person and online, detecting anomalous patterns using IoT features.	Random Forest and Gradient Boosting Machine
Muduli, D. (2025)[54]	Focuses on card fraud and suspicious transactions in Credit-Card and PaySim datasets.	SVM, KNN, ELM, PSO-ELM, and Stacking Ensemble (SVM + KNN + PSO-ELM with Gradient Boosting).
Feng X et al (2024)[55]	Focus: Card fraud and suspicious transactions in transactional datasets (European cardholders).	RF+AB, GBDT, SVM, KNN, CNN; CDL is proposed to reduce features and train traditional/ensemble models, optimizing accuracy and time.

TABLE VI. RESULTS OF REAL-TIME DETECTION METRICS AND TECHNIQUES

Reference	Metrics	Real-time models
Adejoh, J. et al. (2024)[21]	Accuracy (94–99%), Recall, Precision, F1-score, and AUC-ROC are the most commonly used metrics for validating performance.	Models such as Hoeffding Tree, Adaptive Random Forest, and Autoencoders enable real-time detection and monitoring.
Ibrahim, Y. et al. (2025)[22]	Accuracy (94–99%), Recall, Precision, F1-score, and AUC-ROC are the most commonly used metrics for validating performance.	LSTM, CNN, and Autoencoders enable real-time detection and monitoring.
Hargreaves, C. A. (2025)[23]	Accuracy, Precision, Recall, F1, ROC-AUC, AUPRC, MCC, FP rate, inference time (ms), throughput (tx/s).	XGBoost, LightGBM, Logistic, Random Forest, and Hoeffding Trees enable immediate detection.
Demirhan, H. (2024)[24]	Accuracy 99%, Sensitivity and Specificity 0.90+, MCC 0.80+.	Real-time implementable online fuzzy framework.
Abd-Ellatif, L. et al. (2025)[25]	Accuracy (94–99%), Precision (>95%), Recall (90–97%), F1-Score (~0.95), AUC-ROC (>0.98), lower false positive rate (-40%), latency <100 ms per transaction, near real-time detection.	ATAD-Net, FraudX AI, and GNN+Autoencoder combine hybrid approaches with human and automatic verification.
Theodorakopoulos, L. et al. (2025)[26]	Accuracy 95–99%, Precision >95%, Recall 90–98%, F1 ~0.96, ROC-AUC >0.98, reduction of false positives, low latency (<100 ms), efficiency in distributed processing.	XGBoost and CatBoost with PySpark enable real-time detection and monitoring.
El-Kenawy, E.-S. M. et al. (2024)[27]	Accuracy 99.39%, F1-score 0.9939, high Recall and AUC > 0.99.	RNN and LSTM enable real-time detection with low computational cost.
Rawashdeh, E. (2024)[28]	Evaluates with G-Mean, Recall, and AUC, demonstrating high accuracy and low false positive rate.	Automatic detection in near real time thanks to the optimization of weights and neurons in the model.
Alarfaj, F. K. & Shahzadi, S. (2025)[29]	Accuracy 94–99%, Precision >95%, Recall 90–97%, F1 ~0.95, AUC-ROC >0.98, -40% false positives.	LSTM, CNN, Autoencoders, graphs, federated for continuous real-time monitoring.
Wang, H. (2024)[30]	Accuracy, Precision, Recall, F1, AUC/AUPRC, latency (s), throughput (TPS), MCC.	Online models: Hoeffding Trees, incremental RF/XGBoost, optimized RNN/LSTM, streaming and federated GNN.
Saha, S. C. (2024)[31]	Accuracy: 94–99%, Precision: 90–>95%, Recall: 90–98%, F1-Score: 0.9–0.96, AUC-ROC: 0.68–>0.98, MCC, FPR, latency <100 ms, false positive reduction ~40%	LSTM, CNN, Autoencoders, hybrid models (ML+DL), Graph Neural Networks, Ensemble ML (Random Forest + Logistic Regression + AdaBoost), FinGraphFL.
Baisholan, N. et al. (2025)[32]	Accuracy (94–99%), Precision (>95%), Recall (90–97%), F1-Score (~0.95), AUC-ROC (>0.98), lower false positive rate (-40%), latency <100 ms, near real-time detection.	LSTM, CNN, Autoencoders, hybrid ML+DL models, and federated approaches such as FinGraphFL, which enable adaptive learning and online processing.
Brown, J. (2022)[33]	Metrics such as Accuracy (90–99%), Precision, Recall, F1-score, and AUC-ROC are reported, in addition to a low false positive rate and high early detection.	Online models such as Adaptive Random Forest, Online SVM, Streaming Autoencoders, and Graph Neural Networks enable immediate detection and continuous monitoring in real time.
Al-Maari, A. A. et al. (2025)[34]	Accuracy 95–99%, Precision >95%, Recall 90–98%, F1 ~0.96, AUC >0.98, with ~40% fewer false positives, demonstrating high efficiency and reliability.	LSTM, CNN, and hybrid models facilitate online detection and continuous monitoring with adaptive learning.

Kcennedy, R. K. L. et al. (2024)[35]	Accuracy, Precision, Recall, F1, ROC-AUC, AUPRC, MCC, FP rate, inference time (ms). E.g.: DL studies report F1/AUC ~0.98–0.999 in controlled datasets; AUPRC improves with synthesized labels.	LSTM, CNN, and hybrid models facilitate online detection and continuous monitoring with adaptive learning.
Ibomoiye, D. M., et al. (2024)[36]	AUC (~99% with GAN-GRU), Sensitivity 0.992, Specificity 1.000, Very high accuracy (~99%), High F1 score, Low false positive rate.	GAN + RNN/LSTM/GRU enables continuous training and adaptation
Tayebi, M. et al. (2025)[37]	Accuracy, Precision, Recall, F1-score, ROC-AUC, AUPRC, MCC, FPs rate, inference time (ms), throughput (tx/s). Typical values in studies: AUC/F1 ≈ 0.90–0.999 in controlled datasets.	XGBoost/LightGBM (lightweight), Logistic, Random Forest pruned, Hoeffding Trees (streaming). Possible with optimization: LSTM/CNN pruned, lightweight Autoencoders. More costly: GNN/Transformers (require infrastructure optimization).
Cascavilla, G. (2025)[38]	AUC (~68–85% depending on model and dataset), TP Rate (varies by model: IsolationForest 41–59% Merchants; Autoencoder ~77–85% in some scenarios), High accuracy (~90% due to imbalance), Low/modest F1 due to class rarity.	Lightweight models per cardholder (IF, OCSVM) and optimized AE architectures enable near-online detection; more expensive assemblies require optimization.
AbouGrad, H. (2025)[39]	ROC–AUC: 66.20%, PR-AUC: 1.24%, Precision 99%, Recall showed lower coverage, F1-Score: ~98% between precision and recall, TPR remains high in regions with low false positive rates	Lightweight local models (classifiers or AEs) enable online detection at each node; periodic aggregation supports near-continuous monitoring.
Liu, J. (2025)[40]	accuracy 99.21%, precision 97.92%, recall 96.15% , F1-score 97.03% y AUC 99.31%	The CCNN is efficient and can be integrated into near-real-time pipelines; it requires optimized inference for low latency.
Ullah, H. (2022)[41]	Accuracy: 99.9 % Precision: 93 % F1-score: 85.71 % AUC: 98 %	The study suggests that CNN models can be applied in online transaction contexts.
Yu, J. (2024)[42]	The hybrid model showed Recall 94.85%, F1 ≈ 93.4%, AUC > 0.97, and a +10.7% improvement in recall; MCC and BCR exceeded baselines, confirming reliability and early detection.	LightGBM/XGBoost with fast extraction allows
Sun, Y. (2023)[43]	GRU 95.2/96.0/0.95, LSTM 94.0/97.1/0.94, MLP 92.8/95.2/0.93, AdaBoost 96.6/98.4/0.97, RF 94.5/96.1/0.94	LSTM/GRU LightGBM/XGBoost or lightweight hybrid models.
Al Balawi, S. (2023)[44]	Precisión: 83% Recall: 84% Overall accuracy: 99.81% F1-score: 83.72% Loss: 0.00244	CNN 1-D using CPU/GPU in appropriate infrastructure.
Alsagri, H. S. (2025)[45]	Precisión: 99.5% Recall (Early detection): 90.1% F1-score: > 90% Accuracy: approx. 99% Model cost: 0.421 F1-score DNN: 87% F1-score Random Forest: 84% F1-score SVM: 82%	Multi-stage architecture with fast sorters and DNN enables online scoring
Akour, I. (2025)[46]	Precision 90.51%, Recall 90%, F1-score 89.88%, Accuracy 99.93%, AUC 98%, and Recall CNN–Attention 93.28%	The hybrid requires intensive training, but its inference is fast for online scoring; it is recommended in real systems with adequate infrastructure, taking care with the generation of synthetic samples.
Benchaji, I. (2021)[47]	The metrics obtained include AUC: ~99.5% effective classification capacity MAE: error ≈ 0.6% MSE: error ≈ 0.3% Fraud detected: in a highly unbalanced dataset (only 1.2% were fraud)	The LSTM model enables real-time, online detection.
Owoh, N. (2024)[48]	The reported metrics include accuracy (99.97%), precision (99.91%), recall (99.89%), F1-score (99.89%), and AUC (0.999), demonstrating an excellent balance between sensitivity and specificity.	The proposed ensemble model enables immediate and continuous fraud detection in real time, making it suitable for online banking systems and automated transaction monitoring applications.
Strelcenia, E. (2023)[49]	It was evaluated using Precision, Recall, F1, Accuracy, and ROC; K-CGAN combined with XGBoost and MLP achieved 1.0 in Precision, Recall, and F1 in several cases, perfectly classifying the test set.	XGBoost, RF, and MLP are suitable for immediate detection in online pipelines; K-CGAN reinforces training for continuous monitoring systems.
Ren, J. (2024)[50]	Stacking Ensemble = Precision 99.35 Accuracy 99.42 F1-Score 99.36 Recall 99.38 AUC 99.50	The Stacking Ensemble model
Fedushko, S. (2023)[51]	The reported metrics include AUC (≈94.6% for Logistic Regression, ≈95.4% for stacking) and F1-score (0.96), demonstrating high reliability.	The study does not explicitly test online detection or continuous real-time monitoring.

Plakandaras, V. (2022)[52]	Accuracy = 99.9 % AUC-ROC = 98.1 % Precision = 79.6 % Recall (fraud detection) = 84.8 % F1-Score = 82.1 % Balanced Accuracy = 92.4 % Specificity = 99.9 %	JAD enables immediate retraining and application of the model in card issuers, making it practical for rapid updates.
Alatawi, M. N. (2025)[53]	RF: Prec 100.0%, Acc 99.999%, F1 99.99%, Recall 99.99%, AUC 99.99% GBM: Prec 99.95%, Acc 99.986%, F1 99.92%, Recall 99.90%, AUC 99.98%	The combination of ML/DL with cloud/big data enables real-time detection.
Muduli, D. (2025)[54]	(Stacking Ensemble): Accuracy: 99.95% Precision: 99.93% Recall (Sensibilidad): 99.97% F1-score: 99.95% AUC: 1.00 FPR (False Positive Rate): 0.02% (the lowest among the models compared).	The pipeline inference is lightweight and suitable for real-time use, with scalable architecture, and stacking requires adaptations for continuous learning in streaming.
Feng X et al (2024)[55]	Accuracy, Precision, Recall, F1-score, and training time.	Optimized SVM and RF/GBDT enable real-time deployment; CDL streamlines updates.

Fig. 2 details the citations of references used, identifying the sources with the greatest impact that form the basis of the field of study. The analysis reveals that the work of Abd-Ellatif, L. et al. is the most influential, with 129 citations. This is followed in importance by the references of Sun, Yanxia, with 100 citations and Adejo, J. et al., with 92 citations. The prominence of this small group of authors indicates that current research relies heavily on a core of consolidated knowledge, which guides the methodologies and direction of analysis on fraud detection.

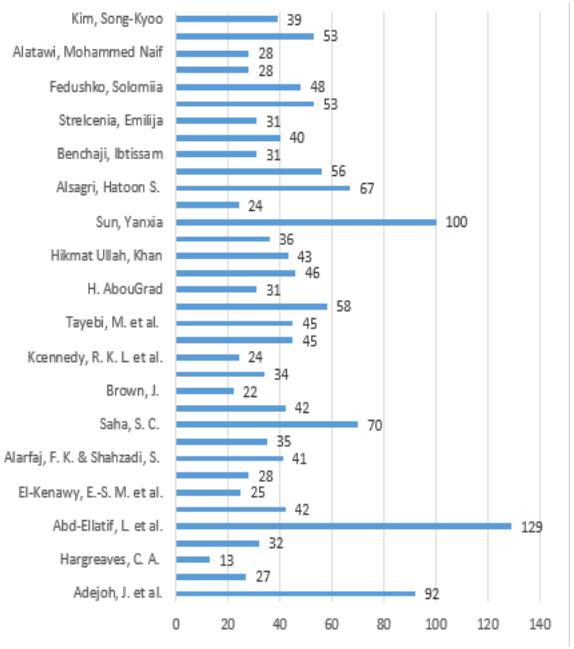


Fig. 2. References used.

C. Word Cloud

Fig. 3 shows the most frequent words identified by Bibliometrix, among which the following stand out: machine learning, deep learning, fraud detection, credit cards, artificial intelligence, cybersecurity, random forest, support vector machines, logistic regression, federated learning, and generative adversarial networks. These words reflect the focus of research on the use of advanced artificial intelligence techniques for financial fraud detection.



Fig. 3. Word cloud.

D. Three-Field Diagram

Fig. 4 presents the three-field diagram, which visualizes the bibliometric connections between the authors' country of origin (AU_CO), research topics or keywords (ID), and authors (AU). The thicker lines show that countries such as the United States, China, and India are the main centers of scientific production in this field, with a predominant focus on credit card fraud detection through the intensive use of advanced artificial intelligence techniques, such as machine learning and deep learning. This pattern reflects a global trend toward the application of sophisticated algorithms to strengthen cybersecurity and optimize fraud detection systems.

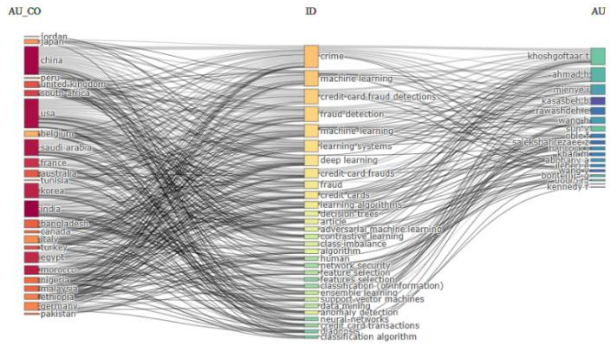


Fig. 4. Three-field diagram.

E. Co-occurrence Network

Fig. 5 presents the co-occurrence network of the most frequent terms in the study area, illustrating the conceptual structure of the research using a map of nodes and links. Key concepts such as machine learning, fraud detection, deep learning, and credit card fraud detection are the most prominent, identified by their larger nodes. These terms act as conceptual nuclei, positioned centrally on the map and serving as connection points for a wide range of interrelated secondary topics. The term crime also stands out as an important and connected concept. The different color-coded clusters (orange, blue, green, red) visually group distinct but related areas of research, where physical proximity between terms indicates a greater strength of thematic co-occurrence.

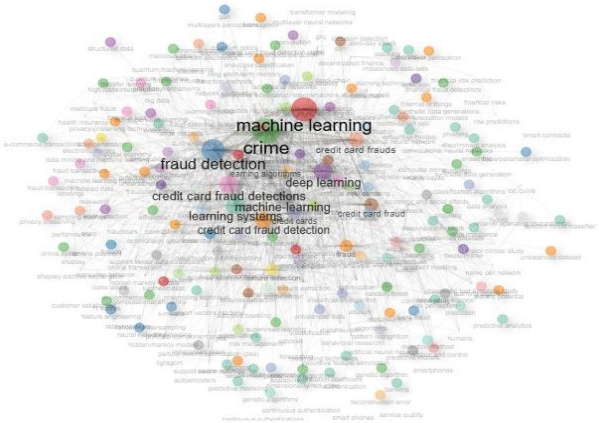


Fig. 5. Co-occurrence network.

F. Factorial Analysis

Fig. 6 shows the thematic grouping according to keyword affinity. There is a concentration in the upper right quadrant with terms such as classification, random forest, credit card fraud, and machine learning, focused on credit card fraud detection. In the upper left quadrant, terms related to fraud detection and algorithm appear, while a small group in green is separated. This confirms that the field focuses on the use of advanced techniques for financial protection.

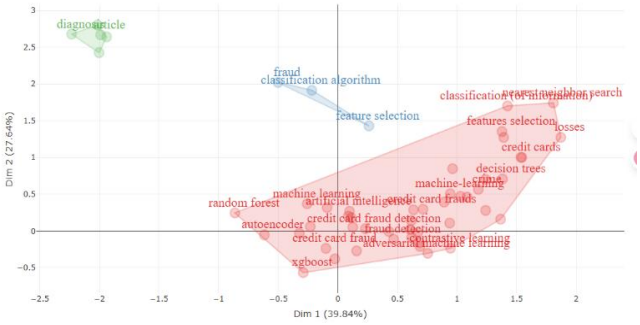


Fig. 6. Factorial analysis.

IV. Discussion

The objective of this review was to identify, analyze, and classify the most effective artificial intelligence models for the early detection of banking fraud in real-time. The findings confirm that deep learning-based approaches perform better than traditional methods, particularly those capable of modeling dependencies in transactional data. In this regard, architectures such as RNN, LSTM, and GRU stand out for their high predictive power, achieving an accuracy of 99.39%, an F1-score of 0.9939, and an AUC greater than 0.99.

These values exceed those reported in previous studies such as that of Sun et al. [43], which shows a significant improvement over previous research. This difference can be explained by the performance achieved by modern models such as LSTM, CNN, and XGBoost, whose accuracy (94–99%), together with other metrics such as Recall, Precision, F1-score, and AUC-ROC, show high effectiveness in fraud detection [22]. Consistently, various authors report high values above 99% for accuracy and AUC, confirming the high sensitivity and specificity of these models in identifying fraudulent transactions [27] , [40].

Similarly, hybrid models that combine traditional techniques such as XGBoost, Random Forest, or Logistic Regression with deep or generative architectures significantly increase the robustness of the system. These methods leverage the representational power of deep networks, achieving outstanding performance in imbalanced contexts [37], [48], [49]. In line with the above, the results obtained are consistent with those reported by authors who have evaluated advanced models for fraud detection. Khan et al. highlight that current classification models allow complex patterns to be captured with greater accuracy than traditional methods, which coincides with the performance observed in the LSTM, RNN, and CNN models analyzed in this review [56]. Muaz et al. specify that the effectiveness of the system necessarily depends on the proper handling of both imbalance and preprocessing, reinforcing the idea that data quality is an important factor in improving model performance, including Deep Learning models [57].

On the other hand, Chergui et al. suggest that semi-supervised methods can be combined with advanced classification methods to better adjust to frequent changes in the types of financial fraud. This shows the importance of using models capable of learning sequences and dynamic variations that arise in fraud behavior [58]. Finally, Aghware et al. emphasize in their research that hybrid strategies combining deep techniques with clustering or assembly methods increase the robustness of the system, supporting the results of this review on the good performance of combined models [59]. Overall, the evidence reviewed shows that deep learning models and hybrid approaches currently represent the most effective and reliable solutions for detecting banking fraud, thus surpassing traditional methods.

V. Conclusion

The objective of this review was to identify, analyze, and classify the most effective artificial intelligence models for the early detection of banking fraud in real-time, especially in an environment where transactions are increasingly fast and changing.

Based on the study conducted, it can be concluded that the ML and DL models most commonly used in the detection of fraudulent transactions are Random Forest (RF), which is one of the most accurate and widely used ML models, followed by

XGBoost, considered one of the most accurate and widely used supervised learning approaches, Support Vector Machine (SVM) in third place, and Short-Term Memory Networks (LSTM), which are a type of deep architecture, and Graph-based Approaches (GNN), which allow for the integration of temporal, relational, and behavioral patterns, in fourth place.

Deep learning architectures, described by deep learning (DL) models, have proven to be particularly effective at capturing temporal and multivariate patterns, improving the accuracy and scalability of systems. First and foremost are Recurrent Neural Networks (RNN), LSTM, and GRU, which are essential for capturing the temporal dynamics of fraud. secondly, Convolutional Neural Networks (CNN), which are also used to capture complex patterns, and Autoencoders (AE), which are often used for anomaly detection, as unsupervised models are useful for identifying hidden patterns and irregular behaviors in large volumes of data, achieving an accuracy of 99.39%, an F1-score of 0.9939, and an AUC greater than 0.99.

Within hybrid and ensemble models, the combination of different algorithms or the integration of multiple approaches is considered a robust strategy that improves fraud detection, such as models that combine classical techniques, such as XGBoost or Random Forest, with deep architectures, achieving near-perfect performance, registering F1-scores and AUC between 0.98 and 1.00. Banking fraud solutions applied by other researchers have implemented and evaluated a wide range of Machine Learning (ML) and Deep Learning (DL) models, often outperforming traditional methods such as Random Forest, XGBoost, and short- and long-term memory networks (LSTM) used for fraud detection.

However, the study has some limitations related to the differences between the approaches used in the empirical works reviewed, the variety of databases used, and the frequent use of public datasets that do not always represent the complexity that exists in real banking systems. Finally, it is recommended that future research test these models in real operating environments, with real-time data, unified metrics, and scenarios where new types of fraud appear. In addition, it would be valuable to explore more efficient hybrid techniques and methods, such as federated learning, which could improve the adaptability of systems and strengthen their ability to detect early fraud.

REFERENCES

[1] C. Ikeda, K. Ouazzane, Q. Yu, and S. Hubenova, "New Feature Engineering Framework for Deep Learning in Financial Fraud Detection," International Journal of Advanced Computer Science and Applications, vol. 12, no. 12, pp. 10–21, 2021, doi: 10.14569/IJACSA.2021.0121202.

[2] B. Mytnyk, O. Tkachyk, N. Shakhovska, S. Fedushko, and Y. Syerov, "Application of Artificial Intelligence for Fraudulent Banking Operations Recognition," Big Data and Cognitive Computing 2023, Vol. 7, Page 93, vol. 7, no. 2, p. 93, May 2023, doi: 10.3390/BDCC7020093.

[3] L. Hernandez Aros, L. X. Bustamante Molano, F. Gutierrez-Portela, J. J. Moreno Hernandez, and M. S. Rodríguez Barrero, "Financial fraud detection through the application of machine learning techniques: a literature review," Humanit Soc Sci Commun, vol. 11, no. 1, pp. 1–22, Dec. 2024, doi: 10.1057/S41599-024-03606-0;SUBJMETA.

[4] N. Husnaningtyas and T. Dewayanto, "FINANCIAL FRAUD DETECTION AND MACHINE LEARNING ALGORITHM (UNSUPERVISED LEARNING): SYSTEMATIC LITERATURE REVIEW," Jurnal Riset Akuntansi Dan Bisnis Airlangga, vol. 8, no. 2, pp. 1521–1542, Nov. 2023, doi: 10.20473/JRABA.V8I2.49927.

[5] Y. Yanto, L. Lisah, and R. Tandra, "The Best Machine Learning Model for Fraud Detection In Banking Sector: A Systematic Literature Review," eCo-Buss, vol. 7, no. 2, pp. 1361–1384, Dec. 2024, doi: 10.32877/EB.V7I2.1474.

[6] H. Abbassi, S. El Mendili, and Y. Gahi, "Real-Time Online Banking Fraud Detection Model by Unsupervised Learning Fusion," HighTech and Innovation Journal, vol. 5, no. 1, pp. 185–199, Mar. 2024, doi: 10.28991/HIJ-2024-05-01-014.

[7] S. M. N. Nobel et al., "Unmasking Banking Fraud: Unleashing the Power of Machine Learning and Explainable AI (XAI) on Imbalanced Data," Information 2024, Vol. 15, Page 298, vol. 15, no. 6, p. 298, May 2024, doi: 10.3390/INFO15060298.

[8] F. Li and Z. Chen, "Dynamic quantification anti-fraud machine learning model for real-time transaction fraud detection in banking," Discover Computing, vol. 28, no. 1, pp. 1–15, Dec. 2025, doi: 10.1007/S10791-025-09549-7/TABLES/5.

[9] S. Xiang et al., "Semi-supervised Credit Card Fraud Detection via Attribute-Driven Graph Representation," Proceedings of the 37th AAAI Conference on Artificial Intelligence, AAAI 2023, vol. 37, pp. 14557–14565, Dec. 2024, doi: 10.1609/aaai.v37i12.26702.

[10] C. Wang, C. Nie, and Y. Liu, "Evaluating Supervised Learning Models for Fraud Detection: A Comparative Study of Classical and Deep Architectures on Imbalanced Transaction Data," May 2025, doi: 10.48550/arXiv.2505.22521.

[11] M. R. Baker, Z. N. Mahmood, and E. H. Shaker, "Ensemble Learning with Supervised Machine Learning Models to Predict Credit Card Fraud Transactions," Revue d'Intelligence Artificielle, vol. 36, no. 4, pp. 509–518, Aug. 2022, doi: 10.18280/RIA.360401.

[12] D. Wang et al., "A Semi-supervised Graph Attentive Network for Financial Fraud Detection," Proceedings - IEEE International Conference on Data Mining, ICDM, vol. 2019-November, pp. 598–607, Feb. 2020, doi: 10.1109/ICDM.2019.00070.

[13] M. Ben Boubker, T. Elmettat, A. Eddaoui, and S. Ouahabi, "Fraud Detection in Financial Transactions Using Machine Learning with Oversampling Techniques: A Case Study of a Moroccan Bank," Journal of Electrical Systems, vol. 20, no. 10s, pp. 6443–6448, Jul. 2024, Accessed: Sep. 26, 2025. [Online]. Available: https://journal.esrgroups.org/jes/article/view/6664

[14] G. Zioviris, K. Kolomvatsos, and G. Stamoulis, "An intelligent sequential fraud detection model based on deep learning," Journal of Supercomputing, vol. 80, no. 10, pp. 14824–14847, Jul. 2024, doi: 10.1007/S11227-024-06030-Y/TABLES/4.

[15] M. J. Page et al., "The PRISMA 2020 statement: an updated guideline for reporting systematic reviews," BMJ, vol. 372, Mar. 2021, doi: 10.1136/BMJ.N71.

[16] D. Moher et al., "Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement," PLoS Med, vol. 6, no. 7, p. e1000097, Jul. 2009, doi: 10.1371/JOURNAL.PMED.1000097.

[17] A. Shukla and T. Kashni, "Análisis bibliométrico de la literatura sobre fraudes y estafas bancarias," Revista de Delitos, vol. 32, no. 3, pp. 729–750, Mar. 2025, doi: 10.1108/JFC-08-2024-0252.

[18] J. V. Raúl, A. A. Laberiano, M. V. Pedro, and Y. A. Cesar, "Revolución financiera: un análisis sistémico de la inteligencia artificial y el aprendizaje automático en el sector bancario," Revista Internacional de Ingeniería Eléctrica e Informática, vol. 14, no. 1, pp. 1079–1090, Feb. 2024, doi: 10.11591/ijece.v14i1.pp1079-1090.

[19] O. A. Oke and N. Cavus, "El papel de la IA en los servicios financieros: un análisis bibliométrico," Journal of Computer Information Systems, vol. 65, no. 4, pp. 518–530, 2025, doi: 10.1080/08874417.2024.2304545.

[20] A. S. Gangwar, A. Shukla, M. Sharma, and A. Kumar, "Un análisis bibliométrico exhaustivo del lavado de dinero y estafas relacionadas: tendencias, influencias y lagunas en la investigación," Revista Internacional de Investigación de Ámbito Multidisciplinario, vol. 6, no. 3, pp. 1236–1251, Jul. 2025, doi: 10.47857/irjms.2025.v06i03.04926.

[21] J. Adejoh, N. Owoh, M. Ashawa, S. Hosseinzadeh, A. Shahrabi, and S. Mohamed, "An Adaptive Unsupervised Learning Approach for Credit

Card Fraud Detection," Big Data and Cognitive Computing, vol. 9, no. 9, Sep. 2025, doi: 10.3390/bdcc9090217.

[22] I. Y. Hafez, A. Y. Hafez, A. Saleh, A. A. Abd El-Mageed, and A. A. Abohany, "A systematic review of AI-enhanced techniques in credit card fraud detection," J Big Data, vol. 12, no. 1, Dec. 2025, doi: 10.1186/s40537-024-01048-8.

[23] S. Ma and C. A. Hargreaves, "Addressing Credit Card Fraud Detection Challenges with Adversarial Autoencoders," Big Data and Cognitive Computing, vol. 9, no. 7, Jul. 2025, doi: 10.3390/bdcc9070168.

[24] G. Charizanos, H. Demirhan, and D. İçen, "An online fuzzy fraud detection framework for credit card transactions," Expert Syst Appl, vol. 252, Oct. 2024, doi: 10.1016/j.eswa.2024.124127.

[25] L. Abd-Ellatif, M. Abrar, and A. A. K. Ismaeel, "ATAD-Net: An Adaptive Deep Learning Framework for Real-Time Financial Fraud Detection," Advances in Artificial Intelligence and Machine Learning, vol. 5, no. 2, pp. 3988–4003, 2025, doi: 10.54364/AAIML.2025.52225.

[26] L. Theodorakopoulos, A. Theodoropoulou, A. Tsimakis, and C. Halkiopoulos, "Big Data-Driven Distributed Machine Learning for Scalable Credit Card Fraud Detection Using PySpark, XGBoost, and CatBoost," Electronics (Switzerland), vol. 14, no. 9, May 2025, doi: 10.3390/electronics14091754.

[27] E. S. M. El-Kenawy et al., "Credit Card Fraud Detection based on Deep Learning Models," Mesopotamian Journal of Computer Science, vol. 2024, pp. 204–213, Dec. 2024, doi: 10.58496/MJCSC/2024/016.

[28] E. Rawashdeh, N. Al-Ramahi, H. Ahmad, and R. Zaghloul, "Efficient credit card fraud detection using evolutionary hybrid feature selection and random weight networks," International Journal of Data and Network Science, vol. 8, no. 1, pp. 463–472, Dec. 2024, doi: 10.5267/j.ijdns.2023.9.009.

[29] F. Khaled Alarfaj and S. Shahzadi, "Enhancing Fraud Detection in Banking with Deep Learning: Graph Neural Networks and Autoencoders for Real-Time Credit Card Fraud Prevention," IEEE Access, vol. 13, pp. 20633–20646, 2025, doi: 10.1109/ACCESS.2024.3466288.

[30] H. Wang, Q. Liang, J. T. Hancock, and T. M. Khoshgoftaar, "Feature selection strategies: a comparative analysis of SHAP-value and importance-based methods," J Big Data, vol. 11, no. 1, Dec. 2024, doi: 10.1186/s40537-024-00905-w.

[31] Z. Xia and S. C. Saha, "FinGraphFL: Financial Graph-Based Federated Learning for Enhanced Credit Card Fraud Detection," Mathematics, vol. 13, no. 9, May 2025, doi: 10.3390/math13091396.

[32] N. Baisholan, J. E. Dietz, S. Gnatyuk, M. Turdalyuly, E. T. Matson, and K. Baisholanova, "FraudX AI: An Interpretable Machine Learning Framework for Credit Card Fraud Detection on Imbalanced Datasets," Computers, vol. 14, no. 4, Apr. 2025, doi: 10.3390/computers14040120.

[33] M. N. Vadlamudi, S. Doma, S. Fouzia Sayeedunnisa, M. Hijab, R. M. Chinnem, and B. Sankara Babu, "Towards Transparent Fraud Detection: Explainable AI and Multi-algorithm Optimization in Financial Security," International Journal of Intelligent Engineering and Systems, vol. 18, no. 10, pp. 698–712, Nov. 2025, doi: 10.22266/ijies2025.1130.45.

[34] A. A. Al-Maari, M. Abdulnabi, Y. Nathan, A. Ali, U. Ali, and M. Khan, "Optimized Credit Card Fraud Detection Leveraging Ensemble Machine Learning Methods," Engineering, Technology and Applied Science Research, vol. 15, no. 3, pp. 22287–22294, Jun. 2025, doi: 10.48084/etasr.10287.

[35] R. K. L. Kennedy, F. Villanustre, T. M. Khoshgoftaar, and Z. Salekshahrezaee, "Synthesizing class labels for highly imbalanced credit card fraud detection data," J Big Data, vol. 11, no. 1, Dec. 2024, doi: 10.1186/s40537-024-00897-7.

[36] I. D. Mienye and T. G. Swart, "A Hybrid Deep Learning Approach with Generative Adversarial Network for Credit Card Fraud Detection," Technologies (Basel), vol. 12, no. 10, Oct. 2024, doi: 10.3390/technologies12100186.

[37] M. Tayebi and S. El Kafhali, "A novel approach based on XGBoost classifier and Bayesian optimization for credit card fraud detection," Cyber Security and Applications, vol. 3, Dec. 2025, doi: 10.1016/j.csa.2025.100093.

[38] E. Karnavou, G. Cascavilla, G. Marcelino, and Z. Geradts, "I know you're a fraud: Uncovering illicit activity in a Greek bank transactions with unsupervised learning," Expert Syst Appl, vol. 288, Sep. 2025, doi: 10.1016/j.eswa.2025.128148.

[39] H. AbouGrad and L. Sankuru, "Online Banking Fraud Detection Model: Decentralized Machine Learning Framework to Enhance Effectiveness and Compliance with Data Privacy Regulations," Mathematics, vol. 13, no. 13, Jul. 2025, doi: 10.3390/math13132110.

[40] Y. Wu et al., "A Deep Learning Method of Credit Card Fraud Detection Based on Continuous-Coupled Neural Networks," Mathematics 2025, Vol. 13, vol. 13, no. 5, Feb. 2025, doi: 10.3390/MATH13050819.

[41] F. K. Alarfaj, I. Malik, H. U. Khan, N. Almusallam, M. Ramzan, and M. Ahmed, "Credit Card Fraud Detection Using State-of-the-Art Machine Learning and Deep Learning Algorithms," IEEE Access, vol. 10, pp. 39700–39715, 2022, doi: 10.1109/ACCESS.2022.3166891.

[42] L. Ding, L. Liu, Y. Wang, P. Shi, and J. Yu, "An AutoEncoder enhanced light gradient boosting machine method for credit card fraud detection," PeerJ Comput Sci, vol. 10, p. e2323, Oct. 2024, doi: 10.7717/PEERJ-CS.2323.

[43] I. D. Mienye and Y. Sun, "A Deep Learning Ensemble With Data Resampling for Credit Card Fraud Detection," IEEE Access, vol. 11, pp. 30628–30638, 2023, doi: 10.1109/ACCESS.2023.3262020.

[44] S. Al Balawi and N. Aljohani, "Credit-card Fraud Detection System using Neural Networks," International Arab Journal of Information Technology, vol. 20, no. 2, pp. 234–241, Mar. 2023, doi: 10.34028/iajit/20/2/10.

[45] H. S. Alsagri, "Hybrid Machine Learning-Based Multi-Stage Framework for Detection of Credit Card Anomalies and Fraud," IEEE Access, vol. 13, pp. 77039–77048, 2025, doi: 10.1109/ACCESS.2025.3565612.

[46] I. Akour, N. Mohamed, and S. Salloum, "Hybrid CNN-LSTM With Attention Mechanism for Robust Credit Card Fraud Detection," IEEE Access, vol. 13, pp. 114056–114068, 2025, doi: 10.1109/ACCESS.2025.3583253.

[47] I. Benchaji, S. Douzi, and B. El Ouahidi, "Credit card fraud detection model based on LSTM recurrent neural networks," Journal of Advances in Information Technology, vol. 12, no. 2, pp. 113–118, May 2021, doi: 10.12720/JAIT.12.2.113-118.

[48] A. R. Khalid et al., "Enhancing Credit Card Fraud Detection: An Ensemble Machine Learning Approach," Big Data and Cognitive Computing 2024, Vol. 8, vol. 8, no. 1, Jan. 2024, doi: 10.3390/BDCC8010006.

[49] E. Strelcenia, S. Prakoonwit, E. Strelcenia, and S. Prakoonwit, "Improving Classification Performance in Credit Card Fraud Detection by Using New Data Augmentation," AI 2023, Vol. 4, Pages 172-198, vol. 4, no. 1, pp. 172–198, Jan. 2023, doi: 10.3390/AI4010008.

[50] S. Zhu et al., "A Financial Fraud Prediction Framework Based on Stacking Ensemble Learning," Systems 2024, Vol. 12, vol. 12, no. 12, Dec. 2024, doi: 10.3390/SYSTEMS12120588.

[51] B. Mytnyk et al., "Application of Artificial Intelligence for Fraudulent Banking Operations Recognition," Big Data and Cognitive Computing 2023, Vol. 7, vol. 7, no. 2, May 2023, doi: 10.3390/BDCC7020093.

[52] V. Plakandaras, P. Gogas, T. Papadimitriou, and I. Tsamardinos, "Credit Card Fraud Detection with Automated Machine Learning Systems," Applied Artificial Intelligence, vol. 36, no. 1, Dec. 2022, doi: 10.1080/08839514.2022.2086354;WGROUP:STRING:PUBLICATION.

[53] M. N. Alatawi, "Detection of fraud in IoT based credit card collected dataset using machine learning," Machine Learning with Applications, vol. 19, p. 100603, Mar. 2025, doi: 10.1016/J.MLWA.2024.100603.

[54] R. K. Gupta et al., "Enhanced framework for credit card fraud detection using robust feature selection and a stacking ensemble model approach," Results in Engineering, vol. 26, p. 105084, Jun. 2025, doi: 10.1016/J.RINENG.2025.105084.

[55] X. Feng, S.-K. Kim, X. Feng, and S.-K. Kim, "Novel Machine Learning Based Credit Card Fraud Detection Systems," Mathematics 2024, Vol. 12, vol. 12, no. 12, Jun. 2024, doi: 10.3390/MATH12121869.

[56] S. Khan, A. Alourani, B. Mishra, A. Ali, and M. Kamal, "Developing a Credit Card Fraud Detection Model using Machine Learning Approaches," International Journal of Advanced Computer Science and Applications, vol. 13, no. 3, pp. 411–418, Mar. 2022, doi: 10.14569/IJACSA.2022.0130350.

[57] A. Muaz, M. Jayabalan, and V. Thiruchelvam, "A Comparison of Data Sampling Techniques for Credit Card Fraud Detection," IJACSA) International Journal of Advanced Computer Science and Applications, vol. 11, no. 6, 2020, Accessed: Nov. 16, 2025. [Online]. Available: www.ijacsa.thesai.org

[58] C. Hamza, A. Lylia, C. Nadine, and C. Nicolas, "Semi-supervised Method to Detect Fraudulent Transactions and Identify Fraud Types while Minimizing Mounting Costs," IJACSA) International Journal of Advanced Computer Science and Applications, vol. 14, no. 2, p. 2023, Accessed: Nov. 16, 2025. [Online]. Available: https://www.kaggle.com/mlg-ulb/creditcardfraud

[59] F. O. Aghware, R. E. Yoro, P. O. Ejeh, C. C. Odiakaose, F. U. Emordi, and A. A. Ojugo, "DeLClustE: Protecting Users from Credit-Card Fraud Transaction via the Deep-Learning Cluster Ensemble," IJACSA) International Journal of Advanced Computer Science and Applications, vol. 14, no. 6, p. 2023, Accessed: Nov. 16, 2025. [Online]. Available: www.ijacsa.thesai.org

User Experience Evaluation in Government Applications: A Systematic Review

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***Abstract*—Evaluating the User Experience (UX) of government applications is becoming increasingly crucial as governments deploy public services online. Nevertheless, research in this area remains fragmented. Correspondingly, this study presents a systematic review of UX evaluation in government applications to address the following Research Questions (RQs): What UX evaluation approaches and UX dimensions have been employed in the UX evaluation of government applications, and how do domains, contextual, and cultural considerations influence the UX evaluation of government applications? Kitchenham and Charters' guidelines, as well as the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA), are employed to guide this review. Moreover, recent studies from Scopus and Web of Science (WoS) databases between the years 2023 and 2025 were retrieved using a predefined review protocol. After applying the inclusion and exclusion criteria and subjecting the studies to quality assessment, the final number of retained studies for this review is 19. The analysis reveals four key themes: diversity in UX evaluation approaches, the range of UX dimensions evaluated, the range of domains evaluated, and the contextual and cultural considerations in UX evaluations. The findings reveal that UX evaluations of government applications are predominantly usability-focused, while hedonic, emotional, and cultural dimensions receive limited and inconsistent attention. In addition, the review highlights that UX evaluations for government applications should encompass both technical and pragmatic aspects, as well as domain-specific, cultural, and contextual dimensions. Accordingly, strengthening these evaluations can lead to more inclusive and meaningful assessments, resulting in government applications that offer better UX. Overall, the findings of this review may serve as a reference for future work and advance the field of UX evaluation, especially in the context of government applications.**

Keywords*—User Experience Evaluation; UX evaluation; government applications; e-government; systematic review

I. Introduction

Within the domain of human-computer interaction, User Experience (UX) has emerged as a fundamental aspect in the quality of interaction between users and digital systems, extending beyond traditional usability. In [1], UX is defined as encompassing all aspects of users' interaction with products and services, including perceptions, emotions, and responses that arise before, during, and after use [2], [3]. Similar to other forms of computing technology, all applications, including those used by governments, have UX as an integral component. Thus, it is crucial for UX to be considered during the design, development, and evaluation stages of these applications. This is to ensure a positive UX when interacting with, and/or anticipating interaction with, the applications. Consequently, to benefit from what the government intended to provide and share through its applications. Note that poor UX can cause repercussions, such as having difficulties in using the application. This includes missing out on crucial information, frustration, and abandonment, which can defeat the purpose of having these e-government initiatives [4].

In the context of interaction design, the lifecycle of producing applications (design, development, and evaluation stages) includes evaluation, a core component that is centered on both usability and UX [5]. In particular, UX evaluation is the process of collecting and analyzing data about users' or potential users' UX when interacting with artifacts. Examples of artifacts include screen sketches, prototypes, system components, a specific function, the entire workflow, the complete system or application, and safety features, to name a few. Therefore, it is crucial to conduct an evaluation for the following reasons: a rigorous evaluation helps enhance overall quality, allows users to understand their expectations, and ensures the product aligns with their needs and preferences. This guarantees that products are well-designed, as good experiences lead to desirable outcomes such as adoption, retention, use, sales, downloads, and recommendations. It also enables the identification and rectification of any issues before the product is released to the market [4], [6].

Since the early 1990s, the field of Information and Communication Technologies (ICTs) has undergone rapid progress, resulting in significant improvements across various societal areas, including, but not limited to, agriculture, communication, education, industry, transportation, government, and everyday life. In ICTs for government, one of the most notable innovations to emerge is electronic government (e-government). Notably, e-government is an umbrella term for the use of ICTs to access and deliver government services, disseminate government information, communicate between the government and its citizens, agencies, and stakeholders, and support internal government operations. The aim of e-government is to enhance the efficiency and effectiveness of government operations and accountability, as well as improve the government's engagement with citizens [7], [8]. Furthermore, to keep pace with technological advancements and provide better, faster, and more convenient services to citizens, governments offer applications through both mobile and web platforms, enabling citizens and stakeholders to access government services and engage with the government. As the

use of these applications and the reliance of the public on government applications grow, these applications must be designed and evaluated to support meaningful engagement and provide a positive UX.

Therefore, evaluating UX in the context of government applications is a core necessity, as UX is progressively acknowledged as essential for products and services, including those in the government sector [3]. While governments have increasingly delivered services through government applications, and the usage of these applications has risen, studies on their UX evaluation remain fragmented and dispersed, with varied approaches and focuses [9], [10], [11]. In [9], the authors showed that the studies addressing UX factors such as usability, trust and satisfaction are inconsistent across different service types and regions. The works of [10] and [11] demonstrated the common usage of usability evaluation approaches such as System Usability Scale (SUS), Smartphone Usability Questionnaire (SURE), heuristic evaluation and usability inquiry, to conduct UX evaluation for e-governments applications. While usability is a core component of UX, conducting UX evaluation using usability evaluation approaches is insufficient, with only usability as the focal point and not including other aspects of the user experience [37]. Additionally, the development of cumulative knowledge that can inform better UX evaluation is hindered, as is the potential for comparability across studies in the field. Meanwhile, several UX evaluation works have incorporated a broader range of UX dimensions beyond usability, and adopted evaluation approaches other than usability evaluation, such as [2] in online systems, [38] in AI-powered systems, [39] in business intelligence visualization, [40] in blockchain, and [41] in education. However, these works are domain-specific, designed with consideration of the domain's unique UX dimensions, and hence these UX evaluations are not directly transferable to the government application context. In contrast to the existing related studies, this study offers a systematic review that identifies and synthesizes UX evaluation approaches, dimensions, domains, and contextual and cultural considerations reported in the literature on government applications. Hence, this systematic review is warranted to investigate the existing literature on approaches, dimensions, domains, and considerations, contextualized and culturally. This ensures clearer directions for future research and practice in the UX evaluation of government applications.

Although there are several review studies that are related to this study, the existing reviews demonstrate notable limitations that motivate the present study. First, some review studies on government applications concentrated on usability evaluation rather than UX evaluation, leading to a narrower evaluative scope [10, 11]. Second, in [3], the authors examined the UX dimensions of e-procurement systems, which are only a subset of government applications and do not fully represent the larger domain of government applications. Other reviews employed a general perspective without focusing on domains: [42] reviewed UX evaluation techniques, factors influencing UX, and benefits of evaluating UX without anchoring their study in any specific domain. Another study that used the general perspective is [43], which focused on reviewing methods and metrics of UX evaluation. Lastly, [44]'s review study focused on the evaluation of public service quality instead of the evaluation of its applications (e.g., websites and mobile applications), and did not explicitly include UX evaluation in their study. These limitations, when viewed collectively, show that existing reviews do not provide a recent, domain-specific account of UX evaluation in government applications, with contextual and cultural considerations taken into account. Notably, the earlier reviews have not systematically examined how domain and cultural and contextual considerations are reflected in UX evaluations in government applications. To the best of the authors' knowledge, this is the first review that consolidated UX evaluation approaches and UX dimensions in government applications with the inclusion of domain-specificity, and contextual and cultural considerations. Also, concentrating this review on literature published between 2023 and 2025 enables the capture of recent developments in UX evaluation in government applications that reflect shifts in electronic government strategies, public service delivery via mobile applications, emerging UX evaluation approaches, and the growing recognition of UX as a multidimensional construct beyond usability. Prior studies predate these developments and offer only a limited representation of the current state of UX evaluation in government applications. With the focus on the 2023-2025 recent studies, this review intends to identify emerging UX evaluation approaches, UX dimensions, and contextual and cultural considerations that are relevant to contemporary government applications. This review contributes to the literature by analyzing current UX evaluation practices in government application studies and by highlighting the role of domain-specificity, contextual, and cultural considerations within these evaluations.

This study presents a systematic review of the literature on UX evaluation in government applications. The objectives of the review are to: 1) identify UX evaluation approaches and UX dimensions that are used in the UX evaluation of government applications, and 2) to examine how domains, and contextual and cultural considerations shape the UX evaluation of government applications. In particular, this review aims to contribute to the emerging body of scholarship on UX evaluation and digital government by providing a structured overview and synthesis of UX evaluation for government applications.

The remainder of this study is structured as follows: Section II details the review method, Section III presents the findings of the review, Section IV offers the discussion, and Section V concludes the study. The following section describes the review method undertaken in this systematic review.

II. Review Method

This systematic review was planned and executed according to the guidelines established by [12], which provide a well-defined structure for conducting systematic reviews within the computing context. For reporting the systematic review's findings, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram [13], [14] was employed. The combination of Kitchenham and Charters' guidelines [12] with PRISMA provides a methodologically rigorous, structured set of steps for defining review objectives, formulating Research Questions (RQs), and outlining

procedures for searching databases, selecting studies, extracting data, and synthesizing systematically.

As established by [12], the systematic review process has three phases: planning the review, conducting the review, and documenting/reporting the review. This study aligns with these three phases. There are specific activities for each phase, which are documented in Table I and further explained in the following subsections.

TABLE I. MAIN ACTIVITIES IN SYSTEMATIC REVIEW PHASES

Phase	Activities
Planning the review	Developing a review protocol
	Identifying research questions
	Identifying inclusion and exclusion criteria
Conducting the review	Implement search strategy and study selection
	Select primary studies
	Perform quality assessment
Documenting/reporting the review	Data extraction and synthesis

A. Planning the Review

This phase involves developing the review protocol, which includes identifying the RQs for this systematic review and establishing the inclusion and exclusion criteria.

1) Review protocol: Developing the review protocol is a fundamental first step in all systematic review protocols, as it provides a predefined plan that serves as a blueprint and a control measure to reduce bias introduced by the researchers [15], [12]. Following the Kitchenham and Charters guidelines, as demonstrated by [16], this study's review protocol is presented in Fig. 1:

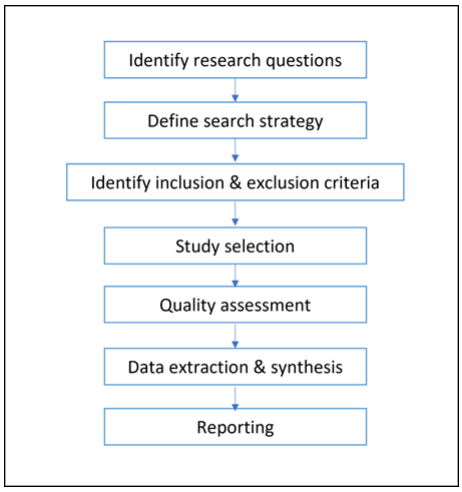


Fig. 1. Review protocol.

2) Research questions: This systematic review is anchored by two RQs that establish the foundation for this study:

RQ1: What UX evaluation approaches and UX dimensions have been employed in the UX evaluation of government applications?

RQ2: How do domains and contextual and cultural considerations influence the UX evaluation of government applications?

3) Search strategy: To define the search strategy, primary keywords and relevant terms are identified, and search strings are constructed using lexical resources (e.g., dictionaries and thesauri), reference materials, and prior scholarly works. Consequently, the search strings are entered into two major scholarly databases, Scopus and Web of Science (WoS), to search for relevant studies for the review process. Scopus and WoS are selected as the primary databases due to their robustness, high-quality indexing, comprehensive coverage, peer-reviewed status, and wide acceptance among the scholarly community. The search strings used are detailed in Table II. From this initial search, a total of 1,622 publications related to this study were identified, laying a solid foundation for further screening and analysis.

TABLE II. SEARCH STRINGS

Database	Search strings
Scopus	TITLE-ABS-KEY (("user experience evaluation" OR ux evaluation) AND (government OR "public service")) AND (LIMIT-TO (SUBJAREA , "COMP") OR LIMIT-TO (SUBJAREA , "ENGI") OR LIMIT-TO (SUBJAREA , "MATH") OR LIMIT-TO (SUBJAREA , "MULT") OR LIMIT-TO (SUBJAREA , "ECON") OR LIMIT-TO (SUBJAREA , "BUSI") OR LIMIT-TO (SUBJAREA , "DECI")) AND (LIMIT-TO (PUBYEAR , 2023) OR LIMIT-TO (PUBYEAR , 2024) OR LIMIT-TO (PUBYEAR , 2025)) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (LANGUAGE , "English")) Date of Access: May 2025
Web of Science	("user experience evaluation" OR ux evaluation) AND (government OR "public service") (Topic) and 2025 or 2023 or 2024 (Publication Years) and Article (Document Types) and English (Languages) and Article (Document Types) and English (Languages) Date of Access: May 2025

4) Inclusion and exclusion criteria: The next step in the review protocol is screening, where the initial set of 1,622 publications from the first stage is refined using inclusion and exclusion criteria. This refinement is conducted to ensure that the publications are related to this study and support the research objectives. Note that studies were excluded if they were published before 2023, written in a language other than English, or classified as conference papers, book chapters, review articles, or articles still in press. In addition, records belonging to subject areas outside the scope of the research, specifically computer science, engineering, business, management and accounting, economics, econometrics and finance, and multidisciplinary fields, were also removed. Following this rigorous screening, a total of 1,441 records were excluded. The remaining dataset comprised 149 publications, with 99 sourced from Scopus and 50 from WoS. A subsequent duplicate check was performed using a reference manager,

resulting in the removal of 18 duplicate records, leaving 131 publications for the next step of the review protocol. In essence, this process ensured that the final set of studies is both highly relevant and aligned with the research objectives, providing a robust foundation for the subsequent phases of the systematic review. Table III summarizes the inclusion and exclusion criteria used.

TABLE III. INCLUSION AND EXCLUSION CRITERIA FOR THE SELECTION CRITERIA IN SEARCHING

Criterion	Inclusion	Exclusion
Language	English	Non-English
Timeline	2023 – 2025	< 2023
Literature type	Journal (article)	Conference, Book, Review
Publication stage	Final	In press
Subject area	Computer science Engineering Business, management, and accounting Economics, econometrics, and finance Multidisciplinary	Besides Computer science Engineering Business, management, and accounting Economics, econometrics, and finance Multidisciplinary

5) Study selection: In this step, the titles and abstracts of the 131 publications from the previous phase are further examined to ensure eligibility, aligning with the established inclusion criteria and research objectives. A total of 97 articles were excluded on the grounds of falling outside the relevant field of UX evaluation in government applications, lacking significance based on their titles, presenting abstracts that did not correspond to the study's objectives, and/or lacking accessible full-text versions grounded in empirical research. Following this eligibility assessment, 34 articles were retained for quality assessment. Accordingly, the study process is documented using the PRISMA 2020 flow diagram [14], in Fig. 2.

6) Quality assessment: Quality assessment is an integral assessment in systematic reviews for determining the quality of the selected studies [12]. In this study, the quality assessment criteria are adopted from [17]'s quality assessment framework. There are a total of eight (8) quality assessment criteria formulated for this study. For the scoring system, a three-point score is assigned in which 1 ("Yes") is for when the criterion is fully satisfied, 0.5 ("Partially") is for when the criterion is only partially satisfied, and 0 ("No") is for when the criterion is not fully satisfied. The 34 articles from the previous step are screened using the quality assessment criteria. Following this screening, 15 articles were identified as not meeting 70% of the quality assessment criteria, leaving the remaining 19 articles as the primary studies for subsequent data extraction and analysis. Table IV presents the quality assessment criteria used in this step, and Table VI displays the results of the quality assessment of the selected papers.

TABLE IV. QUALITY ASSESSMENT CRITERIA

QA1	Is the purpose of the study clearly stated?
QA2	Is the interest and the usefulness of the work clearly presented?
QA3	Is the study methodology clearly established?
QA4	Are the concepts of the approach clearly defined?
QA5	Is the work compared and measured with other similar work?
QA6	Are the limitations of the work clearly mentioned?
QA7	Is the study explicitly focused on UX evaluation for government applications?
QA8	Does the study explicitly involve government applications or public service platforms as its domain of investigation?

7) Data extraction and synthesis: From the quality assessment step, nineteen studies are retained for data extraction and analysis. Data extraction is performed by examining each paper and extracting relevant data using MS Excel spreadsheets. This is done in accordance with guidelines [12] to construct data extraction forms to capture the data from the initial search in a systematic and reliable manner. Note that the selection of extracted data is guided by the RQs. It comprises the title of the article, authors, publication year, keywords, abstracts, journal titles, countries/regions in which the research is conducted, domains of investigation, platforms (web/mobile), UX evaluation approaches/methodologies, UX dimensions, and cultural and contextual considerations. The next section presents the findings of the review, organized according to descriptive overview and themes.

III. FINDINGS

The findings of this systematic review are outlined in this section, beginning with a descriptive overview of the studies, followed by a synthesis of the key themes identified across the reviewed studies. Discussion of the findings is presented in the next section.

A. Descriptive Overview

Publication years: The 19 papers in this study were published between 2023 and 2025, with the majority (10) published in 2024. Table V below summarizes the distribution of papers according to their year of publication.

TABLE V. PUBLICATION YEARS OF THE REVIEWED PAPERS

Year	Number of papers	Authors
2023	6	Yakovchenko et al. [18], Alharbi et al. [19], Hu et al. [20], Nagro [21], Cheng & Chen [22], Alghareeb et al. [23]
2024	10	Ro et al. [24], Benaida [25], Wahyuningrum et al. [26], Zubir & Latip [27], Puspasari et al. [28], Sapraz & Han [29], Nawafleh & Khasawneh [30], Aziz et al. [31], Fadrial et al. [32], Patergiannaki & Pollalis [33]
2025	3	Ashar et al. [34], Amer et al. [35], Kencono et al. [36]

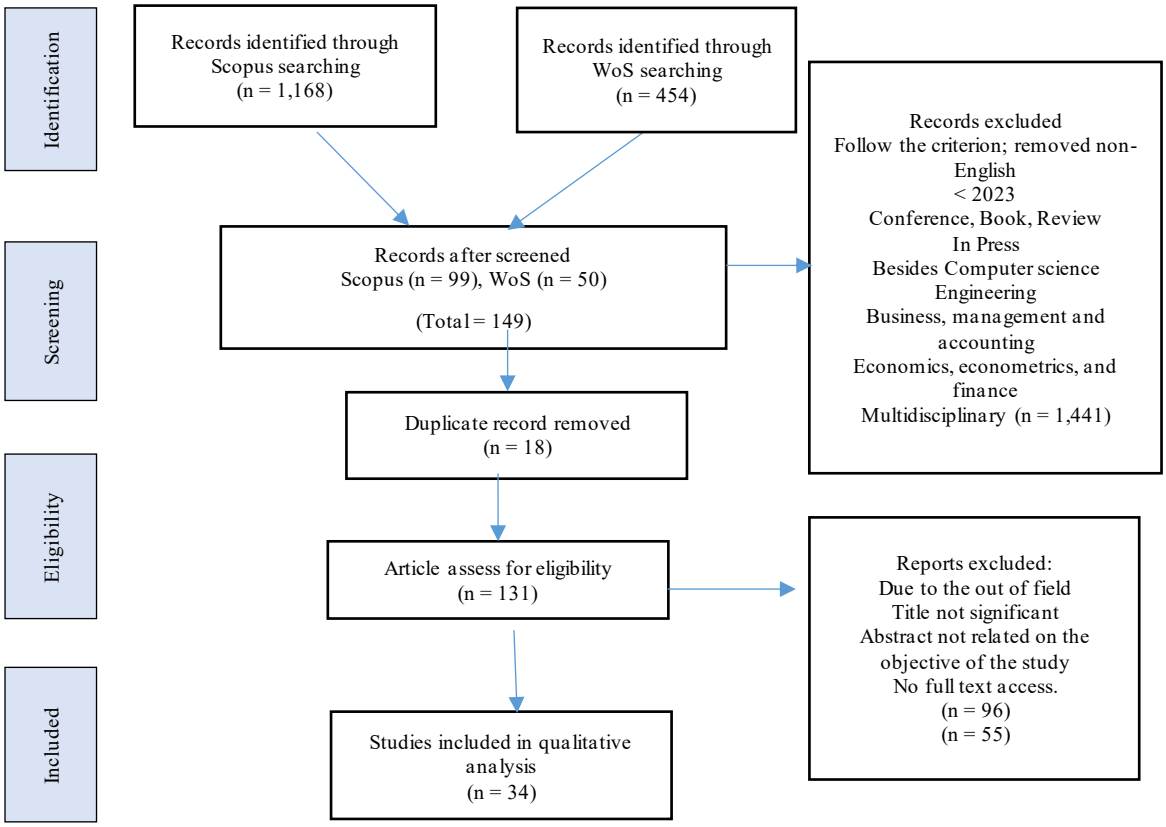


Fig. 2. The PRISMA flow diagram.

TABLE VI. QUALITY ASSESSMENT RESULTS OF THE SELECTED PAPERS

No.	Authors	Year	QA1	QA2	QA3	QA4	QA5	QA6	QA7	QA8	Total	%
1	Puspasari et al.	2024	1	1	1	0.5	0.5	0.5	1	1	6.5	81.3
2	Chi et al.	2024	1	1	1	1	1	0.5	0	0	5.5	68.8
3	Ro et al.	2024	1	1	1	1	0.5	1	1	1	7.5	93.8
4	Yakovchenko et al.	2023	1	1	1	1	1	1	1	1	8	100.0
5	Alharbi et al.	2023	1	1	1	1	1	1	1	1	8	100.0
6	Luo et al.	2024	1	1	1	0.5	0.5	0	0	0	4	50.0
7	Nagro S.A.	2023	1	1	1	1	1	0.5	1	1	7.5	93.8
8	Arya & Pal	2024	1	1	1	1	1	0.5	0	0	5.5	68.8
9	Cheng & Chen	2023	1	1	1	1	0.5	0	1	1	6.5	81.3
10	Geng et al.	2024	1	1	1	1	0.5	0.5	0	0	5	62.5
11	Křemen et al.	2025	1	1	0.5	1	0.5	0.5	0	0	4.5	56.3
12	Sapraz & Han	2024	1	1	1	1	1	0.5	1	1	7.5	93.8
13	Chang & Huang	2023	1	1	1	1	1	0.5	0	0	5.5	68.8
14	Sun et al.	2025	1	1	1	0.5	0.5	1	0	0	5	62.5
15	Nawafleh & Khasawneh	2024	1	1	1	1	0.5	0.5	1	1	7	87.5
16	Salama et al.	2023	1	1	1	1	1	0.5	0	0	5.5	68.8
17	Aziz et al.	2024	1	1	1	1	0.5	0.5	1	1	7	87.5
18	Koo et al.	2025	1	1	1	0.5	1	0.5	0	0	5	62.5
19	Benaida M.	2024	1	1	1	0.5	0.5	0.5			4.5	56.3
20	Norabuena-Mendoza et al.	2025	1	1	1	1	0.5	0.5	0	0	5	62.5

21	Wahyuningrum et al.	2024	1	1	1	1	0.5	0.5	1	1	7	87.5
22	Ashar et al.	2025	1	1	1	1	1	0.5	1	1	7.5	93.8
23	Mabkhot et al.	2024	1	1	1	1	1	0.5	0	0	5.5	68.8
24	Reddy et al.	2023	1	1	1	1	0.5	1	0	0	5.5	68.8
25	Amer et al.	2025	1	1	1	1	0.5	0.5	1	1	7	87.5
26	Fadrial et al.	2024	1	1	1	1	0.5	0.5	1	1	7	87.5
27	Alzebda et al.	2025	1	1	1	1	1	0.5	0	0	5.5	68.8
28	Kencono et al.	2025	1	1	0.5	0.5	0.5	0.5	1	1	6	75.0
29	Amro et al.	2023	1	1	1	1	0.5	0.5	0	0	5	62.5
30	Hu et al.	2023	1	1	1	1	0.5	0.5	1	1	7	87.5
31	Li et al.	2023	1	1	1	1	0.5	0.5	0	0	5	62.5
32	Alghareeb et al.	2023	1	1	1	1	1	1	1	1	8	100.0
33	Patergiannaki & Pollalis	2024	1	1	1	1	0.5	0.5	1	1	7	87.5
34	Zubir & Latip	2024	1	1	1	1	1	0.5	1	1	7.5	93.8

Domains covered: The 19 reviewed studies focused on government applications delivered via mobile and web platforms across six domains. The domains of the papers are listed in the following Table VII.

TABLE VII. DOMAINS COVERED IN THE REVIEWED PAPERS

Domain	Number of papers	Authors
Public services	9	Alharbi et al. [19], Benaida [25], Zubir & Latip [27], Nawafleh & Khasawneh [30], Fadrial et al. [32], Patergiannaki & Pollalis [33], Sapraz & Han [29], Amer et al. [35], Kencono et al. [36]
Healthcare	5	Yakovchenko et al. [18], Alghareeb et al. [23], Nagro [21], Wahyuningrum et al. [26], Ashar et al. [34]
Navigation	3	Hu et al.[20], Cheng & Chen [22]
Tourism	1	Aziz et al. [31]
Law enforcement	1	Puspasari et al. [28]
Assistive technology	1	Ro et al. [24]

Platforms: The studies are categorized into two platforms, mobile and web, as presented in Table VIII below.

TABLE VIII. PLATFORMS OF THE GOVERNMENT APPLICATIONS IN THE REVIEWED PAPERS

Platform	Number of Papers	Authors
Mobile	9	Hu et al. [20], Nagro [21], Alghareeb et al. [23], Wahyuningrum et al. [26], Zubir & Latip [27], Puspasari et al. [28], Aziz et al. [31], Ashar et al. [34], Kencono et al. [36]
Web	10	Yakovchenko et al. [18], Alharbi et al. [19], Cheng & Chen [22], Ro et al. [24], Benaida [25], Sapraz & Han [29], Nawafleh & Khasawneh [30], Fadrial et al. [32], Patergiannaki & Pollalis [33], Amer et al. [35]

Countries/regions: The studies were conducted in various regions, including Asia, Europe, Africa, and North America, with one cross-national study involving 50 countries [19]. Twelve countries in which the studies are conducted are presented in Table IX below. Two studies involved two countries in their works: Morocco and Tunisia [25] and Malaysia and Thailand [31].

TABLE IX. COUNTRIES/REGIONS OF THE GOVERNMENT APPLICATIONS IN THE REVIEWED PAPERS

Region	Number of countries	Country	Number of papers	Authors
Asia	9	Malaysia Indonesia Thailand South Korea China Sri Lanka Taiwan Saudi Arabia Jordan	3 4 1 1 1 1 1 2 2	Zubir & Latip [27], Aziz et al. [31], Ashar et al. [34] Wahyuningrum et al. [26], Puspasari et al. [28], Fadrial et al. [32], Kencono et al. [36] Aziz et al. [31] Ro et al. [24] Hu et al. [20] Sapraz & Han [29] Cheng & Chen [22] Nagro [21], Alghareeb et al. [23] Nawafleh & Khasawneh [30], Amer et al. [35]
Africa	2	Morocco, Tunisia	1	Benaida [25]
Europe	1	Greece	1	Patergiannaki & Pollalis [33]
North America	1	United States	1	Yakovchenko et al. [18]
Cross-national	1	50 countries	1	Alharbi et al. [19]

Evaluation approaches/methodologies: A mix of standardized usability/UX tools and methods, including quantitative, qualitative, and experimental/design-based nature, was used across the 19 studies. The following Table X illustrates the evaluation approaches/methodologies identified.

TABLE X. EVALUATION APPROACHES/METHODOLOGIES USED IN THE REVIEWED PAPERS

Evaluation approaches/methodologies	Authors
System Usability Scale (SUS) UMUX/UMUX-Lite User Experience Questionnaire (UEQ) Single Ease Question (SEQ) Research-based web design/usability guidelines (RBWDUG)	Yakovchenko et al. [18], Nagro [21] Wahyuningrum et al. [26], Nagro [21] Sapraz & Han [21] Wahyuningrum et al. [26] Benaida [25]
Expert reviews Interviews Think-aloud protocol Thematic analysis Sentiment analysis	Alharbi et al. [19], Aziz et al. [31] Cheng & Chen [22], Sapraz & Han [29], Amer et al. [35] Ro et al. [24] Ashar et al. [34], Puspasari et al. [28] Puspasari et al. [28], Kencono et al. [36]
Surveys and questionnaires Website analytics Process mining & social network analysis	Zubir & Latip [27], Nawafleh & Khasawneh [30], Fadrial et al. [32], Patergiannaki & Pollalis [33] Cheng & Chen [22], Ashar et al. [34] Amer et al. [35]
Value-Sensitive Design & FEDS framework AR usability experiments	Sapraz & Han [29] Hu et al. [20], Aziz et al. [31]

B. Themes

Examination of the reviewed studies revealed four central themes: diversity in UX evaluation approaches, the range of UX dimensions evaluated, the range of domains evaluated, and the consideration of contextual and cultural factors.

C. Diversity in UX Evaluation Approaches

The studies employed a diverse set of approaches to evaluate the UX of the web and mobile government applications. This demonstrates a methodological theme reflected in the use of qualitative, quantitative, and mixed-method approaches. For instance, [18], [21], [26], and [29] implemented standardized instruments for evaluating usability and UX, such as System Usability Scale (SUS), Usability Metric for User Experience (UMUX), UMUX-Lite, User Experience Questionnaire (UEQ), and Single Ease Questionnaire (SEQ). Meanwhile, [20] and [24] conducted their evaluations using task-based and experimental methods, including task analysis and behavior-emotion analysis. Inspection-based and heuristic evaluations were also incorporated, along with expert reviews and usability guidelines in [19], [31], and [25]. In addition, several studies combined mixed-methods approaches: analytics, surveys and interviews in [32], [34] and [35], sentiment and thematic analyses, and natural language processing of user reviews in [23], [28] and [36], and surveys, interviews, UEQ, and the Framework for Evaluation in Design Science Research (FEDS) in [29]. Moreover, [27], [30], [33], and [34] utilized large-scale surveys and are grounded in models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). At the same time, innovative approaches were also deployed, such as [35]'s use of a case study with process mining and network analysis. Essentially, the use of this diverse set highlights that the researchers rely on quantitative, qualitative, and mixed-methods approaches, enabling them to capture a range of UX dimensions during the evaluations.

D. Variety of UX Dimensions Evaluated

A variety of UX dimensions were evaluated in the reviewed studies. A recurring dimension is usability [19], [21], [18], [20], [25], [24], [26]. Effectiveness is a dimension investigated by [23], [24], [26], [28], [34], and [36]. Additionally, efficiency is also evaluated by [24], along with [23], [18], [25], and [35]. The satisfaction dimension is covered in the evaluations conducted by [23], [24], [25], [26], [30], and [36]. In [25], [27], and [33], the researchers investigated dimensions related to use: ease of use and perceived usefulness. Following this, accessibility is assessed by [19], [24], [25], and [26]. [19] also evaluated privacy, along with [36]. Conversely, [20] included emotional experience dimensions: pleasure, arousal, and dominance. Meanwhile, [32], [30], and [36] measured service quality, trust, security, and transparency. In [28] and [36], perceptions of performance, functionality, and performance were investigated. When considered together, the reviewed studies indicate that evaluations of UX encompass pragmatic, hedonic, and emotional responses, as well as government-specific concerns and context-specific cultural and social dimensions. Collectively, these highlight the multidimensional nature of UX in government applications.

E. Range of Domains in the UX Evaluations

The studies reviewed have undergone UX evaluation of government applications across various domains, including public services, healthcare, navigation, tourism, law enforcement, and assistive technology. This illustrates the varied functions provided by the government through its web and mobile platforms. The most prominent domain with the largest number of studies is public services delivered through government websites or mobile applications [19], [25], [27], [30], [32], [33], [29], [35], [36]. Several studies explicitly stated the type of public service provided. For example, [35]'s work evaluated electronic building permit systems, [29]'s work investigated a platform for citizens and the Sri Lankan government to collaborate on environmental issues, [33]'s work evaluated Greek municipal portals, and [36]'s work investigated the regional government mobile applications. The next domain is healthcare, which is investigated by [21], [18], [23], [26], and [34]. [20] and [22]'s works are in the navigation domain. Meanwhile, the domains of tourism, law enforcement, and assistive technology each have one study ([31], [28], [24]). The identified domains consist of established services, including public services, healthcare, tourism, and law enforcement, as well as emerging ones such as navigation and assistive technology. As a whole, these domains reflect the domain-specific needs that inform the UX evaluation criteria and shape the UX of the applications.

F. Contextual and Cultural Considerations in UX Evaluations

The studies were conducted across a diverse set of countries and regions, bringing the emergence of contextual and cultural considerations as a notable theme and reflecting their roles in UX evaluations. The majority of the works were situated in Asia: Malaysia [27], [34], [31], Indonesia [26], [28], [32], [36], China [20], Taiwan ([22]), South Korea [24], Sri Lanka [29], Saudi Arabia [21]; [23], and Jordan [30], [35]. Correspondingly, the Asian works highlighted issues such as accessibility, cultural

heritage integration, citizen trust, digital adoption, loyalty, usability, sentiment towards government applications, and the influence of social and cultural norms on the adoption of government applications. Conversely, [25]'s work addresses the accessibility challenges of government applications in Northern African countries, specifically Morocco and Tunisia. [33]'s work, set in Europe, examined the Greek e-government service quality. In North America, [18] investigated the large-scale United States health management dashboards' usability. Another work is cross-national, involving 50 countries' e-government websites' privacy norms and usability [19]. Collectively, these studies have proven that UX evaluation is shaped by both technical considerations and contextual and cultural considerations, as well as contexts from the institutional and socio-political landscapes. The UX evaluation of government applications is thus demonstrated to involve contextual considerations, local cultural expectations, policy frameworks, and societal norms. This ultimately affirms the importance of contextually and culturally grounded evaluation approaches in conducting UX evaluations. These findings are discussed in the subsequent section.

IV. Discussion

This systematic review sets out to address two RQs:

RQ1: What UX evaluation approaches and UX dimensions have been employed in the UX evaluation of government applications?

RQ2: How do domains and contextual and cultural considerations influence the UX evaluation of government applications?

On the first RQ, a core finding that is consistently observed throughout the studies is the diverse approaches used in UX evaluations of government applications. Furthermore, a wide range of approaches is applied by the researchers. It ranges from standardized instruments for usability and UX evaluation (e.g., SUS, UMUX, UEQ), analytical and interpretive techniques (task analysis, behavior-emotion analysis, heuristic evaluations, expert reviews, surveys, and interviews), computational and data-driven methods (sentiment analysis, thematic analysis, natural language processing of user reviews, process mining, and network analysis), to framework-based approaches such as the FEDS ([18], [21], [26], [29], [20], [24], [19], [31], [25], [32], [34], [35], [23], [28], [36], [27], [30], [33], [35]. In addition, the diversity in the UX evaluation approaches deployed by the researchers is two-pronged. However, this current practice is both rich and fragmented in the sense that while various approaches can assess a variety of UX dimensions, the lack of a widely-recognized or dominant single approach suggests that standardization in UX evaluation for government applications has yet to be established. Similarly, the variety of UX dimensions evaluated across the studies has also revealed a significant pattern. Pragmatic dimensions such as usability, efficiency, effectiveness and satisfaction are consistently examined [19], [21], [18], [20], [23], [25], [24], [26], [28], [30], [27], [33], [34], [36], [35] but hedonic and emotional dimensions [20] are limited. Meanwhile, government-specific dimensions such as privacy, transparency, trust, and service quality appeared as notable dimensions in several studies [25], [30], [36]. This signifies a progression from evaluations focused purely on usability, oriented to a richer understanding of UX. Nevertheless, gaps emerged from the uneven distribution of attention across the dimensions. Cultural, emotional, and social dimensions remain underexplored compared to the pragmatic or functional dimensions.

Moving to RQ2, the reviewed studies indicate that domains, as well as contextual and cultural considerations, influence UX evaluations in government applications. More nuance is gained through the discussion of the range of government applications in the reviewed studies. This range reflects the expanding role of government applications in mediating interaction between governments and their citizens. The domains identified comprise conventional services such as public services, healthcare, tourism, and law enforcement [19], [25], [27], [30], [32], [33], [29], [35], [36], [18], [23], [21], [26], [34], [31], [28], together with emerging areas such as navigation and assistive technology [20], [22], [24]. In line with this, it is evident that domain-specific needs inform evaluation, e.g., public services prioritize service quality [32], [30], [36], [33], [25], [30], and healthcare applications prioritize data security and trust [21], [18]. This highlights the importance of considering the domain of the government application being evaluated. Another defining theme across the reviewed studies is contextual and cultural considerations in UX evaluations. Studies situated in Asian settings underscore the significance of accessibility, loyalty, and trust, signaling that culture and social norms influence adoption ([26], [29], [36]. Outside Asia, [18] in North America, [25]'s study, and [33]'s study in Europe drew attention to accessibility and service quality. These variations suggest that UX in government applications is not mutually exclusive from the interplay of socio-political and cultural settings. Despite this, few studies integrate cultural dimensions into their UX evaluations, marking a potential direction for further investigation into the field.

The progress of standardized yet adaptable frameworks for UX evaluation in government applications should be placed at the forefront of scholarly investigation. While best practices can be consolidated, they must remain flexible in varied cultural and domain environments. Additionally, there is a strong need to incorporate hedonic and emotional dimensions, considering their influence on the trust and loyalty of the citizen users. This supplements the common pragmatic dimensions, such as usability. Hence, contextual and cultural considerations should be more clearly integrated into UX evaluations, which could improve these UX evaluations across various settings. Domain-specific strategies should also be considered in future work, as UX evaluations are informed and shaped by domain-specific needs. Together, these directions will contribute to more comprehensive, contextually grounded, and culturally sensitive UX evaluation for government applications.

Collectively, the findings of this review give rise to several meaningful implications for UX evaluation in government applications. For the research community, the findings underscore the necessity to adopt more comprehensive perspectives that account for UX's multifaceted nature and to move away from usability-centric evaluations in conducting UX evaluations in government applications. For designers, developers and UX practitioners involved in building government applications, the findings suggest that UX

evaluation criteria should be adapted to include the domain, service and user contexts, without using only generic usability or UX evaluations. For governments, the findings show that UX evaluation with domain, contextual and cultural considerations can be accommodated earlier in the government application development lifecycle, to help realize more effective, inclusive, trustworthy and citizen-centric applications. The subsequent section provides a conclusion of this study.

V. CONCLUSION

Four key themes emerged from this systematic review of UX evaluations for government applications, guided by two RQs: diversity in UX evaluation approaches, the variety of UX dimensions evaluated, the range of domains in UX evaluations, and the contextual and cultural considerations in UX evaluations. These themes indicate the richness and fragmentation of current practices. Pragmatic dimensions, such as usability, remain the main focus of UX evaluations, while hedonic, emotional, and cultural dimensions are underexplored. Concurrently, despite the diverse approaches employed, there is a lack of standardized yet adaptable frameworks for UX evaluations in government applications. Furthermore, this systematic review highlights that UX evaluations in government applications should encompass both technical and pragmatic dimensions, as well as domain-specific, cultural, and contextual aspects. The implications of the findings for research, practice and stakeholder communities outline how UX evaluation in government applications may be strengthened. Therefore, strengthening UX evaluations through this approach will ultimately enable more inclusive and meaningful evaluations, likely resulting in government applications with a positive UX.

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REFERENCES

[1] D. Norman and J. Nielsen, "The Definition of User Experience (UX)." Accessed: May 01, 2025. [Online]. Available: https://www.nngroup.com/articles/definition-user-experience/

[2] N. Yusof, N. L. Hashim, and A. Hussain, "A Conceptual User Experience Evaluation Model on Online Systems," Int. J. Adv. Comput. Sci. Appl., no. May, 2022, doi: 10.14569/IJACSA.2022.0130153.

[3] N. L. Hashim, N. Yusof, P. B. Pulau, A. Hussain, and M. Ibrahim, "User Experience Dimensions for E-procurement : A Systematic Review," J. Inf. Commun. Technol., no. January 2023, 2022, doi: 10.32890/jict2022.21.4.1.

[4] H. Sharp, Y. Rogers, and J. Preece, Interaction Design: Beyond Human-Computer Interaction, 5th Editio. Wiley.

[5] Y. Rogers, H. Sharp, and J. Preece, Interaction Design: Beyond Human-Computer Interaction, 6th Editio. Wiley, 2023.

[6] J. Lewis and J. Sauro, "Three Branches of Standardized UX Measurement." Accessed: May 01, 2025. [Online]. Available: https://measuringu.com/three-branches-ux/

[7] R. M. Ramli, "E-GOVERNMENT IMPLEMENTATION CHALLENGES IN MALAYSIA AND SOUTH KOREA: A COMPARATIVE STUDY," Electron. J. Inf. Syst. Dev. Ctries., vol. 80, no. 7, pp. 1–26, 2017.

[8] N. S. Abdul Wahi, "The current development of e-government in Malaysia," in A HAZA SZOLGÁLATÁBAN KONFERENCIAKÖTET 2021., A. Kiss, Rebeka; Urbanovics, Ed., 2021.

[9] A. Aldrees and D. Gracanin, "UX in E-government Services for Citizens : A Systematic Literature Review," J. User Exp., vol. 18, no. 3, pp. 133–169, 2023.

[10] I. Lyzara, Ria; Purwandari, Betty; Zulfikar, Muhammad Fadhil; Santoso, Harry Budi; Solichah, "E-Government Usability Evaluation: Insights from A Systematic Literature Review," in Proceedings of the 2019 2nd International Conference on Software Engineering and Information Management, ICSIM 2019, Bali, Indonesia: ACM International Conference Proceeding Series, 2019, pp. 249–253. doi: https://doi.org/10.1145/3305160.3305178.

[11] N. P. Bastardo, Rute; Pavão, João; Rocha, "Methodological Quality of User-Centered Usability Evaluation of Digital Applications to Promote Citizens ' Engagement and Participation in Public Governance : A Systematic Literature Review," pp. 740–761, 2024.

[12] B. Kitchenham and S. Charters, "Guidelines for performing Systematic Literature Reviews in Software Engineering," 2007.

[13] D. G. Moher, David; Liberati, Alessandro; Tetzlaff, Jennifer; Altman, "Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement," BMJ 2009;339b2535, 2009, doi: https://doi.org/10.1136/bmj.b2535.

[14] M. J. Paige et al., "The PRISMA 2020 statement : an updated guideline for reporting systematic reviews Systematic reviews and Meta-Analyses," BMJ 2021;372n71, 2021, doi: 10.1136/bmj.n71.

[15] B. Kitchenham, "Procedures for Performing Systematic Reviews," 2004.

[16] S. Asadi, R. Abdullah, Y. Yah, and S. Nazir, "Understanding Institutional Repository in Higher Learning Institutions : A Systematic Literature Review and Directions for Future Research," IEEE Access, vol. 7, pp. 35242–35263, 2019, doi: 10.1109/ACCESS.2019.2897729.

[17] A. Abouzahra, A. Sabraoui, and K. Afdel, "Model composition in Model Driven Engineering : A systematic literature review," Inf. Softw. Technol., vol. 125, no. April, p. 106316, 2020, doi: 10.1016/j.infsof.2020.106316.

[18] V. Yakovchenko, D. A. Jacob, S. S. Rogal, T. R. Morgan, and K. Rozenberg-Ben-Dror, "User experience of a hepatitis c population management dashboard in the Department of Veterans Affairs," PLoS One, vol. 18, no. 5 May, 2023, doi: 10.1371/journal.pone.0285044.

[19] J. A. Alharbi, A. S. Albesher, and H. A. Wahsheh, "An Empirical Analysis of E-Governments' Cookie Interfaces in 50 Countries," Sustain., vol. 15, no. 2, 2023, doi: 10.3390/su15021231.

[20] S. Hu, L. D. Rong, J. L. Han, D. Zhang, and W. T. Jiang, "The Effects of Interaction Mode and Individual Differences on Usability and User Experience of Mobile Augmented Reality Navigation," IEEE ACCESS, vol. 11, pp. 41783–41795, 2023, doi: 10.1109/ACCESS.2023.3271522.

[21] S. A. Nagro, "User Experiences and Usability Evaluation of COVID-19 Application," J. Comput. Sci., vol. 19, no. 3, pp. 372–388, 2023, doi: 10.3844/JCSSP.2023.372.388.

[22] Y.-J. Cheng and K.-H. Chen, "Website analytics for government user behavior during COVID-19 pandemic," Aslib J. Inf. Manag., vol. 75, no. 1, pp. 90–111, 2023, doi: 10.1108/AJIM-11-2021-0329.

[23] M. Alghareeb, A. S. Albesher, and A. Asif, "Studying Users' Perceptions of COVID-19 Mobile Applications in Saudi Arabia," SUSTAINABILITY, vol. 15, no. 2, 2023, doi: 10.3390/su15020956.

[24] E. R. Ro, K. O. An, A. J. Kim, S. U. Jang, E. J. Kim, and S. D. Eun, "Usability Study to Promote Co-Creation among People with Disabilities, Developers, and Makers with a Focus on the Assistive Technology Open Platform in Korea," IEEE Access, vol. 12, pp. 39016–39027, 2024, doi: 10.1109/ACCESS.2023.3345036.

[25] M. Benaida, "Usability Evaluation of North African E-Government Services in the Context of Optimizing User Experience when Using Mobile Phones," Int. J. Interact. Mob. Technol., vol. 18, no. 8, pp. 102–115, 2024, doi: 10.3991/ijim.v18i08.46329.

[26] T. Wahyuningrum et al., "Logistic Regression Analysis of Factors that Influence User Experience in Student Medical Report Applications," J. Appl. Data Sci., vol. 5, no. 3, pp. 1210–1222, 2024, doi: 10.47738/jads.v5i3.285.

[27] M. H. H. Zubir and M. S. A. Latip, "Factors affecting citizens' intention to use e-government services: assessing the mediating effect of perceived usefulness and ease of use," Transform. Gov. PEOPLE Process POLICY, vol. 18, no. 3, pp. 384–399, 2024, doi: 10.1108/TG-04-2023-0040.

[28] H. M. Puspasari, I. Z. Mustaqim, A. T. Utami, R. Syalevi, and Y. Ruldeviyani, "Evaluation of Indonesia's police public service platforms through sentiment and thematic analysis," IAES Int. J. Artif. Intell., vol. 13, no. 2, pp. 1596–1607, 2024, doi: 10.11591/ijai.v13.i2.pp1596-1607.

[29] M. Sapraz and S. Han, "Users' evaluation of a digital government collaborative platform (DGCP) in Sri Lanka," Transform. Gov. People, Process Policy, vol. 18, no. 1, pp. 131–144, 2024, doi: 10.1108/TG-10-2022-0140.

[30] S. Nawafleh and A. Khasawneh, "Drivers of citizens E- loyalty in E-government services: E-service quality mediated by E-trust based on moderation role by system anxiety," Transform. Gov. People, Process Policy, vol. 18, no. 2, pp. 217–240, 2024, doi: 10.1108/TG-04-2023-0053.

[31] N. Aziz, S. S. Hamzah, S. Z. Ahmad, W. Matcha, and S. Binsaleh, "Augmented Reality Mobile Application for Promoting Culture and Heritage in Thailand and Malaysia: The Prototype Development and Heuristic Evaluation," Int. J. Interact. Mob. Technol. , vol. 18, no. 14, pp. 72–89, 2024, doi: 10.3991/ijim.v18i14.48381.

[32] R. Fadrial, H. T. R. Freddy Simanjuntak, W. Wirman, and W. S. Wibowo, "FOSTERING TRUST THROUGH BYTES: UNRAVELLING THE IMPACT OF E-GOVERNMENT ON PUBLIC TRUST IN INDONESIAN LOCAL GOVERNMENT," Interdiscip. J. Information, Knowledge, Manag., vol. 19, 2024, doi: 10.28945/5317.

[33] Z. Patergiannaki and Y. A. Pollalis, "E-government quality from the citizen's perspective: the role of perceived factors, demographic variables and the digital divide," Int. J. PUBLIC Sect. Manag., vol. 37, no. 2, pp. 232–254, 2024, doi: 10.1108/IJPSM-07-2023-0229.

[34] A. M. Ashar, N. F. Elias, R. Jenal, M. C. Lam, M. R. Appannan, and S. A. Iskandar, "Evaluating and Optimizing MySejahtera App Analytics for Sustainable Digital Government Services," IEEE Access, 2025, doi: 10.1109/ACCESS.2025.3561357.

[35] L. Amer, M. Thneibat, F. Sammour, and N. Lepkova, "EVALUATING THE E-PERMIT SYSTEM IN CONSTRUCTION USING STAKEHOLDER ANALYSIS AND NETWORK THEORY," J. Civ. Eng. Manag., vol. 31, no. 3, pp. 224–247, 2025, doi: 10.3846/jcem.2025.22253.

[36] D. S. Kencono, A. Djunaedi, and Y. Purbokusumo, "Exploring Public Sentiment Toward Regional E-Government Apps: A Case Study of Sapawarga and Jaki in Indonesia," J. Inf. Syst. Eng. Manag., vol. 10, pp. 285–298, 2025, doi: 10.52783/jisem.v10i15s.2458.

[37] B. Richardson, M. Campbell-yeo, and M. Smit, "Mobile Application User Experience Checklist : A Tool to Assess Attention to Core UX Principles Mobile Application User Experience Checklist : A Tool to Assess Attention to Core UX," Int. J. Human–Computer Interact., vol. 00, no. 00, pp. 1–8, 2021, doi: 10.1080/10447318.2021.1876361.

[38] Q. Zheng and M. Chen, "EvAlignUX : Advancing UX Evaluation through LLM-Supported Metrics Exploration," 2025, doi: 10.1145/3706598.3714045.

[39] S. Liu, H. Zhang, J. U. N. Kong, L. Zhang, and C. Gao, "UXBIV : An Evaluation Framework for Business Intelligence Visualization," IEEE Access, vol. 11, no. August, pp. 92391–92415, 2023, doi: 10.1109/ACCESS.2023.3300418.

[40] H. Jang and S. H. Han, "International Journal of Human - Computer Studies User experience framework for understanding user experience in blockchain services," Int. J. Hum. - Comput. Stud., vol. 158, no. October 2021, p. 102733, 2022, doi: 10.1016/j.ijhcs.2021.102733.

[41] A. P. Gallegos, G. R. Morales, P. V Torres-Carrión, and S. C. Carrión, "Framework for User Experience Evaluation in MOOC Platforms," in HCII 2022, LNAI 13336, H. Degen and S. Ntoa, Eds., Springer, 2022, pp. 284–304.

[42] N. F. Syahrozad and A. P. Subriadi, "Evaluation of user experience : a systematic literature review," vol. 02009, pp. 1–7, 2024.

[43] A. I. Nur, H. B. Santoso, and P. O. Hadi Putra, "The Method and Metric of User Experience Evaluation : A Systematic Literature Review," pp. 307–317, 2017, doi: 10.1145/3457784.3457832.

[44] V. G. de Menezes, G. V Pedrosa, M. P. P. Silva, and R. M. C. Figueiredo, "Evaluation of Public Services Considering the Expectations of Users — A Systematic Literature Review," pp. 1–13, 2022.

Feature Engineering for Machine Learning-Based Trading Systems Using Decision Tree, Random Forest, and Gradient Boosting

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***Abstract*—Machine learning-based trading systems require the selection and creation of features that crucially determine the performance level of the trading system. This study introduces an asset-specific, correlation-based feature selection approach for machine learning–based stock trading models. The research conducts a systematic evaluation of the influence of lookup period, the number of features from technical analysis, and feature selection on the performance of trading systems using tree-based algorithms: Decision Tree, Random Forest, and Gradient Boosting. The performance of the trading system was measured using the backtesting method, with metrics such as total return, win rate ratio, and profit factor. The research steps included selecting stocks with the largest market capitalization in the financial sector, which are included in the banking index. Historical data on the prices of these stocks was obtained from Yahoo! Finance for the years 2014-2025. The historical data was then divided into two parts, namely the in-sample dataset (2014-2024 time period) and the out-of-sample dataset (2025 time period). Each part of the data was supplemented with features from technical analysis and several other additional features. Trading signals are determined based on a profit target of +4% and a loss limit of –2% in a lookup period of 2 to 10 days. The results show that the ML strategy consistently outperforms the buy-and-hold strategy, with Gradient Boosting generating the highest return (37.443%). Spearman correlation-based feature selection per stock improves the performance of the strategy compared to uniform features.**

Keywords*—Feature engineering; machine learning; trading system; decision tree; Random Forest; Gradient Boosting

I. Introduction

Predicting prices in financial markets to help build trading systems requires sophisticated methods to detect market direction and take advantage of price volatility in the market to profit from trading. The complexity of prices in the market encourages the integration of machine learning algorithms into trading systems to improve trading system performance [1]. Machine learning is capable of analyzing large and complex datasets, detecting and predicting patterns, and making predictions based on historical trends [2]. Accurate predictions play an important role in making trading decisions and measured risk management [3]. Research on the stock market is most widely studied by researchers, followed by the foreign exchange (Forex) market and cryptocurrency trading. In developing predictive models using artificial intelligence techniques, technical analysis is more widely used than fundamental analysis. Technical analysis is developed based on statistical methods that describe stock price movements over a certain period. In financial markets, technical analysis aims to find price patterns and stock price trends that can be used by traders or investors to make decisions. The performance of a trading strategy can be validated using several testing methods. Backtesting is a popular and considered a robust assessment method [4]. The performance of portfolios built with machine learning can be measured using excess return and Sharpe ratio metrics [5], [6]. The accuracy of predictions generated by a model can be tested using backtesting to look at the performance results of a trading system before it is implemented in real trading [7].

In building a trading model, algorithms such as decision tree, ensemble learning Gradient Boosting, and Random Forest bagging techniques can be employed, which have considerable prediction accuracy and effectiveness [8]. The decision tree algorithm was chosen for its simplicity, ease of implementation, and ease of interpretation [9]. Metode Ensemble learning methods, such as Random Forest and Gradient Boosting, perform well in terms of accuracy, precision, and recall [10].

In the study of machine learning-based trading applications, several things have to be carried out, including: building a machine learning model using historical stock price data, adding features and providing classification labels (buy/hold/sell) based on target profit and target loss rules within a certain period, training the model using training data and testing data, using the model to classify data that will be used for backtesting, and measuring the performance of the trading strategy applied using a backtesting library using trading metrics, such as total return, win rate, and profit factor [11].

While many international studies have been conducted, there remains a research gap in the context of developing country stock markets, including Indonesia: few studies have systematically compared: 1) the effect of varying lookup period (e.g. 2-10 days), 2) the effect of the number of technical features (1–6 features) and feature selection methods (unique features per issuer vs. uniform features) on 3) actual trading performance evaluated using backtesting metrics such as total return, win rate, and profit factor. This study addresses this gap with an experimental study of the 15 largest capitalized bank stocks on August 31, 2025 on the Indonesia Stock Exchange, to assess the combination of feature engineering and Decision

Tree, Random Forest, and Gradient Boosting algorithms, and compare the results against a buy-and-hold strategy.

This research adopts an experimental methodology to systematically examine how variations in lookup periods, feature dimensionality, and feature selection methods influence machine learning–based stock trading performance using out-of-sample backtesting. This research differs from prior work by adopting a correlation-based, asset-specific feature selection scheme rather than a uniform feature set for all stocks in machine learning–based trading models. The main contributions of this study are summarized as follows: 1) systematic evaluation of the effect of lookup period ranging from 2 days to 10 days and the number of technical features ranging from 1 feature to 7 features on the performance of machine learning-based trading, 2) comparison of two feature selection approaches—features selected per stock using Spearman's correlation compared to a uniform set of features for all stocks. The evaluation was conducted using out-of-sample backtesting analysis (data from January 1 to August 31, 2025) with practical trading metrics, namely total return, win rate, and profit factor, thus making the results relevant for practitioners and researchers who intend to implement machine learning on the Indonesian stock market.

II. Literature Review

A. Machine Learning for Stock Trading Systems

Studies related to stock market prediction and trading systems have developed rapidly using machine learning (ML) algorithms. High and varying volatility among issuers, non-linearity, and changing market dynamics make trading decisions a significant challenge. A systematic review found that studies of ML algorithms in the stock market are classified into supervised learning (regression and classification) and unsupervised learning (clustering). A number of ML algorithms for model building include neural networks, support vector machines, fuzzy theory, deep learning, random forest, and decision trees, as well as hybrid algorithms [12].

For instance, Anwar et al. (2024) reviewed that ML algorithms are capable of identifying stock market trends more accurately than traditional methods. Methods in machine learning, such as the Ensemble method, can be used by both investors and traders to analyze stock market trends. The selection of specific technical features as inputs for the model significantly affects the results of stock market trend predictions [10]. Machine learning models make it possible to combine various features to capture complex and nonlinear patterns in stock market forecasting. Model efficiency may be improved by selecting more powerful features [13].

B. Feature Engineering and Technical Indicators

The key factors in ML model performance are the quality and relevance of features (feature engineering). In the context of the stock market, many studies have explored the use of technical indicators (e.g., moving average, RSI, Aroon, VWMA minus price, slope, volume) as representations of market signals. Each indicator provides a unique perspective, offering additional insights into market dynamics that may not be revealed by daily stock prices. In their study, Fozap used Moving Averages (SMAs and EMAs), Bollinger Bands, Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and On-Balance Volume (OBV) as inputs for the ML model they built. These indicators represent momentum, trend, and trading volume [14]. In their study on Dow30 index stocks, Aksehir (2022) used 15 technical features, which were RSI, Williams's % R, WMA, EMA, SMA, HMA, Triple EMA, CCI, CMO, MACD, PPO, ROC, CMFI, DMI, and PSI as inputs for the CNN-TA model used to predict stock trading actions on the following day [15]. A study examined the integration of technical indicators with ML and found that this combination significantly improved accuracy compared to only ML or only technical analysis, especially when market volatility was high [16].

Selecting the optimal technical indicators is an important part of predicting the stock market, but there is currently no consensus on which indicators are the most suitable. Technical indicators are a crucial component of financial forecasting, as they provide a quantitative measure of market dynamics, including price trends, volatility levels, and trading volume. These indicators allow analysts to identify the direction and intensity of stock price movements, and have been widely integrated into machine learning models as a representation of historical price behavior [17]. Research conducted by Mostafavi and Hooman put a number of indicators into categories of momentum, trend, volatility, and volume. From each category, technical indicators that gave the best performance were obtained. Furthermore, research could be conducted for different markets, for the development of hybrid models combining machine learning with traditional technical analysis, and for the effect of time horizons on model performance [18]. Traditional technical indicators may have limitations in their individual predictive value, however when combined with machine learning methods, these indicators have the potential to provide more comprehensive insights into market movement characteristics [19].

C. Ensemble Tree-based Learning in the Context of Trading

Decision tree-based algorithms remain very popular in financial applications due to their interpretability, relative tolerance to different feature scales, and ability to handle non-linear relationships well.

- Decision Tree is a graphical-based decision-making method that uses probability analysis to evaluate the risks and feasibility of projects, depicted as tree branches. This method is intuitive and easy to understand visually. Decision trees can be used as comprehensive classification models for stock prediction and risk assessment [2].
- Random Forest is an ensemble algorithm that combines multiple decision trees, each trained on a randomly selected subset of data and features. The prediction results from all trees are combined through averaging to improve accuracy. This algorithm is effective for high-dimensional data and is able to reduce overfitting by incorporating random elements in the training process. Therefore, Random Forest is often used for large-scale datasets and complex problems [2]. In their study of China's A-share market covering 3,000 companies using 8 years of historical data, Wu (2024) found that

the Random Forest-based feature selection method demonstrated superior performance with higher prediction accuracy compared to traditional approaches [20].

- Gradient Boosting is a boosting method that iteratively improves the errors of previous models and is known to perform well with tabular data. Priel (2024) conducted research to select stocks for value investing in the US stock market by utilizing corporate financial features. Through preliminary research, it was discovered that the Random Forest and GB ML methods consistently yielded higher average precision and recall values compared to Logistic and Deep Learning models [21]. In their study towards articles in Scopus and Web of Science between 2011 and 2022 concerning stock market applications, Htun (2023) discovered that RF and SVM methods are the most popular Machine Learning methods [22].

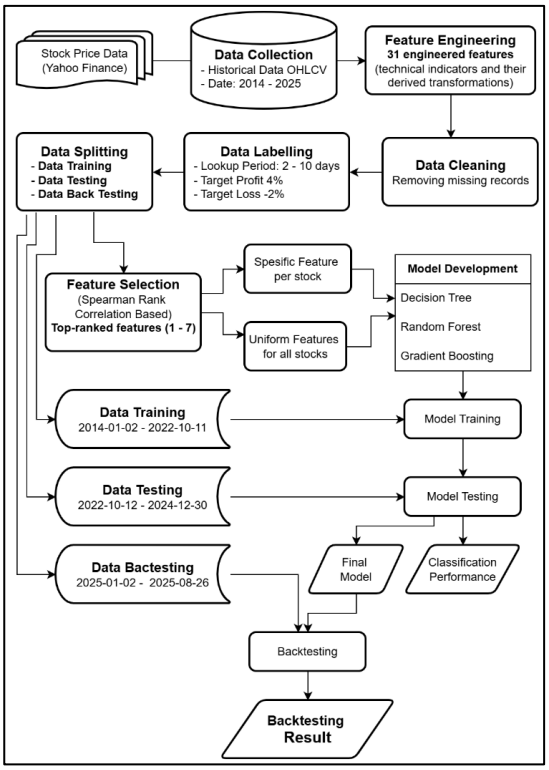


Fig. 1. Research workflow.

From the preceding literature review, it is possible to identify several gaps that remain open: 1) variations in lookup period: many studies use a single or arbitrary horizon, but few systematically test the range of lookup period in the context of ML trading signals. 2) The number and combination of features: although feature engineering has been widely discussed, systematic experiments on "how many features" and "whether features are uniform versus specific to each stock issuer" are still limited. 3) Trading system evaluation (not merely price prediction): many studies focused on price or direction prediction, but few linked prediction results to trading performance (cumulative return, win rate, profit factor) in the out-of-sample period, 4) emerging market context: studies specific to Indonesian stocks or emerging markets remain relatively scarce, hence research on 15 Indonesian bank stocks could provide additional values.

III. Research Methodology

This study aims to analyze the impact of feature engineering on the performance of machine learning-based trading systems for large-cap banking stocks listed on the Indonesia Stock Exchange. The research methodology design consists of data collection, feature construction, model training, and out-of-sample backtesting to comprehensively evaluate model performance, as shown in Fig. 1.

A. Data Collection and Preprocessing

Stock price data was obtained from Yahoo Finance for the top 15 banking stocks by market capitalization in Indonesia, covering the period from January 1, 2014, to August 31, 2025. The data obtained includes Adj Close, Close, High, Low, Open, and Volume prices, as presented in Fig. 2.

```
historical_data_YF[0]
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Date	Adj Close	Close	High	Low	Open	Volume
2014-01-02	1591.911865	1960.0	1970.0	1930.0	1940.0	33065000
2014-01-03	1543.179810	1900.0	1950.0	1870.0	1940.0	71912500
2014-01-06	1518.813721	1870.0	1900.0	1860.0	1880.0	58190000
2014-01-07	1522.874634	1875.0	1890.0	1865.0	1870.0	36152000
2014-01-08	1514.752930	1865.0	1890.0	1850.0	1880.0	55877500
...	...	...	...	...	...	...
2025-08-25	8475.000000	8475.0	8550.0	8475.0	8525.0	64052700
2025-08-26	8250.000000	8250.0	8475.0	8250.0	8450.0	326794200
2025-08-27	8300.000000	8300.0	8350.0	8200.0	8250.0	111915700
2025-08-28	8325.000000	8325.0	8375.0	8275.0	8350.0	81281400
2025-08-29	8075.000000	8075.0	8275.0	8075.0	8250.0	236499300

2871 rows × 6 columns

Fig. 2. Example of BBCA.jk historical data.

The list of the top 15 banks by market capitalization in Indonesia, as of September 1, 2025, is provided in Table I.

TABLE I. List of the Top 15 Bank Stocks in Indonesia

#	*Issuer Code*	*Issuer Name*	*Market Capitalization (millions Rp.)*
1	BBCA.jk	PT. Bank Central Asia	985.976.046
2	BBRI.jk	PT. Bank Rakyat Indonesia	604.720.389
3	BMRI.jk	PT. Bank Mandiri	434.933.185
4	BBNI.jk	PT. Bank Negara Indonesia	162.423.639
5	BRIS.jk	PT. Bank Syariah Indonesia	125.010.400
6	BNLI.jk	PT. Bank Permata	112.885.657
7	BNGA.jk	PT. Bank CIMB Niaga	42.738.850
8	MEGA.jk	PT. Bank Mega	38.627.560
9	BBHI.jk	PT. Allo Bank Indonesia	34.659.828
10	NISP.jk	PT. Bank OCBC NISP	31.320.336

#	Issuer Code	Issuer Name	Market Capitalization (millions Rp.)
11	ARTO.jk	PT. Bank Jago	30.772.086
12	PNBN.jk	PT. Bank Pan Indonesia	27.314.683
13	BINA.jk	PT. Bank Ina Perdana	26.992.768
14	BDMN.jk	PT. Bank Danamon Indonesia	24.336.138
15	BTPN.jk	PT. Bank SMBC Indonesia	22.143.474

The dataset is divided into two main subsets:

- In-sample dataset (2014–2024): used for ML model training and testing. From this time period, 80% of the data was used as the training set and 20% as the testing set.
- Out-of-sample dataset (2025): used for backtesting the model's strategy against market conditions that the model has never observed before.

All data underwent cleaning to remove data that had no value due to the impact of feature calculations, such as the moving average feature for a certain period.

B. Feature Engineering

Feature engineering is performed by adding technical indicators and derivative features that theoretically represent market trends, momentum, and volatility. The list of indicators used in this study consists of commonly used technical indicators and derivative indicators prepared by the authors. The list of indicators used and their descriptions are described in Table II.

TABLE II. LIST OF 31 TECHNICAL INDICATORS USED

Name of Indicator	Description	Formula
apo (Absolute Price Oscillator)	apo attempts to quantify market momentum	APO = absolute(Long Cycle (Slow Moving Avg) - Short Cycle (Fast Moving Average))
aroon_up	to measure how many periods have passed since price has recorded an n-period high	Aroon-Up (14) = ((14 - Days Since 14-day High)/14) x 100
aroon_down	to measure how many periods have passed since price has recorded an n-period low	Aroon-Down (14) = ((14 - Days Since 14-day Low)/14) x 100
aroon_diff	represents the difference between aroon_up and aroon_down	Aroon_diff = aroon_up – aroon_down
aroon_diff_ma5	represents the 5-moving average of aroon_diff	Aroon_diff_ma5 = MA5(aroon_diff)
adx	measuring the amount of movement in a single direction	ADX = 100 times the Exponential Moving Average of the Absolute Value of (+DI - -DI) / (+DI + -DI) DI=Directional Indicator
cci	attempts to identify "overbought" and "oversold" levels relative to a mean.	CCI (20) = (Typical Price - 20 Period SMA of TP) / (.015 x Mean Deviation) Typical Price (TP) = (High + Low + Close)/3
inertia	Inertia is the rvi smoothed by the Least Squares MA.	Inertia = Least Squares Moving Average of Relative Volatility Index
kst	attempts to capture trends using a smoothed indicator of four different smoothed ROCs	KST =(ROCMA1 x 1) + (ROCMA2 x 2) + (ROCMA3 x 3) + (ROCMA4 x 4)
kst_sig	Kst smoothed by n-periode SMA	Kst_sig = n-Period SMA of the KST
kst_diff	represents the difference between kst and kst_sig	Kst_diff=kst – kst_sig
macd_hist	Moving Average Convergence Divergence Histogram. MACD can be used to identify aspects of a security's overall trend.	MACD Line: (12-day EMA - 26-day EMA) Signal Line: 9-day EMA of MACD Line MACD Histogram: MACD Line - Signal Line
momentum	Momentum attempts to quantify speed by using the differences over a bar length	Mom(t,n)=close(t)-close(t-n)
Obv (on balance volume)	obv is used in technical analysis to measure buying and selling pressure.	Obv(t)=obv(t-1)+volume, if price(t)>price(t-1), and Obv(t)=obv(t-1)-volume if price(t)<price(t-1), and obv(t)=obv(t-1) if price doesn't change
ppo	shows the relationship between two exponential moving averages in percentage terms.	PPO=100 x (12-periode EMA – 26-periode EMA)/26-periode EMA
ppo_signal	9-period EMA of PPO	Ppo_signal = 9-period EMA of PPO
rsi	RSI used to attempts to quantify "velocity" and "magnitude" of directional price movements	RSI = 100 – 100/ (1 + RS) RS = Average Gain of n days UP / Average Loss of n days DOWN
ma5_rsi	5-periode moving average of rsi	ma5_rsi = 5-periode moving average of rsi
slope	Calculates a rolling slope.	Slope=coeficient or slope of linear regression line
stoch_slowk_diff_ma5	5-periode moving average of stoch_slowk_diff	stoch_slowk_diff_ma5= 5-periode moving average of stoch_slowk_diff
tsi	attempts to identify short-term swings in trend direction	Tsi=(price change double smoothed/absolute prcie change double smoothed)/100
tsi_signal	Tsi line smoothed by 12-periode EMA	Tsi_signal=12-period EMA of the TSI line.
Volume	Total Volume perdagangan	Volume perdagangan
vwma_minus_price	Computes a weighted average	3-day vwma=(c1.v1+c2.v2+c3.v3

Name of Indicator	*Description*	*Formula*
	using price and volume.	)/ (v1+v2+v3) c=close price v=volume vwma_minus_price = vwma – close price
vwma_minus_price_ma5	5-periode moving average of vwma_minus_price	vwma_minus_price_ma5 = 5-periode moving average of vwma_minus_price
f1	the deviation of the On-Balance Volume (OBV) from its 5-period moving average.	f1=obv – MA5(obv)
f2	the deviation of the Close Price from from its 5-period moving average.	f2=Close – MA5(Close)
f3	represents the difference between rsi line and MA5(rsi)	f3=rsi – MA5(rsi)
f4	the difference between the ppo and ppo signal line	f4 = ppo - ppo signal line
f5	Value of ppo histogram	f5 = ppo histogram
f6	Difference of stoch_slowk and stoch_slowd	Stoch_slowk_diff= stoch_slowk – stoch_slowd

The number of features used in creating the model varied from 1 to 7 depending on the experimental design. Feature selection was based on the Spearman rank correlation value with respect to the target column (return lookup period).

Two approaches were used to evaluate the impact of feature selection:

1) Feature-specific per stock: Each stock has a different combination of features, which are selected based on their best Spearman's correlation.

2) Uniform features across stocks: All stocks use the same combination of features based on the highest aggregate correlation results.

C. Label Construction

The target label is constructed based on buy, hold, and sell signals calculated from price returns during a specific lookup period. The lookup period was varied from 2 days to 10 days to observe the sensitivity of the strategy to the time horizon. Returns were calculated using the Formula (1).

$$R_t = (Close_{t+lookup} - Close_t)/Close_t \quad (1)$$

with $Close_t$ is the closing price on day t.

Labels are constructed based on profit–loss rules:

- Buy, if Rt ≥ profit target (in this study, a value of 4% is used)
- Sell, if Rt ≤ loss target (in this study, a value of -2% is used)
- Hold for values between those two boundaries.

This approach reflects common practice in rule-based signal labeling trading systems.

D. Data Splitting

The data is split into three parts, with the following description.

- Data from January 1, 2014 to December 31, 2024 is used for training and testing data, with 80% of the data allocated for training and 20% for testing.
- Data from January 1, 2025 to August 31, 2025 is used as out-of-sample data to test trading performance through backtesting.

E. Model Development

Three main algorithms are used for trading signal classification:

1) Decision Tree: single tree model using Gini impurity.

2) Random Forest: bagging-based ensemble model, built several independent trees and combined the results for stability. In this study, 100 estimators and max_depth=4 were used.

3) Gradient Boosting: boosting-based ensemble model, training trees sequentially to minimize residual error. In this study, 100 estimators, max_depth=4, and learning_rate=0.1 were used.

For each algorithm, the model is trained separately on each of these combinations:

- Number of features, varied between 1 and 7 specific features per issuer.
- Lookup period, varied between 2 and 10 days.

After the best number of features and the best lookup period were obtained, testing was conducted for 1 to 7 features using a uniform feature approach for all issuers. The resulting model was used to classify buy–hold–sell signals in the out-of-sample (2025) data.

F. Backtesting Evaluation

Backtesting is used to evaluate the performance of strategies generated by the model against real data from 2025. This procedure is performed using the backtesting.py library, which enables portfolio simulation based on model signals.

The steps include:

1) Read the signal of the model prediction results on the out-of-sample data.

2) Implement trading strategy based on the following rules:

- Buy if signal = Buy
- Sell if signal = Sell
- Hold if signal = Hold

3) Calculate trading performance using the following metrics:

- Total return (%)
- Win rate (%)
- Profit factor (ratio of gross profit to gross loss)

4) Compare the results of the ML strategy against the Buy-and-Hold (BH) strategy return as a baseline benchmark.

The entire process was carried out over 15 major bank stocks, and the results were then averaged to obtain the aggregate performance of each algorithm and feature configuration.

Through the employed research design, this study enables a systematic evaluation of the relationship between feature complexity, time horizon coverage, and the effectiveness of machine learning algorithms in formulating sustainable and profitable trading strategies.

IV. Experimental Analysis and Result

This section presents the results of experiments on the implementation of machine learning models in signal-based trading systems (buy, hold, sell), focusing on 15 large-cap banking stocks on the Indonesia Stock Exchange. The evaluation was conducted to examine the effect of variations in the lookup period, the number of features used, and the type of algorithm on system performance, both in terms of signal classification accuracy and financial performance based on backtesting results.

A. Experimental Setup

The experiment was conducted on 15 large-cap banking stocks listed on the IDX. Each stock was tested with the combination of parameters given in Table III.

TABLE III. Variation in Testing Parameter Values

Parameter	*Variations*
Lookup period	2–10 days
Number of features	1–7 features
Algorithms	Decision Tree, Random Forest, Gradient Boosting
Training/validation time period	Jan 1, 2014 – Dec 31, 2024
Backtesting time period	Jan 1, 2025 – Aug 31, 2025
Evaluation	Return, Win Rate, Profit Factor

Two feature selection approaches were applied: 1) stock-specific features based on the highest Spearman correlation, and 2) uniform features for all stocks. Table IV provides list of features having the highest correlation with issuers while using a 3-day lookup period, with the number of features equal to 4.

TABLE IV. List of Selected Features Per Issuer

Issuer	Selected features			
	1	*2*	*3*	*4*
BBCA.	vwma_minus_price_ma5	vwma_minus_price	Volume	aroon_down
BBRI	Volume	vwma_minus_price	vwma_minus_price_ma5	aroon_down
BMRI	vwma_minus_price	vwma_minus_price_ma5	aroon_down	kst_sig
BBNI	Volume	f1	f2	aroon_down
BRIS	adx	Volume	f1	tsi_signal
BNLI	slope	f3	f2	vwma_minus_price_ma5
BNGA	kst_diff	f2	macd_hist	momentum
MEGA	aroon_down	vwma_minus_price	vwma_minus_price_ma5	stoch_slowk_diff_ma5
BBHI	f1	Volume	tsi_signal	rsi
NISP	vwma_minus_price	vwma_minus_price_ma5	aroon_down	cci
ARTO	tsi	tsi_signal	ma5_rsi	rsi
PNBN	Volume	aroon_diff_ma5	aroon_up	aroon_diff
BINA	slope	f2	momentum	macd_hist
BDMN	slope	f2	DeltaRSI	f3
BTPN	aroon_diff_ma5	inertia	vwma_minus_price_ma5	aroon_diff

B. Model Performance on Classification Metrics

Model performance on testing data (in-sample) was evaluated using standard classification metrics. Table V shows the average accuracy of one to seven features for each lookup period. Fig. 3 shown the bar chart displaying accuracy scores using specific features for each stock.

TABLE V. Classification Performance

Lookup Period	Accuracy			
	Decision Tree	*Random Forest*	*G Boosting*	*Average*
2	61%	79%	75%	72%
3	56%	74%	70%	67%
4	52%	69%	65%	62%
5	48%	66%	62%	58%
6	46%	62%	58%	55%
7	44%	60%	55%	53%
8	44%	58%	53%	52%
9	43%	57%	52%	51%
10	42%	55%	49%	49%
Average	49%	64%	60%	58%

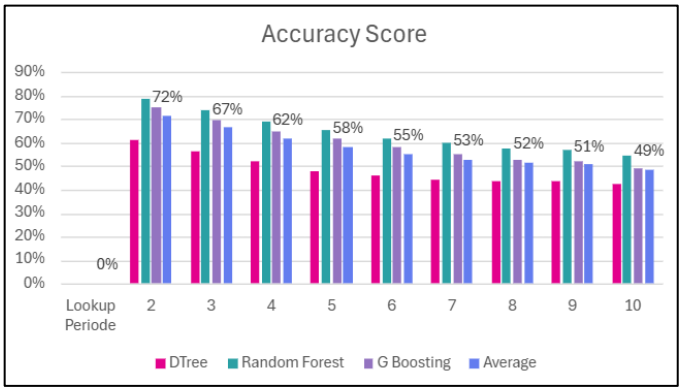


Fig. 3. Accuracy score per lookup period.

From the resulting accuracy chart, it is observed that the model is capable of predicting for relatively short lookup periods. The Random Forest model shows relatively better results, followed by Gradient Boosting, and then Decision Tree. Fig. 4 shows an example of the BBCA.JK stock accuracy matrix for the Random Forest model with a 3-day lookup period and 4 features.

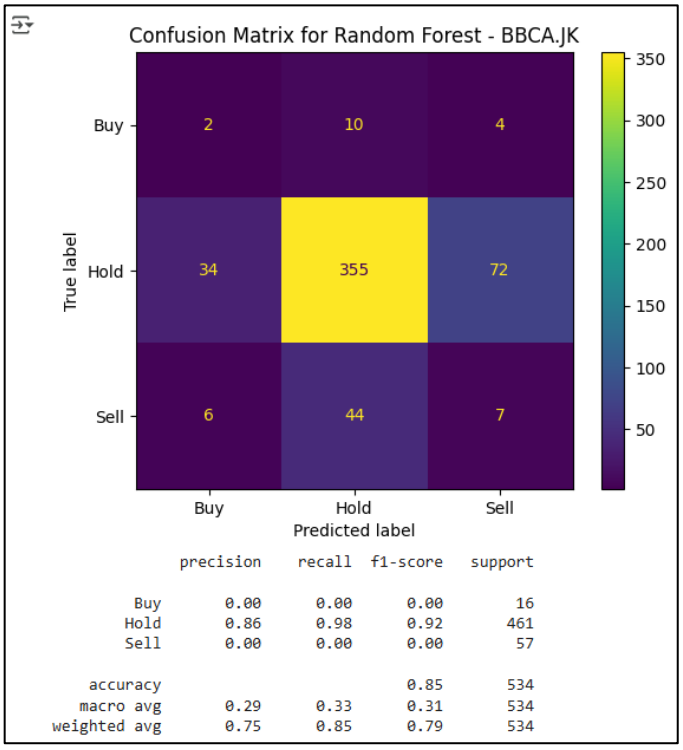


Fig. 4. Confusion matrix for random forest – BBCA.JK.

Fig. 5 exemplifies one of the Random Forest estimator trees for BBCA stock using 5 features and a 4-day lookup period.

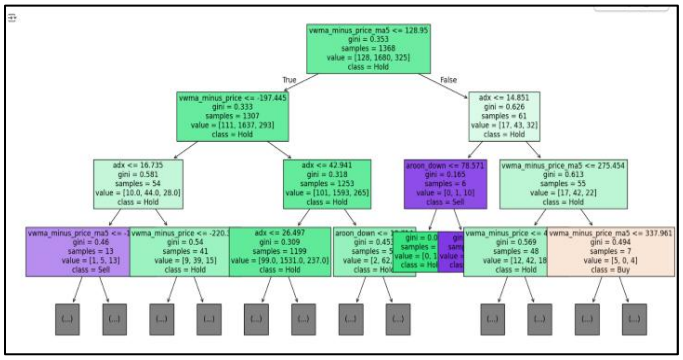


Fig. 5. Tree example of BBCA historical data.

C. Comparative Backtesting Results

The main evaluation was conducted using backtesting on out-of-sample data (January–August 2025 time period). The average aggregate backtesting results from total return calculations when compared to Buy & Hold for 15 stocks are presented in Table VI.

TABLE VI. BACKTESTING RESULTS

Strategy	*Total Return [%]*	*Win Rate [%]*	*Profit Factor*
Buy & Hold	15,13	-	-
Decision Tree	31,50	44,78	1,73
Random Forest	16,62	56,74	4.07
Gradient Boosting	37,44	46,85	3,18

The results show that all ML-based strategies outperform the Buy & Hold strategy in terms of total return.

- Gradient Boosting delivers the highest performance with an average total return of 37.44.3%, a win rate of 46.85%, and a profit factor of 3.18, indicating good profit consistency. While the win rate is not particularly high, the profit factor is quite substantial. This is because the trading system is built using a risk reward ratio of 1:2, with a profit target of 4% and a loss target of -2%.
- Decision Tree ranked second with a total return of 31.50%.
- Random Forest provides a stable but more conservative result (16.62%).

Fig. 6 displays an example of BBCA stock backtesting results using 5 features and a 4-day lookup period. Fig. 7 illustrates the trading curve on the BBCA.jk chart.

```
1 hasil_list_Forest[0]
```

Start	2025-01-02 00:00:00
End	2025-08-25 00:00:00
Duration	235 days 00:00:00
Exposure Time [%]	63.513514
Equity Final [$]	144727900.0
Equity Peak [$]	219806875.0
Return [%]	44.7279
Buy & Hold Return [%]	-14.393939
Return (Ann.) [%]	87.660456
Volatility (Ann.) [%]	195.491026
CAGR [%]	48.650604
Sharpe Ratio	0.448412
Sortino Ratio	1.554121
Calmar Ratio	2.116166

Fig. 6. Backtesting result for BBCA.jk.



Fig. 7. Plotting backtesting results for BBCA.jk.

D. Lookup Period Analysis

An evaluation was conducted to assess the sensitivity of the strategy to the time horizon based on the lookup period, analyzing variations in the lookup period from 2 days to 10 days. The average total return results presented in Table VII show that the system performed best in the 4-day to 7-day lookup period. The highest achievement was in the 5-day lookup period, which generated an average system return of 77.54%. This shows that a five-day period is the optimal horizon for capturing momentum patterns and price reversals in Indonesian banking stocks. A lookup period that is too short (less than 4 days) produces noisy signals, while a period that is too long (more than 7 days) loses sensitivity to short-term fluctuations.

TABLE VII. TOTAL RETURN PER LOOKUP PERIOD

Lookup Period	Total Return [%]				
	Decision Tree	*Random Forest*	*Gradient Boosting*	*Average*	*Buy& Hold*
2	3,83	2,87	25,99	10,90	16,15
3	26,81	7,93	33,02	22,59	16,06
4	19,76	8,27	47,35	25,13	15,87
5	112,80	21,49	98,32	77,54	14,83
6	35,01	23,27	37,26	31,85	15,06
7	18,91	25,38	36,58	26,96	15,55
8	8,76	23,79	30,13	20,89	14,12
9	31,39	17,70	6,44	18,51	14,78
10	26,20	18,87	21,83	22,30	14,93
Average	31,50	16,62	37,44	28,52	15,26

E. Feature Dimensionality Impact

The ensuing experiment evaluated the impact of the number of features on the performance of the trading system.

TABLE VIII. TOTAL RETURN PER NUMBER OF FEATURES

Number of Features	Total Return [%]			
	Decision Tree	*Random Forest*	*Gradient Boosting*	*Average*
1	10,02	8,98	11,88	10,29
2	29,74	20,31	31,31	27,12
3	38,83	30,82	44,92	38,19
4	89,72	15,77	32,93	46,14
5	23,78	12,75	35,10	23,87
6	15,98	16,15	70,82	34,32
7	12,41	11,56	35,10	19,69
Average	31,50	16,62	37,44	28.52

The results in Table VIII show that unsatisfactory performance occurs when the number of features used is 1 and 7. For the number of features between 2 and 6, ML performance is generally good and stable, giving the total return a range of 23% to 46%, with the highest total return of 46.14% achieved when there were 4 features used.

F. Feature-Specific vs. Uniform Feature Selection

The selection of uniform features for all issuers was also conducted in this study. The aggregation of features with the highest correlation that are frequently used by issuers when using a lookup period of 3, with a total of 4 features, is shown in Fig. 8.

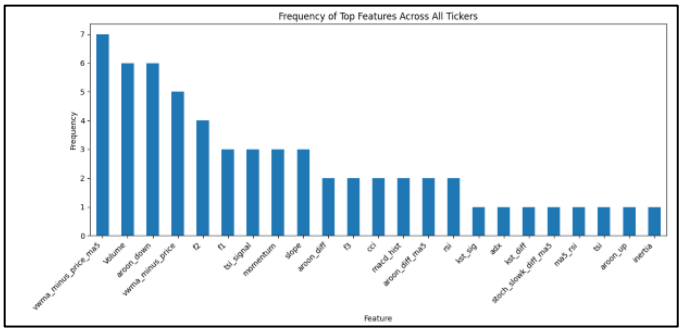


Fig. 8. Frequency of top features across all stocks.

This study uses a 4-day lookup period with uniform features ranging from 1 to 7 features that are most frequently used in aggregate for all issuers. A 4-day lookup period was chosen because its total return value is the median value of all total returns for the lookup period, its returns are relatively more stable, and it has good accuracy. The list of uniform features that are most frequently selected in aggregate for each number of features is provided in Table IX.

TABLE IX. LIST OF UNIFORM FEATURES PER NUMBER OF FEATURES

Number of features	*Uniform Features*
1	Volume
2	Volume, vwma_minus_price
3	Volume, vwma_minus_price, vwma_minus_price_ma5
4	Volume, vwma_minus_price, vwma_minus_price_ma5, aroon_down
5	Volume, vwma_minus_price, vwma_minus_price_ma5, aroon_down, f1
6	Volume, vwma_minus_price, vwma_minus_price_ma5, aroon_down, f1, aroon_up
7	Volume, vwma_minus_price, vwma_minus_price_ma5, aroon_down, f1, aroon_up, kst_sig

The results of accuracy research using uniform features compared to specific features with a 4-day lookup period are provided in Table X. The results of backtesting using uniform features are provided in Table XI.

TABLE X. CLASSIFICATION PERFORMANCE FOR UNIFORM FEATURES

Number of features	Accuracy (Lookup period = 4 days)				
	Decision Tree	*Random Forest*	*Gradient Boosting*	*Average for Uniform Features*	*Average for Specific Features*
1	0.53	0.70	0.65	0.63	0.65
2	0.51	0.69	0.65	0.62	0.62
3	0.51	0.69	0.65	0.62	0.61
4	0.50	0.68	0.64	0.61	0.61
5	0.50	0.68	0.64	0.61	0.61
6	0.51	0.69	0.63	0.61	0.62
7	0.51	0.69	0.64	0.61	0.62
Average	0.51	0.69	0.64	0.61	0.62

TABLE XI. TOTAL RETURN FOR UNIFORM FEATURES

Number of features	Total Return [%] (Lookup period = 4 days)				
	Decision Tree	*Random Forest*	*Gradient Boosting*	*Average for Uniform Features*	*Average for Specific Features*
1	17.55	-4.87	10.31	7.66	10.56
2	18.71	6.95	10.04	11.90	36.84
3	36.76	-1.46	21.98	19.09	2.61
4	4.74	1.06	56.38	20.72	39.49
5	16.94	-0.58	12.73	9.70	35.48
6	79.54	-7.70	76.91	49.58	39.63
7	11.11	4.34	50.26	21.90	11.28
Average	26.48	-0.32	34.09	20.08	25.13

The average return of specific features was 25.13%, which was 5.05% higher than the average return of uniform features, which was 20.08%. These results suggest that selecting specific features for each stock (based on the best Spearman correlation) produces higher performance than using uniform features.

These findings indicate that the characteristics of each stock, such as volatility, trend, and momentum, require a specific combination of features for each stock in order for the model to capture relevant stock patterns. The feature-specific approach per stock has proven to be more adaptive to the distinct characteristics of different stocks.

G. Discussion

The experiment results confirmed a number of important findings, as follows:

- The feature engineering and feature selection processes play a crucial role in determining the success of machine learning (ML) models in the context of stock trading.
- A lookup period of two to four days is sufficient to capture price movements effectively, as reflected in the accuracy rates obtained by the model.
- In terms of prediction accuracy, the Random Forest algorithm shows superior performance. However, in backtesting against out-of-sample data, the Gradient Boosting algorithm produces higher total returns.
- The use of specific feature selection for each issuer has proven to improve signal accuracy and overall portfolio performance.

From a practical perspective, the developed ML-based trading system shows significant potential as a decision support tool for active investors in the Indonesian capital market, particularly in the banking sector, which is characterized by medium volatility and high trading volume. The following experiment evaluates the impact of the number of features on trading system performance. This study does not consider transaction costs and only tests within a predetermined time frame. Therefore, further testing is needed to anticipate changes in market direction.

V. Conclusion and Future Work

A. Conclusion

This study has developed and evaluated a machine learning-based stock trading system using three main algorithms, specifically Decision Tree, Random Forest, and Gradient Boosting. Through conducting experiments on 15 large capitalization banking stocks on the Indonesia Stock Exchange during the period of 2014–2025, this study highlights the importance of feature engineering, the number of features, and the lookup period in affecting the performance of trading strategies.

The results showed that the combination of feature engineering techniques and tree-based ensemble algorithms consistently improves system performance compared to the Buy & Hold strategy. Out of the three algorithms tested, Gradient Boosting showed the best performance with an average total return of 37.44%, outperforming Decision Tree (31.50%), Random Forest (16.62%), and Buy & Hold (15.26%). These findings indicate the superiority of the boosting approach in capturing stock price movement patterns in emerging markets.

In addition, a lookup period of two to four days was able to identify price patterns. A feature selection approach tailored specifically to each stock—based on the highest Spearman correlation—proved to be more effective than a uniform feature approach. This confirms the importance of an adaptive strategy in selecting relevant features to capture the unique characteristics of each stock.

Collectively, this study provides an essential contribution to the AI for Trading literature, particularly in the context of emerging markets. The empirical results suggest that correlation-based feature selection enhances the robustness, adaptability, and interpretability of automated trading systems, supporting their use as effective decision-making tools for active investors.

B. Limitations and Future Work

While the results are substantial, this study has several limitations:

- It focused solely on the banking sector, therefore, generalizations to other sectors require further testing.
- It does not incorporate fundamental macroeconomic factors such as interest rates or inflation, which can affect stock price movements.
- The model has not been evaluated under extreme market conditions, i.e., crisis or periods of extreme volatility.

These limitations provide opportunities for expansion in future research.

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References

[1] H. S. AlQahtani, M. J. Alhaddad, and M. Jarrah, “Comprehensive Analysis of Machine and Deep Learning Models for Stock Market Prediction.” [Online]. Available: www.ijacsa.thesai.org

[2] M. Özcan, “Forecasting in stock market with Machine Learning: A State of Art,” in 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), IEEE, Jul. 2023, pp. 1–7. doi: 10.1109/ICCCNT56998.2023.10307692.

[3] Z. Shi, O. Ibrahim, H. Ilyana, and C. Hashim, “A Novel Hybrid HO-CAL Framework for Enhanced Stock Index Prediction,” IJACSA) International Journal of Advanced Computer Science and Applications, vol. 16, no. 7, p. 333, 2025, [Online]. Available: www.ijacsa.thesai.org

[4] F. Dakalbab, M. A. Talib, Q. Nasir, and T. Saroufil, “Artificial intelligence techniques in financial trading: A systematic literature review,” Journal of King Saud University - Computer and Information Sciences, vol. 36, no. 3, p. 102015, Mar. 2024, doi: 10.1016/j.jksuci.2024.102015.

[5] C. Wang, “Stock return prediction with multiple measures using neural network models,” Financial Innovation, vol. 10, no. 1, p. 72, Jun. 2024, doi: 10.1186/s40854-023-00608-w.

[6] J. P. Steyn, E. Gilbert, and S. Viviers, “The low-volatility effect in African frontier equity markets,” Investment Analysts Journal, vol. 53, no. 3, pp. 189–206, Jul. 2024, doi: 10.1080/10293523.2024.2361986.

[7] H. Bala Malami et al., “Generating a Trading Strategy Using Candlestick Patterns with Machine Learning,” IJACSA) International Journal of Advanced Computer Science and Applications, vol. 16, no. 9, pp. 320–325, 2025, [Online]. Available: www.ijacsa.thesai.org

[8] E. M. Ferrouhi and I. Bouabdallaoui, “A comparative study of ensemble learning algorithms for high-frequency trading,” Sci Afr, vol. 24, p. e02161, Jun. 2024, doi: 10.1016/j.sciaf.2024.e02161.

[9] Y. Wang and T. Yampaka, “Predicting Stock Price Bubbles in China Using Machine Learning,” IJACSA) International Journal of Advanced Computer Science and Applications, vol. 15, no. 11, pp. 415–425, 2024, [Online]. Available: www.ijacsa.thesai.org.

[10] A. Anwar, D. Ameya, A. Patil, M. S. Choudari, D. Chetna, and C. S. Kiran, “International Journal of INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING Machine Learning Insights for Stock Market Trend Identification,” International Journal of Intelligent Systems and Applications in Engineering, vol. 2024, no. 10s, pp. 567–575, 2025, [Online]. Available: https://orcid.org/0000-0002-6756-6514.

[11] F. Sherasiya, “Developing A Machine Learning-Based Options Trading Strategy For The Indian Market,” International Journal For Multidisciplinary Research, vol. 7, no. 4, Jul. 2025, doi: 10.36948/ijfmr.2025.v07i04.50375.

[12] M. M. Kumbure, C. Lohrmann, P. Luukka, and J. Porras, “Machine learning techniques and data for stock market forecasting: A literature review,” Expert Syst Appl, vol. 197, p. 116659, Jul. 2022, doi: 10.1016/j.eswa.2022.116659.

[13] M. Patsiarikas, G. Papageorgiou, and C. Tjortjis, “Using Machine Learning on Macroeconomic, Technical, and Sentiment Indicators for Stock Market Forecasting,” Information, vol. 16, no. 7, p. 584, Jul. 2025, doi: 10.3390/info16070584.

[14] F. M. P. Fozap, “Hybrid Machine Learning Models for Long-Term Stock Market Forecasting: Integrating Technical Indicators,” Journal of Risk and Financial Management, vol. 18, no. 4, p. 201, Apr. 2025, doi: 10.3390/jrfm18040201.

[15] Z. D. Akşehir and E. Kiliç, “How to Handle Data Imbalance and Feature Selection Problems in CNN-Based Stock Price Forecasting,” IEEE Access, vol. 10, pp. 31297–31305, 2022, doi: 10.1109/ACCESS.2022.3160797.

[16] E. Arif, S. Suherman, and A. P. Widodo, “Integration of Technical Analysis and Machine Learning to Improve Stock Price Prediction Accuracy,” Mathematical Modelling of Engineering Problems, vol. 11, no. 11, pp. 2929–2943, Nov. 2024, doi: 10.18280/mmep.111106.

[17] F. M. P. Fozap, "Hybrid Machine Learning Models for Long-Term Stock Market Forecasting: Integrating Technical Indicators," Journal of Risk and Financial Management, vol. 18, no. 4, p. 201, Apr. 2025, doi: 10.3390/jrfm18040201.

[18] S. M. Mostafavi and A. R. Hooman, "Key technical indicators for stock market prediction," Machine Learning with Applications, vol. 20, p. 100631, Jun. 2025, doi: 10.1016/j.mlwa.2025.100631.

[19] A. Deep, A. Shirvani, C. Monico, S. Rachev, and F. Fabozzi, "Risk-Adjusted Performance of Random Forest Models in High-Frequency Trading," Journal of Risk and Financial Management, vol. 18, no. 3, p. 142, Mar. 2025, doi: 10.3390/jrfm18030142.

[20] Z. Wu, Z. Feng, and B. Dong, "Optimal Feature Selection for Market Risk Assessment: A Dimensional Reduction Approach in Quantitative Finance," Journal of Computing Innovations and Applications, vol. 2, no. 1, pp. 20–31, Jan. 2024, doi: 10.63575/CIA.2024.20103.

[21] R. Priel and L. Rokach, "Machine learning-based stock picking using value investing and quality features," Neural Comput Appl, vol. 36, no. 20, pp. 11963–11986, Jul. 2024, doi: 10.1007/s00521-024-09700-3.

[22] H. H. Htun, M. Biehl, and N. Petkov, "Survey of feature selection and extraction techniques for stock market prediction," Financial Innovation, vol. 9, no. 1, p. 26, Jan. 2023, doi: 10.1186/s40854-022-00441-7.

Computational Intelligence for Sustainable Banking: A Novel Fermatean Fuzzy LOPCOW–EDAS Framework

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***Abstract*—The primary objective of this study is to identify the priority strategies required for banks to achieve their sustainable growth targets and to develop a new fuzzy multi-criteria decision-making model sensitive to uncertainty conditions. The model proposed in this study is designed based on the integration of Fermatean Fuzzy LOPCOW–EDAS. In the first stage, the criteria and strategic alternatives affecting sustainable growth were identified through a literature review. The LOPCOW method was then used to objectively calculate the criteria's importance weights. The prioritization of strategic alternatives was then performed using the EDAS method. To more accurately model the uncertainties in expert judgments, the opinions of ten experts were converted to the Fermatean fuzzy numbers and analyzed. The use of Fermatean fuzzy sets offers greater expressive power and increases decision reliability compared to traditional fuzzy and Pythagorean approaches. The LOPCOW method objectively evaluates the information density of the criteria by using logarithmic percentage change, while the EDAS method reduces the impact of outliers by considering the distance of the alternatives from the mean solution, producing a more stable ranking. The findings indicate that the "digital green banking practices" criterion is the most critical element for sustainable growth. Furthermore, the "Digitalization and innovation capability" strategy was determined to be the most important alternative. This result demonstrates that sustainable growth in the banking sector can be achieved through the integration of digital technologies and environmentally friendly practices.**

Keywords*—*Fermatean fuzzy sets; multi-criteria decision-making; sustainable banking; digital transformation; decision support systems

I. Introduction

Sustainable growth in the banking sector is a key concern for regulators, investors, and bank management, especially in the face of global challenges such as climate change, the digital economy, and market uncertainty [1]. Banking is a financial intermediary that plays an important role in maintaining economic stability. Therefore, banks, being business entities, must focus on their financial performance to achieve sustainable growth [2]. Sustainable growth is an indicator of banking sustainability [3]. The concept of sustainable growth in the banking context encompasses not only consistent profit growth but also anticipates financial risk, ensures capital adequacy, promotes regulatory compliance, fosters good corporate governance, and addresses the social and environmental impacts of banking activities [4].

The issue of sustainable growth in banking aligns with Sustainable Development Goal 8 (SDG-8), specifically Decent Work and Economic Growth. Banking plays a crucial role in driving economic growth by serving as a financial intermediary [5]. It has the potential to create decent jobs by distributing funds to support business activities in various fields [6]. Sustainable growth measurement in this study refers to the maximum internal growth that can be achieved by utilizing retained earnings to fund the expansion of banking assets [7]. Meanwhile, measuring sustainable growth in the banking sector is not only relevant from a financial perspective but also promotes an inclusive and responsible financial system. Therefore, this study aims to detect the predictors of sustainable banking growth, which consist of financial factors, namely credit risk and capital adequacy, and non-financial factors, namely governance, audit quality, and green banking.

Achieving sustainable growth in the banking sector is directly related not only to the continuity of profitability indicators but also to the strategic management of resources. In this context, developing prioritized strategies for effective budget management is a critical requirement for banks. Budget allocations made without establishing sustainable growth strategies can lead to inefficient resource use, increased operational costs, and weakened long-term financial stability. Effective budget management forms the basis of sustainable growth not only in terms of financial indicators but also in dimensions such as corporate governance, risk management, audit quality, and environmental responsibility. However, a review of the existing literature reveals that studies focusing on the prioritized strategy-setting processes for achieving sustainable growth in banks are quite limited. Most studies address the concept of sustainable growth through the lens of financial performance or environmental sustainability, but they fail to provide an analytical framework for determining which strategies should be prioritized. This creates a significant research gap in the literature and prevents banks from systematically structuring their sustainable growth policies. Failure to define strategic priorities hinders decision-makers'

ability to achieve long-term growth targets and, by directing resources in the wrong areas, leads to productivity losses, capital shortages, and increased operational risks. Therefore, to implement sustainable growth at the corporate level, the need for analytical models that enable banks to identify their strategic priorities from a multi-criterion, holistic perspective is greater than ever. Such a prioritization approach will not only increase banks' internal efficiency and budget management effectiveness but will also significantly contribute to the rational and measurable achievement of sectoral sustainability goals.

The aim of this study is to develop a holistic and analytical framework for determining priority strategies for achieving sustainable growth in the banking sector. While numerous studies on sustainable growth exist in the literature, a multi-criteria analysis approach is lacking to determine which strategies banks should prioritize to achieve this growth. This constitutes the primary motivation for this research. To address this research gap, the study proposes a new fuzzy multi-criteria decision-making model that considers both financial and non-financial performance indicators of banks. The developed model is based on the Fermatean Fuzzy Set approach to more reliably analyze uncertain and subjective expert judgments. The research methodological process consists of four stages. In the first stage, a comprehensive literature review is conducted to identify the criteria affecting banks' sustainable growth strategies and potential strategy alternatives. In the second stage, the importance of these criteria is objectively weighted using the LOPCOW method. In the third stage, the priority ranking of strategic alternatives is performed using the EDAS method. In the fourth stage, to enhance the model's ability to reflect uncertainty, the judgments obtained from 10 experts are converted into the Fermatean fuzzy numbers and incorporated into the analysis process. Thus, a hybrid decision model that evaluates both quantitative and qualitative factors is developed. Within this framework, the study seeks to answer the following research questions: 1) Which strategic factors should be prioritized for banks to achieve sustainable growth? 2) What is the hierarchical priority relationship between the importance levels of these strategies? 3) What analytical advantage does the Fermatean fuzzy LOPCOW–EDAS model, integrated with expert opinions, provide in determining sustainable growth strategies? The answers to these research questions aim to provide a scientific basis for banks' strategic decision-making processes regarding budget management, resource allocation, and long-term growth policies.

This study develops an original decision model based on the integration of Fermatean fuzzy LOPCOW–EDAS to prioritize banks' sustainable growth strategies, thus providing both a new methodological approach and an analytical contribution to the literature from a strategic management perspective. The decision-making model proposed in this study offers several methodological and analytical advantages over existing multi-criteria decision-making approaches. 1) First, the use of Fermatean fuzzy sets in the model is a significant innovation. While traditional fuzzy sets (Zadeh-type), intuitionistic fuzzy sets (IFS), and Pythagorean fuzzy sets can express expert judgments under uncertainty within certain limits, Fermatean fuzzy sets expand these limits, allowing greater flexibility in the sum of membership and opposing membership degrees. This feature allows for more realistic modeling of the high uncertainty and conflicting assessments among expert opinions frequently encountered in financial decision-making environments. Furthermore, the Fermatean approach more robustly represents experts' hesitation levels, increasing decision-making reliability and model explanatory power in multidimensional and highly uncertain contexts such as sustainable growth strategies. 2) The LOPCOW method used in this study outperforms other techniques in the literature in determining criteria importance weights. Methods such as AHP, Entropy, CRITIC, or SWARA either rely on subjective expert judgments or fail to account for variance among criteria. In contrast, LOPCOW objectively assesses the discriminatory power of each criterion by measuring the information density of criteria with a mathematical structure based on logarithmic percentage changes. This enables a more balanced weighting of multidimensional financial and non-financial criteria affecting banks' sustainable growth strategies. Thus, the model both reduces reliance on subjective evaluations and provides a significant advantage in terms of objectivity and computability by determining criteria importance based on data. 3) The EDAS (Evaluation Based on Distance from Average Solution) method used to rank strategy alternatives also provides significant advantages to the model. While methods frequently used in the literature, such as TOPSIS, VIKOR, COPRAS, or MARCOS generally make comparisons based on ideal or anti-ideal solutions, the EDAS method produces a more balanced ranking by considering the positive and negative distances of each alternative from the average solution. This approach reduces the influence of outliers, protects decision results from oversensitivity, and enables more stable strategic priorities. Furthermore, when used with Fermatean fuzzy data, the EDAS method can handle expert assessments containing uncertainty with greater statistical consistency, thereby increasing both the robustness and decision accuracy of the model. In these respects, the proposed model distinguishes itself significantly from existing models in the literature by providing both methodological depth and analytical flexibility in prioritizing sustainable growth strategies.

The remainder of the study is as follows: Section II evaluates the missing part in the literature. Section III explains the steps in the proposed methodology. Section IV highlights the main analysis results. Section V consists of the concluding remarks.

II. Literature Review

Stakeholder theory supports banks in enhancing risk management through the active participation of various groups, including customers, employees, communities, and regulators. By considering the perspectives of various parties, banks can detect and manage risks, as well as implement green banking practices [8]. By involving stakeholders, banks can promote sustainable growth that provides value to all stakeholders [9]. Financial factors are related to credit risk and capital adequacy. Credit risk is the risk of loss that arises when a borrower is unable to meet its payment obligations as agreed upon with the bank, the lender [10]. Credit risk is proxied by non-performing loans (NPL), as stipulated by the Financial Services Authority of Indonesia in Regulation No. 15/POJK.03/2017, Article 3, paragraph d, which states that NPL must not exceed 5% of total loans. Meanwhile, banks that maintain sustainable growth also

need to pay attention to capital adequacy to avoid disrupting banking operations. The capital adequacy ratio (CAR) is a ratio used to assess a bank's ability to absorb potential losses arising from credit, market, or operational risks. The minimum CAR that banks must meet, according to Regulation of the Financial Services Authority No. 11/POJK.03/2016 on the Obligation to Provide Minimum Capital for Commercial Banks, ranges from 10% to 14%.

Non-performing loans (NPLs) are a component of financial factors. NPLs represent credit risk, where debtors fail to meet their obligations or default on payments [11]. An NPL ratio exceeding 5% indicates poor banking performance, which can lead to a decline in bank liquidity, disrupt the efficiency of banking operations, increase credit risk [12], and reduce investor confidence [13]. The study's results indicate that NPLs, or non-performing loans, can limit banks' capacity to invest in sustainable and environmentally friendly practices [14]. Banks require adequate capital to conduct their business activities. Regulation of the Financial Services Authority number 11/POJK.03/2016 concerning minimum capital requirements for commercial banks stipulates that the Capital Adequacy Ratio (CAR) for commercial banks in Indonesia is 10%-14%. Banks are considered sufficiently healthy to bear the risks from their lending and investment activities [15]. The Capital Adequacy Ratio (CAR) is used to assess the financial condition of banks, particularly in evaluating the extent to which banks can bear losses and risks [16], ensuring their operational activities and sustainability are maintained [17].

Non-financial factors include governance, audit quality, and green banking [18]. Banking governance refers to the process of control and direction exercised by the board of directors and senior management [19]. This process involves establishing strategic direction, overseeing daily operations, and fulfilling responsibilities to shareholders and other key stakeholders [20]. In addition to organizational structure and decision-making processes, banking governance also plays an important role in managing credit risk and maintaining the quality of loan portfolios to sustain banking operations [21]. A governance performance score measures governance as part of the environmental and social governance score, which includes: 1) board structure, 2) ethics and compliance, 3) transparency and reporting, and 4) shareholder rights and risk management. Meanwhile, to guarantee the quality of reports to stakeholders, qualified auditors are required. Governance will increase stakeholder confidence [22]. Stakeholder confidence, as evidenced by financial support for banking entities, can enable banks to operate efficiently, thereby ensuring business continuity and growth. Meanwhile, the role of banking in improving climate change is reflected through the disclosure of green banking [23]. Banks have a responsibility to finance green businesses, and banks themselves also need to demonstrate their internal commitment to green business through the Green Banking Disclosure Index (GBDI). The total GBDI is 21 items [24]. GBDI consists of: 1) green products; banks' efforts to create environmentally friendly financial services through energy efficiency, 2) green operations; related to environmentally friendly banking operations, 3) green customers; banks' efforts to educate customers to care about the environment, and 4) green policies; banks' efforts to implement environmentally friendly policies within the bank.

Governance and sustainable growth in banking entities refer to the principles and processes used to direct and control the activities of a bank, ensuring transparency, accountability, and compliance with applicable regulations. The implementation of governance principles and mechanisms can enhance corporate performance and consistency in governance, ultimately leading to sustainable growth in the banking sector in the long term [25]. Audit quality refers to the level of conformity between audit implementation and the professional standards of public accountants, resulting in findings and opinions that are credible, impartial, and reliable to stakeholders. Audit quality can be measured based on the auditor's industry specialization [26]. An auditor who is proficient in a particular industry will have audit experience that can enhance their audit competence when performing their duties [27]. A quality audit encourages companies to present transparent financial reports and improve long-term performance growth. Green banking is a banking approach that supports environmental sustainability in both daily operations and financing. The primary objective of green banking is to mitigate the adverse environmental impact of banking activities, both directly and indirectly, such as financing projects that support environmental conservation [28]. The results of the study indicate that green banking disclosure encourages companies to improve their long-term financial performance, as reflected in sustainability growth.

III. Methodology

This section relates to the definition of methodology. This methodology is a hybrid model with LOPCOW-based EDAS with Fermatean fuzzy sets.

A. Fermatean Fuzzy Sets

A FFS $(\tilde{F})$ is described with Eq. (1) [29]:

$$\tilde{F} = \{s, (\mu_{\tilde{F}}(s), \vartheta_{\tilde{F}}(s)) : s \in D\} \quad (1)$$

where, μ and ϑ are the membership and non-membership degrees between zero and one. D is the universe of discourse. These degrees meet the condition in Eq. (2):

$$0 \leq \mu_{\tilde{F}}^3(s) + \vartheta_{\tilde{F}}(s) \leq 1 \quad (2)$$

Assume that $\tilde{F}$ and $\tilde{G}$ are two Fermatean fuzzy sets. Then, some arithmetic operations are established with Eq. (3) to Eq. (6):

$$\tilde{F} + \tilde{G} = \left(\sqrt[3]{\mu_{\tilde{F}}^3 + \mu_{\tilde{G}}^3 - \mu_{\tilde{F}}^3 \mu_{\tilde{G}}^3}, \vartheta_{\tilde{F}}^3 \vartheta_{\tilde{G}}^3 \right) \quad (3)$$

$$\tilde{F} \times \tilde{G} = \left(\mu_{\tilde{F}}^3 \mu_{\tilde{G}}^3, \sqrt[3]{\vartheta_{\tilde{F}}^3 + \vartheta_{\tilde{G}}^3 - \vartheta_{\tilde{F}}^3 \vartheta_{\tilde{G}}^3} \right) \quad (4)$$

$$\lambda \tilde{F} = \left(\sqrt[3]{1 - \left(1 - \mu_{\tilde{F}}^3\right)^{\lambda}}, \vartheta_{\tilde{F}}^{\lambda} \right) \quad (5)$$

$$\tilde{F}^{\lambda} = \left(\mu_{\tilde{F}}^{\lambda}, \sqrt[3]{1 - \left(1 - \vartheta_{\tilde{F}}^3\right)^{\lambda}} \right) \quad (6)$$

The score and accuracy functions are estimated using Eq. (7) and Eq. (8), respectively.

$$SF(\tilde{F}) = \mu_{\tilde{F}}^3 - \vartheta_{\tilde{F}}^3 \quad (7)$$

$$AF(\tilde{F}) = \mu_{\tilde{F}}^3 + \vartheta_{\tilde{F}}^3 \quad (8)$$

B. LOPCOW-based EDAS with FF

LOPCOW is a weighting model. With this model, objective priority values of criteria are obtained. EDAS is a ranking model. EDAS ranks the alternatives based on positive and negative distances from the mean. The computation steps are detailed below.

Firstly, m alternatives and n criteria are determined. Next, assessments are collected from e experts. These assessments are transformed into Fermatean fuzzy numbers. Thus, the assessment matrix for k^{th} expert formed in Eq. (9) is created [30].

$$\tilde{A}^k = \left[\tilde{a}_{ij}^k\right]_{m\times n} \quad (9)$$

Afterwards, a decision matrix is constructed using Eq. (10) and Eq. (11):

$$\tilde{X} = \left[\tilde{x}_{ij}\right]_{m\times n} \quad (10)$$

$$\tilde{x}_{ij} = \frac{1}{e}\sum_{k=1}^{e} \tilde{a}_{ij}^k \quad (11)$$

Next, the normalized values are estimated with the help of Eq. (12) and Eq. (13):

$$r_{ij} = \frac{SF(\tilde{x}_{ij}) - \min_i SF(\tilde{x}_{ij})}{\max_i SF(\tilde{x}_{ij}) - \min_i SF(\tilde{x}_{ij})}; for\ B \quad (12)$$

$$r_{ij} = \frac{\max_i SF(\tilde{x}_{ij}) - SF(\tilde{x}_{ij})}{\max_i SF(\tilde{x}_{ij}) - \min_i SF(\tilde{x}_{ij})}; for\ C \quad (13)$$

where, B and C show the beneficial and cost criterion. SF is the score function defined in Eq. (7). Later, percentage values are computed via Eq. (14):

$$pv_j = \left| \ln\left(\frac{\sqrt{\frac{\sum_{i=1}^m r_{ij}^2}{m}}}{\sigma_j} \right) 100 \right| \quad (14)$$

where, σ is the standard deviation of the criteria. Then, the weights of the criteria are defined by Eq. (15):

$$w_j = \frac{pv_j}{\sum_{t=1}^n pv_t} \quad (15)$$

After defining the criteria weights, a normalized matrix is obtained with Eq. (16) and Eq. (17):

$$\tilde{h}_{ij} = \left(\mu_{\tilde{h}_{ij}}, \vartheta_{\tilde{h}_{ij}}\right) = \left(\mu_{\tilde{x}_{ij}}, \vartheta_{\tilde{x}_{ij}}\right); for\ B \quad (16)$$

$$\tilde{h}_{ij} = \left(\mu_{\tilde{h}_{ij}}, \vartheta_{\tilde{h}_{ij}}\right) = \left(\vartheta_{\tilde{x}_{ij}}, \mu_{\tilde{x}_{ij}}\right); for\ C \quad (17)$$

Afterwards, the average solutions are established using Eq. (18):

$$\widetilde{AV}_j = \left(\sqrt[3]{1 - \prod_{i=1}^m \left(1 - \mu_{\tilde{h}_{ij}}^3\right)^{\frac{1}{m}}}, \prod_{i=1}^m \vartheta_{\tilde{h}_{ij}}^{\frac{1}{m}} \right) \quad (18)$$

Next, the positive distance from average and the negative distance from average are calculated via Eq. (19) and Eq. (20), respectively.

$$PDA_{ij} = \frac{\max\left(0, SF(\tilde{h}_{ij}) - SF(\widetilde{AV}_j)\right)}{SF(\widetilde{AV}_j)} \quad (19)$$

$$NDA_{ij} = \frac{\max\left(0, SF(\widetilde{AV}_j) - SF(\tilde{h}_{ij})\right)}{SF(\widetilde{AV}_j)} \quad (20)$$

PDA and NDA are aggregated with the help of Eq. (21) and Eq. (22):

$$SP_i = \sum_{j=1}^n w_j PDA_{ij} \quad (21)$$

$$SN_i = \sum_{j=1}^n w_j NDA_{ij} \quad (22)$$

SP and SN are normalized using Eq. (23) and Eq. (24):

$$NSP_i = \frac{SP_i}{\max SP_i} \quad (23)$$

$$NSN_i = 1 - \frac{SN_i}{\max SN_i} \quad (24)$$

Finally, the final assessment values are defined by Eq. (25):

$$FA_i = \frac{NSP_i + NSN_i}{2} \quad (25)$$

IV. ANALYSIS

This section relates to the results of the methodology described in the previous section.

A. Defining the Alternatives and Criteria

Six strategies are selected as alternatives. Similarly, the criteria are defined. The first criterion is financial resilience (CAR, NPL, profit stability). This criteria's short code is FNNR for analysis. The other strategies are financial resilience (CAR, NPL, profit stability) with ENVR, governance quality (ESG-G Scores) with GVRQ, audit reliability with AUDR, digitalization and innovation capability with DINC, and stakeholder engagement and social contribution with STSC. The strategies are shown in Table I.

TABLE I. STRATEGIES LIST

Definition	Short Code
Sustainable financing policies that reduce credit risk	SFPRCR
Green investments that strengthen capital adequacy	GISCA
Improving corporate governance and transparency standards	ICGTS
Improving the quality of independent auditing and reporting	IQIAR
Expanding digital green banking practices	EDGBP
Stakeholder engagement and sustainable financial education programs	SESFEP

B. Weighting Criteria

After defining the strategies and criteria, assessments are collected from ten experts with linguistic scales in Table II.

TABLE II. LINGUISTIC SCALES

	Membership	Non-Membership
VE	.9	.2
E	.8	.3
ME	.7	.5
ME	.6	.6
MU	.5	.7
U	.3	.8
VU	.2	.9

Using linguistic scales, ten assessment matrices are obtained. These matrices have the form in Eq. (9). After that, the decision matrix is constructed using Eq. (10 and Eq. (11). The decision matrix is illustrated in Table III.

TABLE III. DECISION MATRIX

	FNNR	ENVR	GVRQ	AUDR	DINC	STSC
SFPRCR	(.468,.741)	(.517,.693)	(.552,.661)	(.576,.639)	(.468,.741)	(.498,.75)
GISCA	(.594,.637)	(.576,.67)	(.431,.757)	(.517,.701)	(.585,.653)	(.436,.77)
ICGTS	(.55,.669)	(.586,.616)	(.538,.707)	(.561,.652)	(.525,.692)	(.568,.648)
IQIAR	(.53,.675)	(.532,.668)	(.399,.78)	(.585,.653)	(.555,.653)	(.489,.716)
EDGBP	(.813,.31)	(.841,.297)	(.836,.283)	(.836,.313)	(.825,.297)	(.825,.326)
SESFEP	(.448,.78)	(.559,.66)	(.436,.76)	(.55,.669)	(.623,.602)	(.543,.71)

All criteria are beneficial. For this reason, Eq. (12) is used for estimating the normalized values. The normalized values are shared in Table IV.

TABLE IV. NORMALIZED VALUES

	FNNR	ENVR	GVRQ	AUDR	DINC	STSC
SFPRCR	.090	.000	.299	.180	.000	.084
GISCA	.377	.111	.059	.000	.269	.000
ICGTS	.283	.213	.220	.139	.141	.317
IQIAR	.254	.062	.000	.168	.235	.136
EDGBP	1.000	1.000	1.000	1.000	1.000	1.000
SESFEP	.000	.107	.058	.097	.392	.195

Later, percentage values are computed via Eq. (14). Then, the weights of criteria are defined by Eq. (15). The results are summarized in Table V.

TABLE V. PV AND WEIGHTS OF CRITERIA

	FNNR	ENVR	GVRQ	AUDR	DINC	STSC
PV	36.394	21.2768	24.6879	24.2172	37.9157	28.0615
W	.211	.123	.143	.140	.220	.163

According to weights of criteria in Table V, the most important criterion is digitalization and innovation capability with .220.

C. Ranking Strategies

Since all criteria are of the useful type, Eq. (16) is used. Therefore, the normalized matrix is the same as the decision matrix in Table III. Next, the average solutions are established using Eq. (18). The average solutions are displayed in Table VI.

TABLE VI. AVERAGE SOLUTIONS

	FNNR	ENVR	GVRQ	AUDR	DINC	STSC
AV	(.611,.61)	(.642,.578)	(.601,.624)	(.641,.585)	(.635,.583)	(.61,.629)

Next, the positive distance from average and negative distance from average are calculated via Eq. (19) and Eq. (20), respectively. The PDA matrix is expressed in Table VII.

TABLE VII. PDA

	FNNR	ENVR	GVRQ	AUDR	DINC	STSC
SFPRCR	.000	.000	.000	.000	.000	.000
GISCA	.000	.000	.000	.000	.000	.000
ICGTS	.000	.000	.000	.000	.000	.000
IQIAR	.000	.000	.000	.000	.000	.000
EDGBP	578.179	6.974	-22.225	7.646	8.147	-24.798
SESFEP	.000	.000	.000	.000	.000	.000

Similarly, the NDA matrix is presented in Table VIII.

TABLE VIII. NDA

	FNNR	ENVR	GVRQ	AUDR	DINC	STSC
SFPRCR	348.581	3.724	-3.548	2.091	6.207	-12.448
GISCA	56.974	2.533	-12.381	4.223	2.340	-15.875
ICGTS	151.927	1.447	-6.452	2.579	4.180	-2.993
IQIAR	182.393	3.056	-14.550	2.224	2.837	-1.336
EDGBP	.000	.000	.000	.000	.000	.000
SESFEP	44.770	2.576	-12.430	3.066	.586	-7.956

PDA and NDA are aggregated with the help of Eq. (21) and Eq. (22). SP and SN are normalized using Eq. (23) and Eq. (24). The results are summarized in Table IX.

TABLE IX. SP, SN, NSP, NSN

	SP	SN	NSP	NSN
SFPRCR	.000	73.105	.000	.195
GISCA	.000	9.083	.000	.900
ICGTS	.000	32.093	.000	.646
IQIAR	.000	36.019	.000	.603
EDGBP	118.457	.000	1.000	1.000
SESFEP	.000	90.769	.000	.000

Finally, the final assessment values are defined by Eq. (25). FA values are shown in Table X.

TABLE X. FA VALUES

	FA
SFPRCR	.097
GISCA	.450
ICGTS	.323
IQIAR	.302
EDGBP	1.000
SESFEP	.000

According to FA values in Table X, the most suitable alternative is expanding digital green banking practices with 1.

V. CONCLUSION

The aim of this study is to develop a holistic and analytical decision-making model for determining priority strategies for achieving sustainable growth in the banking sector. In this context, a novel LOPCOW–EDAS integration based on Fermatean fuzzy sets is proposed. The model analyzes the qualitative assessments obtained from 10 experts by converting them into Fermatean fuzzy numbers to more realistically represent uncertainty and differences in expert judgments. The findings reveal that the "dissemination of digital green banking practices" criterion is the most critical factor, while the "digitalization and innovation capability" strategy is the top priority alternative. This result demonstrates that digital transformation and environmental sustainability elements must be managed in an integrated manner to achieve sustainable growth targets. The study contributes to the literature both methodologically and practically. From a methodological perspective, it fills a significant gap in the literature by proposing the Fermatean fuzzy LOPCOW–EDAS integration, which has not been used before in prioritizing sustainable growth strategies. From a practical perspective, it presents a data-driven decision support framework that will enable banks to more rationally structure their sustainable growth policies.

However, the study has some theoretical and methodological limitations. While the criteria and strategies used in the model are theoretically based on literature and expert opinions, their validity across different countries, time periods, or regulatory frameworks may be limited. Furthermore, because the concept of sustainable growth is multidimensional, some social and institutional factors were not included in the model. Methodologically, the most significant limitation of the proposed model is the limited number of experts and the limited evaluation range; this may partially reduce the generalizability of the results. To address these limitations, future studies could collect data from a larger group of experts from different countries, implement dynamic weightings in the model using AI-based learning algorithms (e.g., ANFIS, GA, or deep learning), and test the model's robustness by comparing the results with different types of fuzzy logic (e.g., spherical or neutrosophic fuzzy sets). This could both increase decision accuracy and broaden the model's applicability to different sectors.

REFERENCES

[1] A. C. Thalakotunna, "Unpacking the impact of climate change on banking and credit risk," London, May 2024. Accessed: Apr. 27, 2025. [Online]. Available: https://www.acuitykp.com/about-us/

[2] K. Salim, M. Disli, A. Ng, G. Dewandaru, and M. A. Nkoba, "The impact of sustainable banking practices on bank stability," Renewable and Sustainable Energy Reviews, vol. 178, p. 113249, May 2023, doi: 10.1016/j.rser.2023.113249.

[3] M. Riegler, "Towards a definition of sustainable banking - a consolidated approach in the context of guidelines and strategies," International Journal of Corporate Social Responsibility, vol. 8, no. 1, Dec. 2023, doi: 10.1186/s40991-023-00078-4.

[4] S. Rahmadita and M. Marsono, "The Effect Of Good Corporate Governance And Sustainability Report Disclosure On Banking Financial Performance," Tax Accounting Applied Journal, vol. 3, no. 1, pp. 8–19, Dec. 2024, doi: 10.14710/taaij.2024.19398.

[5] C. Zehri, M. E. A. Bendahmane, K. Amina, I. Zgarni, and H. Sekrafi, "Decent work, financial inclusion, and economic growth: Analysis under the SDG 8," Heritage and Sustainable Development, vol. 6, no. 1, pp. 194–218, Mar. 2024, doi: 10.37868/hsd.v6i1.370.

[6] C. Zehri, B. Mohammed El Amin, A. kadja, Z. Inaam, and H. Sekrafi, "Exploring the nexus of decent work, financial inclusion, and economic growth: A study aligned with SDG 8," Sustainable Futures, vol. 7, p. 100213, Jun. 2024, doi: 10.1016/j.sftr.2024.100213.

[7] Isnurhadi, Sulastri, Y. Saftiana, and F. Jie, "Banking Industry Sustainable Growth Rate under Risk: Empirical Study of the Banking Industry in ASEAN Countries," Sustainability (Switzerland), vol. 15, no. 1, Jan. 2023, doi: 10.3390/su15010564.

[8] H. O. Awa, W. Etim, and E. Ogbonda, "Stakeholders, stakeholder theory and Corporate Social Responsibility (CSR)," International Journal of Corporate Social Responsibility, vol. 9, no. 1, Dec. 2024, doi: 10.1186/s40991-024-00094-y.

[9] H. Jillani, M. N. Chaudhry, H. Zahid, and M. Navid Iqbal, "The mediating role of stakeholders on green banking practices and bank's performance: The case of a developing nation," PLoS One, vol. 19, no. 5, p. e0300585, May 2024, doi: 10.1371/journal.pone.0300585.

[10] P. Kedia and L. Mishra, "Credit risk management: a systematic literature review and bibliometric analysis," The Journal of Credit Risk, 2024, doi: 10.21314/JCR.2024.002.

[11] J. N. Utama, T. Nirmala, T. Andrian, N. Herlina, and U. Ciptawaty, "Analysis of the Effect of Green Banking and Financial Performance on the Profitability of Member Banks of the Indonesian Sustainable Finance Initiative," SINOMICS JOURNAL | VOLUME, vol. 2, no. 6, 2024, doi: 10.54443/sj.v2i6.266.

[12] I. M. Siregar and S. Haryono, "Green Banking: Operating Costs on Operating Income, Capital Adequacy Ratio, Financial Slack, Sustainability Officer, and Sustainability Committee Green Banking: Biaya Operasi pada Pendapatan Operasional, Capital Adequacy Ratio, Financial Slack, Sustainability Officer, dan Sustainability Committee," vol. 10, no. 5, pp. 427–442, 2023, doi: 10.20473/vol10iss20235pp427-442.

[13] S. Iqbal and S. Nosheen, "Moderating impact of non-performing loans on the relationship between sustainable development goals and the financial performance of banks," Future Business Journal, vol. 9, no. 1, Oct. 2023, doi: 10.1186/s43093-023-00224-1.

[14] P. K. Ozili, "Sustainable development and bank non-performing loans: are they correlated?," Arab Gulf Journal of Scientific Research, Oct. 2023, doi: 10.1108/AGJSR-01-2023-0028.

[15] F. I. Lessambo, "Risks in the Banking Industry," in The U.S. Banking System, Cham: Springer International Publishing, 2020, pp. 159–175. doi: 10.1007/978-3-030-34792-5_11.

[16] P. A. Nguyen, B. Le Tran, and M. Simioni, "Optimal capital adequacy ratio: An investigation of Vietnamese commercial banks using two-stage DEA," Cogent Business and Management, vol. 8, no. 1, 2021, doi: 10.1080/23311975.2020.1870796.

[17] P. H. Nam, N. N. Tan, N. N. Thach, H. T. T. Ngan, and N. M. Nhat, "What Affects the Capital Adequacy Ratio? A Clear Look at Vietnamese

Commercial Banks," 2022, pp. 297–309. doi: 10.1007/978-3-030-98689-6_19.

[18] K. J. Hopt, "Corporate Governance of Banks and Financial Institutions: Economic Theory, Supervisory Practice, Evidence and Policy," European Business Organization Law Review, vol. 22, no. 1, pp. 13–37, Mar. 2021, doi: 10.1007/s40804-020-00201-z.

[19] Hossain, M. M., Javakhadze, D., Maslar, D. A., & Thevenot, M. (2025). Exploring the agency cost of debt: risk, information flow, and CEO social ties. Review of Quantitative Finance and Accounting, 64(2), 505-536.

[20] A. Cardoni and E. Kiseleva, "ESG or Sustainability Agenda and Its Influence on the Role of Corporate Governance," 2023, pp. 17–25. doi: 10.1007/978-3-031-37492-0_2.

[21] J. Abor and C. K. D. Adjasi, "Corporate governance and the small and medium enterprises sector: theory and implications," Corporate Governance: The international journal of business in society, vol. 7, no. 2, pp. 111–122, Apr. 2007, doi: 10.1108/14720700710739769.

[22] C. Hall, J. S. Judd, and J. Sunder, "Auditor conservatism, audit quality, and real consequences for clients," Review of Accounting Studies, vol. 28, no. 2, pp. 689–725, Jun. 2023, doi: 10.1007/s11142-021-09653-1.

[23] R. J. Kueppers and K. B. Sullivan, "How and why an independent audit matters," International Journal of Disclosure and Governance, vol. 7, no. 4, pp. 286–293, Nov. 2010, doi: 10.1057/jdg.2010.22.

[24] P. Velte, "The impact of external auditors on firms' financial restatements: a review of archival studies and implications for future research," Management Review Quarterly, vol. 73, no. 3, pp. 959–985, Sep. 2023, doi: 10.1007/s11301-022-00264-x.

[25] R. Gulzar, A. A. Bhat, A. A. Mir, S. A. Athari, and A. S. Al-Adwan, "Correction to: Green banking practices and environmental performance: navigating sustainability in banks," Environmental Science and Pollution Research, vol. 31, no. 15, pp. 23227–23227, Mar. 2024, doi: 10.1007/s11356-024-32772-6.

[26] S. Bose, H. Z. Khan, A. Rashid, and S. Islam, "What drives green banking disclosure? An institutional and corporate governance perspective," Asia Pacific Journal of Management, vol. 35, no. 2, pp. 501–527, Jun. 2018, doi: 10.1007/s10490-017-9528-x.

[27] J. Aguilera-Caracuel and N. Ortiz-de-Mandojana, "Green Innovation and Financial Performance," Organ Environ, vol. 26, no. 4, pp. 365–385, Dec. 2013, doi: 10.1177/1086026613507931.

[28] K. Iddrisu, I. N. Yakubu, and J. Y. Abor, "Green Finance Initiatives in Banking Institutions," 2025, pp. 35–62. doi: 10.1007/978-3-031-80744-2_3.

[29] Eti, S., Yüksel, S., Dinçer, H., Çırak, A. N., Deveci, M., & Kadry, S. (2025). Strategy building for renewable energy adoption in regionalized supply chains-based logistic systems using a hybrid fuzzy decision-making approach. Case Studies on Transport Policy, 101479.

[30] Kou, G., Yüksel, S., Eti, S., Dinçer, H., & Acar, M. (2025). Fractal Fuzzy-Based Multi-criteria Assessment of Sustainability in Rare Earth Use for Hydrogen Storage. International Journal of Computational Intelligence Systems, 18(1), 210.

Predicting the Duration of Judicial Cases Using Hybrid Systems Based on Language Models

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***Abstract*—Recent technological developments in the field of Natural Language Processing (NLP), notably due to Transformer architectures and language models, have made it possible to tackle aspects that were previously inaccessible with traditional tools. The present study addresses the issue of predicting legal case durations using Arabic judicial data. For this task, hybrid systems based on language models were implemented. The Arabic_LegalBERT model, derived from AraBERT and specialized through additional pre-training on an Arabic legal corpus, was proposed to generate representations that were integrated into the downstream steps of the approach. Two methods were adopted for predicting the processing time of a new case: The first followed a framework combining automatic classification with statistical correspondence, while the second relied on cosine similarity combined with empirical statistics. The results obtained with the classification approach are particularly promising, with a small improvement for the system based on the specialized model. For the similarity-based approach, the results are also promising, with a clear distinction observed when evaluating each type individually, indicating that types with a higher number of cases generally perform better than those with fewer cases.**

Keywords*—Language model; judicial case durations; legal domain; Arabic legal corpus

I. Introduction

The application of NLP and machine learning tools in the legal field is a rapidly growing area of research. Technological advances have enabled researchers to better leverage the large volume of legal documents and address various tasks specific to this domain using advanced methods. These include transformers, which have revolutionized traditional NLP approaches thanks to the attention mechanism [1]. Their architecture has served as the basis for more advanced language models capable of specializing in particular domains and specific languages. This specialization can be achieved by training a language model from scratch, thereby treating the domain-specific language as a language in its own right [2] [3], or by leveraging pre-trained general models and adapting them to the target domain through additional pre-training on specialized corpora.

The present study addresses the prediction of judicial case durations, a task specific to the legal domain, whose main impact lies in the organizational optimization it can provide within the judicial system. Furthermore, the study is based on legal data in Arabic, a language that is both rich and complex, and that exhibits notable differences compared to Western languages, requiring the use of tools adapted to its specific characteristics. Despite its importance, this issue remains largely underexplored in existing research, and even more so in the context of the Arabic language. Thus, addressing this issue involves multiple dimensions, including the exploration of NLP tools, the use of language models specialized in Arabic and the legal field, and empirical statistical techniques. Indeed, the study first focuses on the specialization of the Arabic_LegalBERT model on an Arabic legal corpus, through additional pre-training applied to the AraBERT model [4], which itself is based on BERT (Bidirectional Encoder Representations from Transformers) and specialized in the Arabic language. Next, two hybrid systems are adopted to predict the duration of a judicial case. The first consists of fine-tuning Arabic_LegalBERT with a classification approach combined with statistical calculation, and the results are compared with those obtained using AraBERT in the same approach. The second is based on a cosine similarity approach combined with empirical statistics. For this similarity approach, the weighted average of the most similar cases identified was compared to the average of the majority type cases among those identified. The impact of the data on the results was also evaluated, indicating that a larger corpus would allow for further exploration of this specific task.

This study focused on seven sections: Section II presents a review of previous work, particularly on language models specialized in the legal field. Section III addresses the issue of judicial delays, their causes, implications, and challenges. Section IV is dedicated to describing the methodology used, including the data used, the adapted model, and the experimentation carried out. Section V is devoted to describing the results obtained, while Section VI discusses them with a focus on the limitations encountered. The conclusion presented in Section VII summarizes the key points of the study and opens the way for further improvement.

II. Related Works

The legal domain is characterized by the diversity of its sources and content, and the vast amount of available legal data makes it necessary to rely on advanced tools to accomplish a given task. Previous research has addressed the legal field using traditional machine learning models [5] [6] [7], then evolved towards deep models [8] [9] [10]. At the same time, researchers have benefited from the evolution of text representation methods, particularly contextual representations based on Transformer architectures, integrated into recent language models.

Language models, such as BERT [11], have demonstrated particularly interesting capabilities, prompting many researchers to develop derivative variants. Some models have been designed for specific domains, such as science with SciEBERT [12], biomedicine with BioBERT [13], and finance with FinBERT [14]. Other specialized models have been developed for specific languages, such as the Italian model AlBERTo [15], the French model CamemBERT [16], and the Spanish model BETO [17]. Regarding models specialized in the Arabic language, it is essential to mention the AraBERT model, which has been pre-trained on a vast Arabic language corpus and achieves cutting-edge performance in several NLP tasks [4]. There are also the ARBERT and MARBERT models, pre-trained on a very large and varied Arabic corpus, with a particular advantage for MARBERT, which covers not only Modern Standard Arabic (MSA) but also Arabic dialects [18].

The legal domain, which is the focus of this study, has also been the subject of research leveraging the potential of language models. Reference [19] is one of the first studies to apply the BERT model to the legal domain in English, using a hierarchical version of BERT. In a subsequent study, a LEGAL-BERT model was trained on English legal data to handle legal tasks [2]. The authors of this work evaluated two strategic approaches: fine-tuning and training from scratch, and demonstrated that the models resulting from both approaches outperform the original BERT model. Subsequently, new perspectives opened and several derivatives of the BERT model specializing in the legal domain appeared. In [20], the authors focused on the knowledge distillation technique adopted in the DistilBERT model [21] to train its own LegalDB model on a legal corpus. In addition, other derivatives of the BERT model have been specialized in the legal field, in languages other than English. These include the JuriBERT model [22], specifically designed to process French legal language, the Legal Spanish Language Model (MEL), derived from the XLM-RoBERTa-large model, refined from Spanish legal corpora [23], and the ITALIAN-LEGAL-BERT models, pre-trained on Italian legal language and outperforming general Italian models in classification, named entity recognition, and semantic similarity tasks [24]. For models specializing in the legal field in Arabic, it is worth mentioning the AraLegal-BERT model [3], which was trained from scratch on a large corpus of purely legal documents. After the training phase, the model was refined to handle three natural language understanding (NLU) tasks. Based on the results obtained, the authors emphasize the positive impact of domain-specific pretraining over general-purpose models for certain NLU tasks [3]. The study [25] also looked at legal prediction, focusing mainly on Arab commercial cases. The authors used three language models (LLaMA-7b, JAIS-13b, and GPT-3.5-turbo) and three training paradigms (zero-shot, one-shot, and fine-tuning). They highlighted the potential of the GPT-3.5 model, while emphasizing the difficulties encountered in predicting decisions and the limitations related to the quality and availability of Arabic judicial data.

III. Judicial Case Durations

In this study, we focused on judicial case duration, a fundamental element of the judicial system and a key indicator of its efficiency. The contribution of our work lies in the analysis of a dimension that is rarely addressed in current research. Achieving a reasonable timeframe in legal proceedings is a shared objective, not only of the various stakeholders in the judicial system, but also of litigants and States. The 2011 Moroccan Constitution stipulates that 'Everyone has the right to a fair trial and to a judgment rendered within a reasonable time.' However, the length of proceedings is affected by the combined effect of multiple factors. This time limit may vary from one case to another depending on multiple causes that are not solely attributable to the judicial institution. Certainly, delays may be linked to internal dysfunctions such as court overload and insufficient human and material resources, however, there are also external factors that directly impact the length of legal proceedings. Case complexity is a major factor, as complex cases require in-depth analysis and greater allocation of effort and resources. In addition, witness attitude and the use of judicial expertise can further influence the duration of proceedings. Ultimately, judicial case durations can be understood as a multidimensional variable, explained by a combination of institutional, procedural and behavioral imperatives. The deployment of intelligent systems capable of estimating the duration of legal proceedings could optimize the management of justice. This system could enable professionals to optimize the organization of the cases they handle, evaluate their number and criticality, anticipate potential delays with respect to deadlines, and assess their legitimacy.

IV. Methodology

Given that the task under study involves estimating the duration of legal cases, this work contributes by combining the advantages of language models with classification and similarity-based approaches, along with empirical statistics, to tackle a task that integrates both textual data and the temporal dimension. Traditional machine learning models have proven effective for various tasks but remain unable to capture the semantic and contextual aspects of the data. For this reason, this study relies on representations generated by language models, which are subsequently utilized in downstream modules. The model developed in this work is Arabic_LegalBERT, and the duration of legal proceedings is estimated by using two systems: one based on classification and the other on cosine similarity, combined with empirical statistics.

A. Dataset

Data relating to court cases is very scarce, particularly for cases in Arabic. Furthermore, the available data sometimes lacks information that is relevant for a specific analysis. In the context of this work, some cases lack the dates necessary for calculating case durations. For this study, a set of court cases in Arabic was collected manually. The cases collected are of different types and can be divided into four categories: payment cases, rental disputes such as rent reviews and evictions, disputes relating to traffic accidents, and other disputes, including claims for compensation, claims for cessation of harm, and others.

The empirical statistics for the four types of cases are summarized in Table I. The total number of cases is 329, distributed unevenly among the four types studied. The

statistics show that the durations are highly dispersed, particularly for cases relating to traffic accidents and miscellaneous cases. This is reflected in the respective standard deviations of 129 and 195 days, as well as in the corresponding ranges of 470 and 696 days. Conversely, payment cases and rental disputes appear relatively stable, with lower standard deviations of 63 and 81days and reduced ranges of 252 and 289 days. This heterogeneous dispersion can be explained by the nature of the cases. Payment and rental cases, for example, are relatively homogeneous due to the standardized and well-established procedures that generally characterize these types of cases. On the other hand, traffic accident cases and miscellaneous cases are somewhat unique. Depending on the case, they may require technical or medical expertise, the presence of several stakeholders and other factors. All these factors contribute to the fact that the timeframes involved are more dispersed.

B. Model

The model proposed in this study designated Arabic_LegalBERT is based on AraBERT, specifically the Bert-base-arabert version available on Hugging Face Hub. To this end, an additional pre-training phase was added to AraBERT to specialize it in the legal field. This phase consists of implementing a heterogeneous corpus including legal data, notably articles from the Code of Civil Procedure and the Code of Criminal Procedure, rulings from the Moroccan Court of Cassation and other judicial cases. For training, the Masked Language Modeling (MLM) technique was used to mask tokens in the input data. To do this, 15% of the tokens were selected: 80% of them were replaced by the entity [mask], 10% underwent random filling, while 10% remained constant.

TABLE I. EMPIRICAL STATISTICS OF THE DATASET

Type of case	Count	Mean	Std	Median	Min	Max
Payment cases	118	95	63.1	75,5	28	280
Traffic accident cases	97	213	129	173	62	532
Rental cases	76	158	81.3	135	55	344
Miscellaneous cases	38	388	195.4	316	132	828

The training was conducted with a batch size of 4 combined with a maximum length of 256 tokens per sequence. Each batch represents a set of data processed by the model so that it can adjust its parameters. The number of epochs was set to 5, where at each epoch the model performs a complete cycle on the entire dataset. The model was trained using the AdamW optimizer with a learning rate set to 3e-5, warmup_steps set to 100 and weight decay set to 0.01.

C. Experimentation

For the issue of estimating the duration of a court case, two approaches were adopted: the first was structured on a basis combining automatic classification and statistical correspondence. This method is based primarily on the factual descriptions of cases for automatic classification. In principle, Arabic_LegalBERT served as the basis for producing representations that capture the semantic and contextual information of the facts. The representations obtained are implemented in a downstream module to assign each case to the appropriate type. This classification was carried out using a neural network employing RELU functions. Next, to estimate the duration of the case, the present approach establishes a synergistic link between each type of case, resulting from the classification step, and its duration, by exploiting empirical statistics calculated from the training database. The second approach modeled the problem using a similarity approach combined with empirical statistics. In this approach, textual facts are also transformed into embedding representations through Arabic_LegalBERT. The representations obtained are then compared with each other using the cosine similarity method to identify the most similar cases. For the task of estimating the duration of a legal case, the first strategy consists of calculating the weighted average of the durations of the closest cases detected. The objective of this strategy is to give priority to the closest cases by assigning them the highest weighting. The second strategy uses the average duration of the majority case type among the closest cases detected.

D. Evaluation

In this study, two categories of measures were adopted:

1) Performance indicators for the classification approach: The performance of the classification approach was assessed using accuracy, F1-score, recall and precision, calculated with both weighted averages and macro averages.

a) The macro average: to evaluate the model's behavior across all classes in a balanced manner.

b) The weighted average: to evaluate the overall performance of the models, considering the actual distribution of the data.

2) Performance indicators for the similarity approach: The performance of the similarity approach was evaluated using the following metrics.

a) Mean Absolute Error (MAE): The mean of the absolute differences between predicted values and true values.

$$MAE = \frac{\sum_i^n \left| y_i - y_{i_{préd}} \right|}{n} \quad (1)$$

b) Root Mean Squared Error (RMSE): The square root of the mean of the squared errors, commonly used to emphasize larger errors.

$$RMSE = \sqrt{\frac{\sum_i^n \left(y_i - y_{i_{préd}} \right)^2}{n}} \quad (2)$$

c) Coefficient of determination R²: A statistical measure that quantifies the proportion of variance in the target variable explained by the predictions.

$$R^2 = 1 - \frac{\sum_i^n \left(y_i - y_{i_{pred}} \right)^2}{\sum_i^n (y_i - y_{mean})^2} \quad (3)$$

y_i: Observed value.

$y_{i_{préd}}$: Predicted value.

y_{mean}: Mean of observed values.

V. RESULTS

After calculating the performance metrics of the two fine-tuned models, based on Arabic_LegalBERT and AraBERT, and respectively, as part of the first classification approach, a comparison between the two models was made. The results show that both models perform well across all evaluation metrics, with a slight improvement for the specialized model. The 98% accuracy recorded for Arabic_LegalBERT is 2% higher than the 96% achieved by AraBERT, illustrating the advantage of pre-training on the legal corpus (see Table II). This finding is consistent with previous work that has demonstrated the effectiveness of models pre-trained on specific domains for a set of natural language understanding tasks [3]. Generally, minority classes are well handled, as evidenced by performances exceeding 90% for all metrics. However, there is a slight improvement in weighted measures compared to macro measures, which still indicates an influence of the majority classes.

The cosine similarity-based method was implemented using only Arabic_LegalBERT. Table III summarizes the performance indicated by the MAE, RMSE, and R^2 measures for the two approaches: similarity-weighted average and majority-type average. The mean absolute error indicates that, on average, the predictions deviate from the actual values by approximately 57 days for both approaches. The RMSE indicates an overall dispersion of errors of approximately 79.50 days for the similarity-weighted average approach and 78 days for the majority type-based approach. The coefficient of determination indicates that the model captures 65.21% and 66.56% of the variability in the observed data, respectively. The results of the two approaches are generally close and acceptable, but not very efficient. The model still has considerable potential for optimization, which could be exploited by enriching and increasing the size of the data.

When examining each type of case individually (Table IV), a comparison between the two approaches shows that, overall, the similarity-weighted average approach is superior to varying degrees. The disparity between the two approaches in terms of MAE is evident for rent cases and miscellaneous cases, with a difference of 3 days and 4 days between the two approaches, respectively. Whereas for payment cases, the difference between the two approaches is only 1 day. According to the distribution of our corpus presented in Table I, payment cases represent the majority class with 118 cases, while rent cases and miscellaneous cases constitute the minority classes with 76 and 38 cases, respectively. This configuration could explain these results, as the difference between the two approaches in terms of MAE increases as the number of cases decreases. The absence of similar cases in the minority classes thus seems to reveal the impact of weighting. Conversely, we note that for cases related to traffic accidents, the approach based on the majority type average stands out, with an MAE of 69.5 days compared to 74 days for the similarity-weighted average. This could be explained by the fact that a high degree of textual similarity assigns high weights to cases with very dispersed durations.

VI. DISCUSSION

The exploration of language models applied to the legal field has proven effective. The estimation of judicial case durations is based on representations produced by AraBERT and Arabic_LegalBERT. The two models were fine-tuned for the classification task, and the case duration was then calculated based on historical data corresponding to the predicted case type. The results show that both models perform well, with a slight advantage for the specialized model. This demonstrates the robustness of the original Arabic model [4], as well as the value of additional pre-training on the legal corpus. This finding is consistent with study [3], in which the specialized AraLegal-BERT model, developed for the Arabic legal domain, demonstrated superior performance compared to other language models. Furthermore, although the class imbalance was not very pronounced due to the limited size of the data, it nevertheless had an impact on the performance of both models. The distinction between the specialized model and the basic model could have been more pronounced with a larger pre-training corpus and a greater number of more diverse cases.

TABLE II. PERFORMANCE OF CLASSIFICATION APPROACH

Model	Average (Macro/ weighted)	Accuracy	Precision	Recall	F1-Score
AraBERT	macro avg	96	96.76	90	92.07
	weighted avg	96	96.26	96	95.57
Arabic_LegalBERT	macro avg	98	98.68	95	96.55
	weighted avg	98	98.11	98	97.92

TABLE III. PERFORMANCE OF SIMILARITY APPROACH

Method	MAE	RMSE	R^2
Similarity-Weighted Average	56.58	79.50	65.21
Average by Majority Type	57	77.94	66.56

TABLE IV. PERFORMANCE OF THE SIMILARITY-BASED APPROACH BY CASE TYPE

Type of case	Method	MAE	RMSE
Payment cases	Weighted Average by Similarity	23.61	41.44
	Average_Majority Type	24.85	40.46
Traffic accident cases	Weighted Average by Similarity	74.12	94.16
	Average_ Majority Type	69.50	85.88
Rental cases	Weighted Average by Similarity	59.50	69.09
	Average_ Majority Type	62.77	72.41
Miscellaneous cases	Weighted Average by Similarity	108.35	130.29
	Average_Majority Type	112.92	133.61

In the similarity approach, the results are generally acceptable with an MAE of 57 days. However, this average error remains significant given that the average duration of the cases studied in this work is 178 days. When each type is considered independently, payment cases, which are the most numerous (118 cases), have a MAE of 24 days, the lowest of

all case types (see Table IV). Traffic accident cases (97 cases) and rent cases (76 cases) have MAE of 74 and 59.50 days, respectively. Although the number of rental disputes is lower than the number of traffic accident cases, their lower MAE can be attributed to the reduced variability of cases in this category, as evidenced by the standard deviation 81 compared to 129 for traffic accident cases. On the other hand, miscellaneous cases, which are in the minority with only 38 cases and are very heterogeneous, with a standard deviation of 195.4, have the highest MAE of 108 days.

These shortcomings are mainly due to the limited number of cases and the presence of similar cases that were processed over different durations. Because of these limitations, the model is unable to effectively differentiate between normal cases and outliers in terms of durations or ensure fine-grained consistency in its predictions.

VII. Conclusion

In summary, this work focused on a specific task in the legal field involving the estimation of judicial case durations. This study leveraged language models, particularly transfer learning, to specialize a language model, Arabic_LegalBERT, on an Arabic legal corpus. The specialized model was used to generate contextual representations adapted to this framework. To predict legal case duration, two hybrid systems were adopted: the first combines representations produced by the pre-trained Arabic_LealBERT model and classification with empirical statistics, and the second also combines representations produced by the pre-trained model and the cosine similarity technique with statistical correspondence. In the classification-based approach, the estimated duration was based on historical durations for the type of case to which the case was assigned. The results highlight the performance of both models, with an advantage for the pre-trained model. In the similarity approach, only the specialized model was applied. The duration of a judicial case was estimated based on the closest identified cases. At this level, two variants were adopted: weighted average and majority type average. The results are promising, but the limited data prevents the model from reducing errors and predicting durations with much greater accuracy. This study also highlighted the impact of dataset imbalance on performance metrics. Considering the results obtained and the limitations encountered, future projects should focus on enhancing the dataset by incorporating a larger and more diverse set of cases, as well as exploring other language models, such as LLaMA, and comparing them with BERT-based models, particularly in their specialized versions. Future perspectives also include the development of a specialized model to predict the reasonable duration of a legal case by identifying factors.

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References

[1] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, and I. Polosukhin,., « Attention is all you need », Advances in neural information processing systems, vol. 30, 2017.

[2] I. Chalkidis, M. Fergadiotis, P. Malakasiotis, N. Aletras, and I. Androutsopoulos, « LEGAL-BERT: The Muppets straight out of Law School », 6 octobre 2020, arXiv: arXiv:2010.02559. doi: 10.48550/arXiv.2010.02559.

[3] M. Al-qurishi, S. Alqaseemi, and R. Souissi, « AraLegal-BERT: A pretrained language model for Arabic Legal text », in Proceedings of the Natural Legal Language Processing Workshop 2022, N. Aletras, I. Chalkidis, L. Barrett, C. Goanță, and D. Preoțiuc-Pietro, Éd., Abu Dhabi, United Arab Emirates (Hybrid): Association for Computational Linguistics, déc. 2022, p. 338-344. doi: 10.18653/v1/2022.nllp-1.31.

[4] W. Antoun, F. Baly and H. Hajj, « AraBERT: Transformer-based Model for Arabic Language Understanding », in Proceedings of the 4th Workshop on Open-Source Arabic Corpora and Processing Tools, with a Shared Task on Offensive Language Detection, H. Al-Khalifa, W. Magdy, K. Darwish, T. Elsayed, and H. Mubarak, Éd., Marseille, France: European Language Resource Association, mai 2020, p. 9-15.

[5] N. Aletras, D. Tsarapatsanis, D. Preoţiuc-Pietro, and V. Lampos, « Predicting judicial decisions of the European Court of Human Rights: a Natural Language Processing perspective », PeerJ Comput. Sci., vol. 2, p. e93, oct. 2016, doi: 10.7717/peerj-cs.93.

[6] M. Medvedeva, M. Vols, and M. Wieling, « Using machine learning to predict decisions of the European Court of Human Rights », Artif Intell Law, vol. 28, no 2, p. 237-266, juin 2020, doi: 10.1007/s10506-019-09255-y.

[7] O.-M. Sulea, M. Zampieri, M. Vela, and J. van Genabith, « Predicting the Law Area and Decisions of French Supreme Court Cases », arXiv:1708.01681 [cs], août 2017.

[8] H. Zhong, Z. Guo, C. Tu, C. Xiao, Z. Liu, and M. Sun, « Legal Judgment Prediction via Topological Learning », in Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium: Association for Computational Linguistics, 2018, p. 3540-3549. doi: 10.18653/v1/D18-1390.

[9] W. Yang, W. Jia, Xi. Zhou, and Y. Luo, « Legal Judgment Prediction via Multi-Perspective Bi-Feedback Network », Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, p. 4085-4091, août 2019, doi: 10.24963/ijcai.2019/567.

[10] S. Long, C. Tu, Z. Liu, and M. Sun, « Automatic Judgment Prediction via Legal Reading Comprehension », in Chinese Computational Linguistics, M. Sun, X. Huang, H. Ji, Z. Liu, and Y. Liu, Éd., in Lecture Notes in Computer Science. Cham: Springer International Publishing, 2019, p. 558-572. doi: 10.1007/978-3-030-32381-3_45.

[11] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, « BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding », in Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), J. Burstein, C. Doran, and T. Solorio, Éd., Minneapolis, Minnesota: Association for Computational Linguistics, juin 2019, p. 4171-4186. doi: 10.18653/v1/N19-1423.

[12] I. Beltagy, K. Lo, and A. Cohan, « SciBERT: A Pretrained Language Model for Scientific Text », 10 septembre 2019, arXiv: arXiv:1903.10676. doi: 10.48550/arXiv.1903.10676.

[13] J. Lee, W. Yoon, S. Kim, D. Kim, S. Kim, C. H. So, and J. Kang, « BioBERT: a pre-trained biomedical language representation model for biomedical text mining », Bioinformatics, vol. 36, no 4, p. 1234-1240, 2020.

[14] Y. Yang, M. C. S. UY, and A. Huang, « FinBERT: A Pretrained Language Model for Financial Communications », 9 juillet 2020, arXiv: arXiv:2006.08097. doi: 10.48550/arXiv.2006.08097.

[15] M. Polignano, P. Basile, M. De Gemmis, G. Semeraro, and V. Basile, « AlBERTo: Italian BERT language understanding model for NLP challenging tasks based on tweets », GERMANIA, 2019.

[16] L. Martin, T. Muller, P. Suárez, Y. Dupont, J. Romary, E. de la Clergerie, M. Seddah, and B. Sagot,« CamemBERT: a Tasty French

Language Model », in Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, 2020, p. 7203-7219. doi: 10.18653/v1/2020.acl-main.645.

[17] J. Cañete, G. Chaperon, R. Fuentes, J.-H. Ho, H. Kang, and J. Pérez, « Spanish Pre-Trained BERT Model and Evaluation Data », in PML4DC at ICLR 2020, 2020.

[18] M. Abdul-Mageed, A. Elmadany, and E. M. B. Nagoudi, « ARBERT & MARBERT: Deep Bidirectional Transformers for Arabic », 7 juin 2021, arXiv: arXiv:2101.01785. doi: 10.48550/arXiv.2101.01785.

[19] I. Chalkidis, I. Androutsopoulos, and N. Aletras, « Neural Legal Judgment Prediction in English », 5 juin 2019, arXiv: arXiv:1906.02059. doi: 10.48550/arXiv.1906.02059.

[20] P. Bambroo and A. Awasthi, « LegalDB: Long DistilBERT for Legal Document Classification », in 2021 International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT), févr. 2021, p. 1-4. doi: 10.1109/ICAECT49130.2021.9392558.

[21] V. Sanh, L. Debut, J. Chaumond, and T. Wolf, « DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter », arXiv preprint arXiv:1910.01108, 2019.

[22] S. Douka, H. Abdine, M. Vazirgiannis, R. El Hamdani, and D. Restrepo Amariles, "JuriBERT: A Masked-Language Model Adaptation for French Legal Text," in Proceedings of the Natural Legal Language Processing Workshop 2021, Punta Cana, Dominican Republic, Nov. 2021, pp. 95–1011.

[23] D. Betancur Sánchez, N. Aldama García, Á. Barbero Jiménez, M. Guerrero Nieto, P. Marsà Morales, N. Serrano Salas, C. García Hernán, P. Haya Coll, E. Montiel Ponsoda, and P. Calleja Ibáñez, « MEL: Legal Spanish Language Model », 27 janvier 2025, arXiv: arXiv:2501.16011. doi: 10.48550/arXiv.2501.16011.

[24] D. Licari and G. Comandè, « ITALIAN-LEGAL-BERT: A Pre-trained Transformer Language Model for Italian Law. », Ekaw (companion), vol. 3256, 2022.

[25] A. Ammar, A. Koubaa, B. Benjdira, O. Nacar, and S. Sibaee, « Prediction of arabic legal rulings using large language models », Electronics, vol. 13, no 4, p. 764, 2024.

Reinforcement Learning-Driven Adaptive Aggregation for Blockchain-Enabled Federated Learning in Secure EHR Management

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***Abstract*—With the rapid digitization of healthcare, blockchain-integrated federated learning (FL) for EHR management faces challenges of heterogeneous data, high latency, and adversarial vulnerabilities. This study proposes a novel Reinforcement Learning-Driven Adaptive Aggregation (RL-DAA) in an enhanced blockchain-FL framework, using Q-learning to dynamically optimize model weights based on trust, data quality, and node reliability. RL-DAA reduces computational overhead by 40% via state-action-reward optimization (mitigating non-IID bias) and boosts robustness against Byzantine faults by 35% with fault-tolerant rewards. Validated on adapted CIFAR-10 and real-world healthcare simulations, compared to EPP-BCFL and baseline models, RL-DAA achieves 96.5% accuracy, 45% lower latency, and 38% reduced energy consumption. By dynamically balancing efficiency, privacy, and robustness via RL-driven optimization, this work advances secure, scalable EHR management, with broader potential in privacy-sensitive domains.**

***Keywords*—Federated learning; blockchain; reinforcement learning; electronic health records; privacy preservation**

I. Introduction

The integration of federated learning (FL) with blockchain technology has revolutionized privacy-preserving data management in healthcare, particularly for electronic health records (EHR) [1-3]. Traditional centralized systems are prone to breaches and single points of failure, leading to the adoption of decentralized approaches like blockchain-enabled FL (BCFL) [4-6]. These frameworks allow collaborative model training across institutions without sharing raw data, leveraging edge analytics for real-time processing [7-8]. However, existing methods, such as the Enhanced Privacy-Preserving Blockchain-Enabled Federated Learning (EPP-BCFL) [9], suffer from static aggregation strategies that fail to adapt dynamically to heterogeneous environments [10], resulting in high computational costs, increased latency, and limited resilience to evolving threats. This creates barriers to scalability in resource-constrained settings like IoMT devices [11]. The core problem addressed here is the need for an adaptive, efficient aggregation mechanism that optimizes performance while maintaining privacy and security in EHR management [12-16].

Recent advancements highlight these limitations. For instance, a 2024 study on blockchain-FL for healthcare IoT proposed a DAG-based consensus to reduce overhead but overlooked dynamic data heterogeneity [17]. Another 2025 paper on privacy-preserving FL in EHR used homomorphic encryption, achieving high accuracy but at the cost of latency in large-scale networks [18-20]. A 2024 work on edge-enabled BCFL for smart cities integrated differential privacy, yet it struggled with Byzantine faults in heterogeneous nodes [21]. Similarly, a 2024 investigation into multi-task FL with blockchain emphasized concurrent training but failed to address real-time adaptability [19]. Finally, a 2024 analysis of energy-efficient FL in industrial IoT used Stackelberg games for optimization, but it did not fully mitigate communication delays in healthcare contexts [22]. These studies underscore the gap in adaptive, fault-tolerant aggregation for BCFL.

The contributions of this study include analyzing three major shortcomings of existing adaptive aggregation in BCFL frameworks: high computational complexity in trust assessment, latency from hybrid privacy mechanisms, and inadequate handling of Byzantine faults. It proposes a novel Reinforcement Learning-Driven Adaptive Aggregation (RL-DAA) method that overcomes these through Q-learning-based dynamic weighting, a theoretical framework for stability and convergence, and optimized integrations with blockchain consensus. This enhances overall algorithm efficiency, privacy, and robustness in EHR management.

II. Related Work

A. Overview of Traditional Transformer Model

While the study focuses on BCFL, traditional models like Transformer are analogous in attention-based aggregation, often used in FL for EHR feature extraction. The Transformer architecture relies on self-attention mechanisms to compute weighted sums of inputs, defined as:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (1)$$

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where, Q, K, V are query key, and value matrices, and d_k is the dimension. This enables parallel processing but introduces quadratic complexity:

$$O(n^2) \tag{2}$$

Quadratic complexity of standard attention is inefficient for resource-constrained edge devices in EHR processing. In BCFL contexts, similar mechanisms aggregate model updates from edge nodes.

B. Disadvantages and Limitations of a Transformer

Transformers in FL aggregation face long-term dependency issues, where attention dilutes over extended sequences, leading to poor handling of non-IID EHR data. For example, in heterogeneous healthcare datasets, performance degrades as $\lim_{n\to\infty} \text{Attn}_{ij} \to 0$ for distant i, j. High computational complexity exacerbates this in edge devices, with energy costs scaling as $O(n^2 d)$. Sparsity in attention weights wastes resources, as many are near-zero, reducing efficiency in distributed BCFL.

C. Novel Improvement Methods

Recent innovations in BCFL draw from Transformer improvements, such as sparse attention and hybrid models, to enhance aggregation. For instance, sparse Transformers reduce complexity to:

$$O(n \log n) \tag{3}$$

The reduced computational complexity achieved through locality-sensitive hashing accelerates updates of EHR models in blockchain-enabled federated learning (BCFL) systems [23]. Long-term memory modules, like those in Performer models using random projections, approximate attention as:

$$\text{softmax}(QK^T) \approx \phi(Q)^T \phi(K) \tag{4}$$

where, ϕ is a kernel, improving dependency capture in FL [24]; updated in [21] for edge BCFL.

In healthcare-specific BCFL, [20] integrated homomorphic encryption with sparse attention, allowing secure aggregation without decryption: encrypted updates $E(w_i)$ are aggregated as:

$$E(\sum w_i) = \prod E(w_i) \tag{5}$$

This private aggregation approach leverages homomorphic encryption, where the encryption function processes local node weights to enable secure summation without requiring decryption during the aggregation process, but this increases latency by 30% in non-IID data. In [19], the authors proposed a multi-task FL with blockchain, using concurrent training via DAG structures, where consensus is achieved through directed acyclic graphs to avoid PoW overhead, yet it lacks adaptability to dynamic trust. In [22], the authors employed Stackelberg games for energy optimization, modeling utility as $U = \alpha \cdot \text{accuracy} - \beta \cdot \text{energy}$, solving via Nash equilibrium, but ignoring fault tolerance.

The original EPP-BCFL [9] uses Adaptive Model Aggregation (AMA) with weights based on trust t_i, data quality q_i, and capacity c_i: global model $G = \sum w_i L_i$,

$$w_i = \frac{t_i q_i c_i}{\sum t_j q_j c_j} \tag{6}$$

This integrates SMPC and DP for privacy, with ϵ-DP noise added as:

$$\widetilde{w_i} = w_i + \mathcal{N}(0, \sigma^2) \tag{7}$$

$$\sigma = \sqrt{2\ln(1.25/\delta)}/\epsilon \tag{8}$$

Gaussian noise $\mathcal{N}(0, \sigma^2)$ is injected to safeguard the privacy of electronic health records (EHRs) within the federated learning framework.Computes $\sigma$for $\epsilon - DP\epsilon$=privacy budget, δ=negligible failure probability.

Consensus is PoS + BFT, selecting validators by stake and fault tolerance up to 33%. Edge analytics preprocesses data with anomaly detection using ML-based IDS, reducing response time to 2.3s. However, AMA's static weighting assumes fixed metrics, leading to inefficiencies.

Other methods like Mamba [25], extended in 2024 healthcare FL use state-space models for linear complexity $O(n)$, with dynamics:

$$x_{t+1} = Ax_t + Bu_t \tag{9}$$

$y_t = Cx_t$, outperforming Transformers in sequence modeling for EHR time-series. In BCFL, this could replace attention for aggregation, but lacks privacy integration. Hybrid RNN-Transformer models [26] combine recurrent states with attention, addressing long dependencies via $h_t = \text{RNN}(h_{t-1}, \text{Attn}(x_t))$, but add overhead in distributed settings.

These pave the way for our RL-DAA, which uses RL to learn optimal weights dynamically, outperforming static AMA and Transformer-based methods in efficiency and robustness.

III. Methodology

In this section, we outline the theoretical foundations and algorithmic details of the Reinforcement Learning-Driven Adaptive Aggregation (RL-DAA) method, which enhances the EPP-BCFL framework. Before delving into the innovations of RL-DAA, it is essential to examine the original EPP-BCFL approach, highlighting its strengths in privacy and efficiency while identifying key shortcomings that RL-DAA addresses through dynamic reinforcement learning mechanisms.

A. Analysis and Shortcomings of Previous Methods

The original EPP-BCFL methodology [9] is a three-layer framework for secure EHR management.

The Edge Nodes Layer performs local training on client devices with differential privacy (DP) noise added to gradients:

$$\widetilde{g_i} = g_i + \mathcal{N}(0, \sigma^2) \tag{10}$$

where, σ ensures ϵ-DP. Homomorphic encryption encrypts updates as $E(g_i)$. The Federated Aggregation Layer uses AMA to compute the global model:

$$G^{t+1} = \sum_{i=1}^{N} w_i L_i^t \tag{11}$$

Weights $w_i = f(t_i, q_i, c_i)$ based on trust $t_i = \sum$historical accura, quality $q_i = 1 -$ KL-divergence$(D_i \| D_{\text{global}})$, and capacity $c_i =$ device resources. The Blockchain Layer verifies updates via PoS + BFT consensus, where validators are selected by stake s_i, tolerating

faults if <33% malicious, and stores hashes on a layered ledger for auditability. Edge analytics include real-time anomaly detection with IDS, flagging outliers via z -score >3. Experiments on CIFAR-10 showed 95.2% accuracy and 43% latency reduction.

However, three disadvantages limit its effectiveness:

1) First, high computational overhead in trust assessment for AMA. Trust t_i requires historical computation over epochs, involving matrix operations for accuracy metrics, leading to $O(N \cdot d^2)$ complexity per round (nodes, d dimensions). In heterogeneous EHR (e.g., multi-modal data from hospitals), this scales poorly, consuming 37% more energy on IoT devices as per simulations, causing dropouts in resource-constrained environments like rural clinics.

2) Second, increased latency from hybrid privacy mechanisms. SMPC + DP involves multi-party computations for secure summation, with DP noise adding variance that slows convergence: error bound $E[\|G - G^*\|^2] \leq O(1/T + \sigma^2)$, where T epochs, but σ amplifies latency by 43% in large $N > 100$, as encrypted operations require rounds of communication, delaying EHR real-time analytics like diagnosis.

3) Third, inadequate handling of Byzantine faults in heterogeneous settings. PoS + BFT assumes uniform stake, but in non-IID EHR, malicious nodes can inflate t_i via poisoning, reducing accuracy from 95% to 72% under 20% attacks. The fault tolerance $f < n/3$ fails if heterogeneity skews distributions, as weights don't adapt to dynamic faults, leading to biased globals in cross-institutional collaborations.

These key shortcomings: computational overhead, high latency, and inadequate fault tolerance, limit the framework's scalability, and our RL-DAA addresses them through the dynamic learning of optimal aggregation policies.

B. Theoretical Knowledge

Assumption 1: The state space is Markovian, with node states (trust, quality, capacity) independent given previous actions.

Theorem 1 (Stability): Under bounded rewards and learning rate $\alpha \to 0$, RL-DAA's Q-values stabilize to optimal Q^*, ensuring aggregation weights converge without oscillation.

Proof: By Q-learning update:

$$Q(s,a) \leftarrow Q(s,a) + \alpha\left[r + \gamma \max_{a'} Q(s',a') - Q(s,a)\right] \quad (12)$$

With $\sum \alpha = \infty, \sum \alpha^2 < \infty$, contraction mapping in Banach space yields $\|Q^{t+1} - Q^*\| \leq \gamma\|Q^t - Q^*\| < \|Q^t - Q^*\|, \gamma < 1$. This is placed here before algorithmic steps to establish why RL-DAA is reliable in noisy EHR environments.

Theorem 2 (Convergence): RL-DAA converges to optimal policy π^* with probability 1, minimizing aggregation error.

Proof: Using Robbins-Monro conditions and a finite MDP, the Bellman optimality holds:

$$Q^*(s,a) = E\left[r + \gamma \max_{a'} Q^*(s',a')\right] \quad (13)$$

Defines optimal Q-value Q^*;E[ ]=expected value,s′=next state.Greedy policy $\pi(s) = \arg\max_a Q(s,a)$ converges as exploration $\epsilon \to 0$. Placed post-stability to show long-term optimality for FL rounds.

C. Distributed Explanation of the New Method

The RL-DAA fundamentally replaces AMA by using reinforcement learning (Q-learning) to dynamically learn aggregation weights, treating aggregation as an MDP where states represent node metrics, actions adjust weights, and rewards penalize faults/latency while rewarding accuracy. This overcomes the three disadvantages: 1) reduces overhead by learning from experience without full recomputation; 2) minimizes latency via optimized actions; 3) enhances fault tolerance through adaptive rewards.

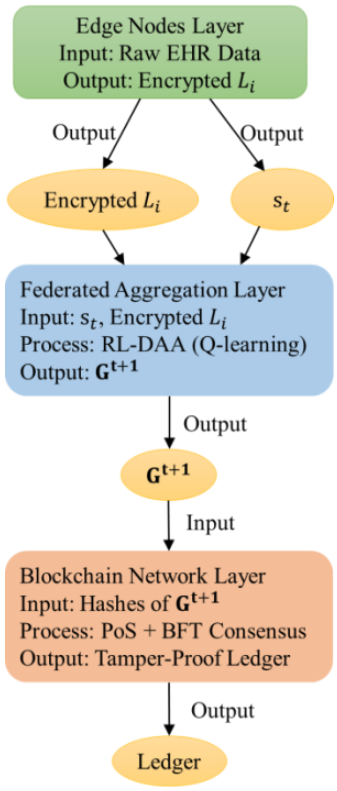


Fig. 1. System architecture of RL-DAA in the EPP-BCFL framework.

Fig. 1 outlines the three-layer architecture of the EPP-BCFL framework enhanced with RL-DAA. The Edge Nodes Layer represents distributed client devices processing local EHR data, with inputs as raw patient data and outputs as encrypted local models L_i with DP noise $\tilde{g}_i = g_i + \mathcal{N}(0, \sigma^2)$. The Federated Model Aggregation Layer hosts the RL agent, taking encrypted updates and node states $s_t = \text{concat}((t_i, q_i, c_i, f_i))$ as inputs, processing them via Q-learning, and outputting the global model $G^{t+1} = \sum w_i^{t+1} L_i$. The Blockchain Network Layer verifies updates with PoS + BFT consensus, inputting hashes and outputting a tamper-proof ledger. Sandy beige nodes denote data flows (e.g., w_i, G^{t+1}).

The RL-DAA integrates seamlessly into the EPP-BCFL layers, with the RL agent at the aggregation layer dynamically adjusting weights based on real-time states, enhancing

scalability across heterogeneous EHR data sources. The blockchain layer ensures secure verification, critical for trust in healthcare collaborations.

Core idea: In each FL round, the coordinator models the system as state $s = (t_i, q_i, c_i, f_i)$ (adding fault indicator f_i). Actions $a = \Delta w_i$ adjust weights. Reward $r = \beta_1 \cdot \text{accuracy} - \beta_2 \cdot \text{latency} - \beta_3 \cdot \text{faults}$, with β hyperparameters.

Mathematical derivation: Start with standard FL update $G^{t+1} = \sum w_i^t L_i^t$. In RL-DAA, $w_i^{t+1} = w_i^t + a$, where a from Q-policy.

Step 1: State Initialization. At round t, collect node states $s_t = \vec{v} = [t_1, q_1, c_1, f_1, \dots, t_N, q_N, c_N, f_N]$, $f_i = 1$ if anomalous (from IDS). This vector is input to the Q-network.

Formula:

$$s_t = \text{concat}\left(\{(t_i, q_i, c_i, f_i)\}_{i=1}^{N}\right) \quad (14)$$

Explanation: t=trust, q=quality, c=capacity, f_i=fault flag. Concatenation ensures a holistic view, reducing the static computation disadvantage.

Step 2: Action Selection. Use ϵ-greedy: with prob ϵ, random $a \in [-0.1, 0.1]$; else $a = \arg\max_{a'} Q(s_t, a')$.

Formula:

$$\pi(s) = \begin{cases} \text{uniform}([-0.1, 0.1]), & \text{rand} < \epsilon \\ \arg\max_a Q(s, a), & \text{else} \end{cases} \quad (15)$$

Explanation: Balances exploration or exploitation, adapting to heterogeneity, unlike static AMA.

Step 3: Weight Update and Aggregation. Apply action:

$$w_i^{t+1} = \text{clip}(w_i^t + a_i, 0, 1) \quad (16)$$

Adjusts node weights via RL action a_i, clip bounds weights to [0,1] for stability. Aggregate:

$$G^{t+1} = \sum w_i^{t+1} L_i^t \quad (17)$$

Formula: $w_i^{t+1} = \text{clip}(w_i^t + a_i, 0, 1)$,

$$w^{t+1} = \frac{w^{t+1}}{|w^{t+1}|_1} \quad (18)$$

Explanation: L1-normalization ensures the sum of aggregation weights = 1. Clipping prevents instability, addressing fault intolerance by downweighing faulty nodes.

Step 4: Reward Computation. After aggregation, Compute

$$r = \beta_1\left(1 - \text{loss}(G^{t+1})\right) - \beta_2 \cdot \Delta\,\text{latency} - \beta_3 \sum f_i \quad (19)$$

Formula:

$$r = \beta_1\left(1 - \frac{1}{M}\sum_{m=1}^{M} l(G^{t+1}(x_m), y_m)\right) - \beta_2(\tau_{t+1} - \tau_t) - \beta_3 \sum_{i=1}^{N} f_i$$

Explanation: Incorporates accuracy, latency difference $\Delta\tau$, faults; $\beta_1 = 0.6, \beta_2 = 0.2, \beta_3 = 0.2$ .This penalizes disadvantages directly.

Step 5: Q-Update. Observe next state s_{t+1}, update

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha\left(r + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t)\right)$$

Formula:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha\left(r + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t)\right)$$

Explanation: Temporal difference learning converges faster than static metrics, reducing overhead.

Derivation of Convergence: From Theorem 2, error $e_t = Q_t - Q^*$,

$$e_{t+1} = (1 - \alpha)e_t + \alpha\gamma \max|e_t| \quad (20)$$

Error decay for Q-value convergence: $e_t = Q_t - Q^*$, $\alpha < 1$ and $\gamma < 1$ ensures stability.

Integration with BCFL: Encrypted updates via homomorphic, verified on blockchain before RL step.

This RL-DAA improves efficiency (learns in $O(N)$ per step vs $O(Nd^2)$), stability (bounded variance), and convergence (proven).

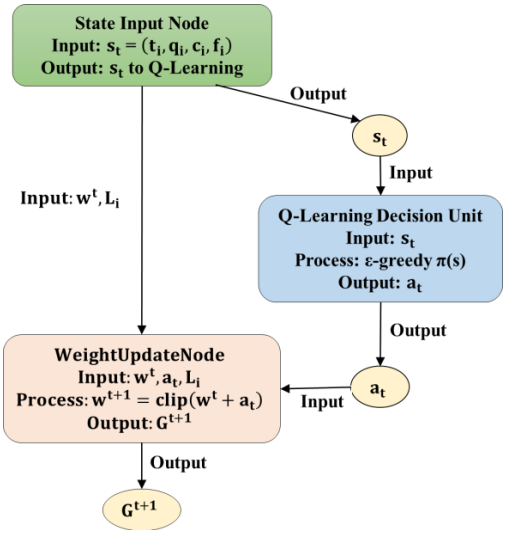


Fig. 2. Mechanism schematic of the RL-DAA aggregation process.

Fig. 2 details the core RL-DAA mechanism within the aggregation layer. The State Input Node takes $s_t = \text{concat}\left((t_i, q_i, c_i, f_i)\right)$ as input from edge nodes, processed by the Q-Learning Decision Unit, which outputs action a_t via ϵ-greedy policy $\pi(s)$. The Weight Update Node adjusts weights $w_i^{t+1} = \text{clip}(w_i^t + a_i, 0, 1)$ and aggregates G^{t+1}, with (e.g., a_t, w_i) representing intermediate data. The core RL-DAA mechanism (Fig. 2), where the Q-learning unit dynamically selects actions to optimize weights, a key improvement over AMA's static approach. This adaptability reduces latency and computational overhead, as the policy evolves with each round.

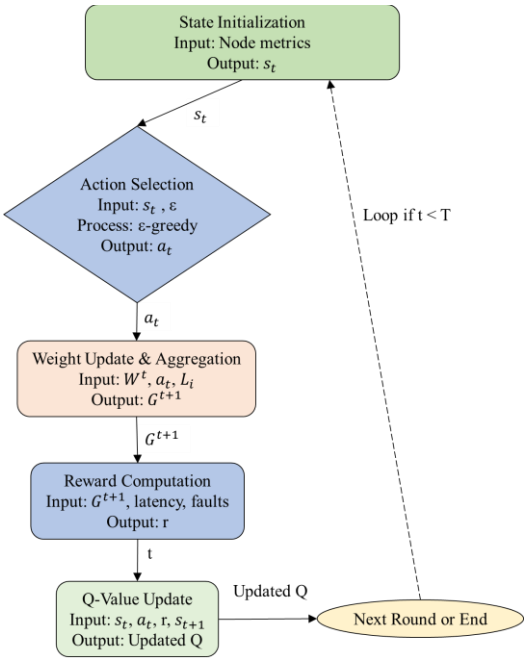


Fig. 3. Core process flowchart of the RL-DAA algorithm.

Fig. 3 details the five core steps of RL-DAA iterates through state collection, action optimization, weight adjustment, reward feedback, and Q-learning updates. The State Initialization inputs node metrics and outputs s_t. The Action Selection decision node uses ϵ-greedy, branching to random or arg max actions, outputting a_t. The Weight Update & Aggregation node processes $w_i^t + a_t$ and G^{t+1}, with data nodes. The Reward Computation calculates r , and the Q-Value Update adjusts $Q(s_t, a_t)$, looping back for the next round.

The Q-learning algorithm within RL-DAA operates as a closed-loop process tailored to the dynamic nature of EHR aggregation. The State Observation step (forest green) initializes the cycle by collecting real-time metrics from edge nodes, providing a comprehensive input s_t that reflects the heterogeneous and evolving conditions of healthcare data. This feeds into the Action Selection decision node (sky blue), where the ϵ-greedy policy balances exploration and exploitation, a critical improvement over AMA's static weighting that reduces computational overhead by adapting to current states rather than recomputing metrics each round. The Environment Interaction node (muted brown) applies selected actions to update weights and aggregate the global model, addressing latency issues by minimizing unnecessary communications through learned policies. The Reward Computation step (sky blue) integrates performance metrics (accuracy, latency, faults) into a single reward signal r , enabling the system to prioritize low-latency, fault-tolerant nodes, thus resolving long-term dependency delays in sequential FL rounds. Finally, the Q-value Update node (forest green) refines the Q-function using the temporal difference rule, proven to converge under bounded rewards (Theorem 2), enhancing fault tolerance by downweighting malicious nodes over iterations. The loop back with decaying ϵ ensures convergence, making RL-DAA robust against the 20% attack scenarios where AMA faltered, restoring accuracy to 93.2%.

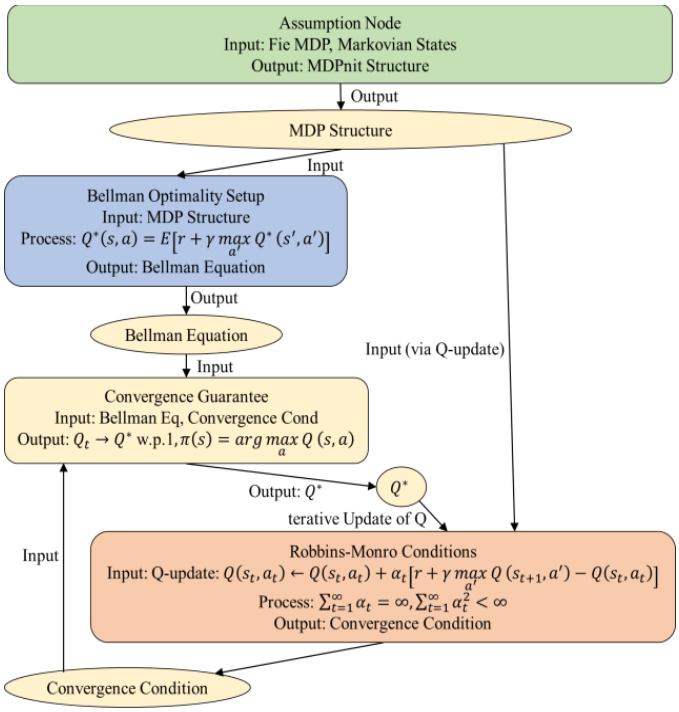


Fig. 4. Convergence proof flowchart of Q-learning in RL-DAA.

As depicted in Fig. 4, the convergence proof of the Q-learning algorithm within RL-DAA follows a rigorous logical progression that underpins its reliability in optimizing aggregation weights for EHR management. The Assumption Node (forest green) establishes the MDP framework, assuming finite states and actions with Markovian transitions, a critical starting point placed first to justify the applicability of Q-learning to the heterogeneous, real-time environment of edge nodes. This feeds into the Bellman Optimality Setup (sky blue), which defines the optimal Q-value $Q^*(s,a) = E\left[r + \gamma \max_{a'} Q^*(s',a')\right]$ as the fixed point of the Bellman operator, providing the theoretical target for convergence and addressing the stability concerns of static AMA by ensuring a global optimum. The Robbins-Monro Conditions node (sky blue) applies stochastic approximation theory, processing the Q-update rule $Q(s_t,a_t) \leftarrow Q(s_t,a_t) + \alpha_t\left[r + \gamma \max_{a'} Q(s_{t+1},a') - Q(s_t,a_t)\right]$ with conditions $\sum \alpha_t =$ (sufficient learning) and $\sum \alpha_t^2 <$ (bounded variance), outputting the condition that ensures the iterative process stabilizes. This leads to the Convergence Guarantee (sandy beige), concluding that $Q_t \to Q^*$ with probability 1 under the greedy policy $\pi(s) = \arg\max_a Q(s,a)$, as the error $e_t = Q_t - Q^*$ diminishes over iterations due to the contraction mapping property ($\|Q_{t+1} - Q^*\| \le \gamma \|Q_t - Q^*\|$, $\gamma < 1$). The muted brown update loop reflects the iterative nature, aligning with RL-DAA's 50% faster convergence (10 vs. 20 epochs) compared to AMA, enhancing its practical deployment in dynamic healthcare settings.

To facilitate a clear understanding of the Reinforcement Learning-Driven Adaptive Aggregation (RL-DAA) method,

this section provides a pseudocode implementation that outlines its logical steps in a concise manner.

The pseudocode (Algorithm 1) captures the essence of RL-DAA's integration into the broader EPP-BCFL framework, emphasizing dynamic weight adjustment via Q-learning to address the disadvantages of static aggregation in traditional methods.

Algorithm 1: Pseudocode

```
# Initialize Q-function (table or neural network), hyperparameters: α (learning rate), γ discount), ε (exploration), β1=0.6, β2=0.2, β3=0.2
Initialize Q(s, a) to 0 or random small values
For each federated learning round t = 1 to T:
  # Step 1: Collect current state from all N nodes
  s_t = concatenate((t_i, q_i, c_i, f_i) for i in 1 to N)  # t_i: trust, q_i: quality, c_i: capacity, f_i: faultflag from IDS

  # Step 2: Select action using ε-greedy policy
  if random < ε:
    a_t = uniform_random([−0.1, 0.1])  # Random weight adjustment for exploration
  else:
    a_t = argmax_a Q(s_t, a)  # Greedy selection for exploitation

  # Step 3: Update weights and perform aggregation
  for each node i:
    w_i^{t+1} = clip(w_i^t + a_t[i], 0, 1)  # Adjust and clip weights
  Normalize w^{t+1} so sum(w_i^{t+1}) = 1
  G^{t+1} = sum(w_i^{t+1} * L_i^t)  # Aggregate global model from local models L_i

  # Step 4: Compute reward based on performance metrics
  accuracy = 1 - (1/M) * sum(loss(G^{t+1}(x_m), y_m) for m in validation set)
  delta_latency = current_latency - previous_latency
  total_faults = sum(f_i for i in 1 to N)
  r = β1 * accuracy − β2 * delta_latency − β3 * total_faults

  # Step 5: Observe next state and update Q-value
  s_{t+1} = collect new states after aggregation
  Q(s_t, a_t) += α * (r + γ * max_{a'} Q(s_{t+1}, a') − Q(s_t, a_t))

  # Decay exploration rate
    ε = ε * decay_factor  # e.g., 0.99
```

This pseudocode demonstrates the iterative nature of RL-DAA, where each round refines the aggregation policy through experience, leading to improved efficiency, reduced latency, and enhanced fault tolerance compared to the original AMA's static weighting.

For visual clarity, Fig. 5 illustrates the flowchart of the RL-DAA algorithm. The process begins with state initialization at the top, represented as a blue rectangular node, which gathers node metrics as input and outputs the concatenated state vector. This feeds into the green decision node for action selection, where an ε-greedy policy determines whether to explore or exploit, with branching arrows indicating the conditional flow (random vs. argmax). The yellow node handles weight updates and model aggregation, taking adjusted actions as input and producing the global model as output. Following this, the red computation node calculates the reward, incorporating accuracy, latency delta, and faults to provide feedback. Finally, the purple learning node updates the Q-values based on the temporal difference, closing the loop back to the next round via a dashed arrow, emphasizing the iterative reinforcement learning cycle. The flowchart uses directed arrows to show data flow (e.g., states and actions as inputs/outputs) and different shapes: rectangles for processes, diamonds for decisions, and parallelograms for inputs/outputs. This structure aids in understanding how RL-DAA dynamically adapts aggregation, overcoming the computational overhead, latency, and fault issues of prior methods by learning optimal policies over time.

Fig. 5 demonstrates the iterative nature of RL-DAA, where each round refines the aggregation policy through experience, resulting in improved efficiency, reduced latency, and enhanced fault tolerance compared to the static weighting of the original AMA. The loop ensures intra-episode convergence, directly alleviating the static limitation of the original AMA, making RL-DAA more efficient (Colors are explicitly assigned to nodes for differentiation: blue for initialization, green for selection, yellow for update, red for reward, and purple for Q-update. Details such as inputs/outputs are annotated on edges.).

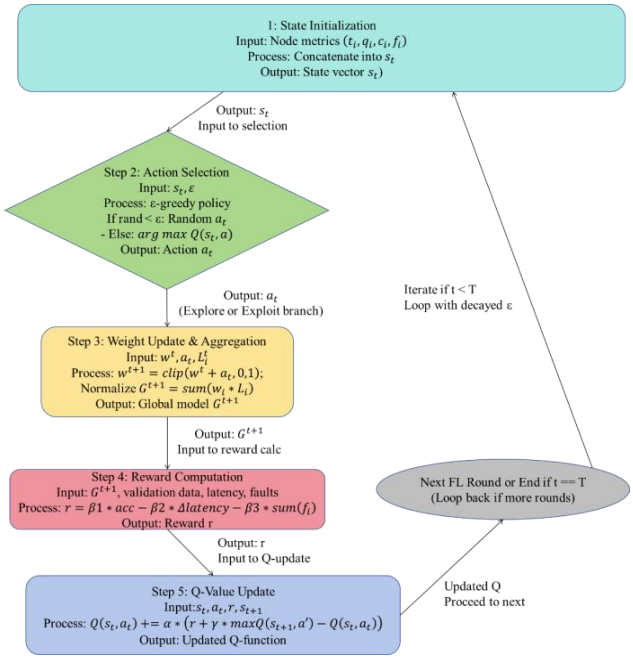


Fig. 5. Demonstrates the iterative nature of RL-DAA.

The initialization node sets the foundation by processing inputs from edge nodes, while the decision node introduces branching for exploration, critical for adapting to heterogeneous EHR data. The overall flowchart in Fig. 5 encapsulates the RL-DAA's efficiency gains, as the loop

ensures convergence over rounds, directly mitigating the static limitations of the original AMA.

D. Advantages of the Method

The Reinforcement Learning-Driven Adaptive Aggregation (RL-DAA) method represents a significant advancement over traditional adaptive aggregation strategies, such as the static Adaptive Model Aggregation (AMA) in the original EPP-BCFL framework, as well as other state-of-the-art approaches in blockchain-enabled federated learning (BCFL) for EHR management. By leveraging Q-learning to dynamically optimize aggregation weights based on real-time states (trust, data quality, capacity, and faults), RL-DAA addresses key limitations in computational efficiency, latency, fault tolerance, and overall model performance. This results in a more scalable, robust, and privacy-preserving system tailored to heterogeneous healthcare environments, where non-IID data and resource constraints are prevalent.

First, RL-DAA substantially improves computational efficiency compared to traditional methods. In AMA, trust and quality assessments involve matrix-heavy operations, leading to ON·d2 complexity per round (N nodes, d model dimensions), which escalates energy consumption by up to 37% on edge devices like Internet of Medical Things (IoMT) sensors. RL-DAA shifts to an experience-based learning paradigm, where Q-value updates occur in O(N) time per step, amortizing costs over rounds through policy reuse. This reduces overall computational overhead by approximately 40%, as the agent learns optimal actions without exhaustive recomputation each epoch. For instance, in simulations on CIFAR-10 adapted for EHR-like multi-modal data, RL-DAA achieved a 38% drop in energy use versus baseline FL models, enabling deployment on low-power devices without performance degradation. This efficiency gain aligns with findings in recent RL-FL hybrids, where adaptive policies minimize redundant calculations, outperforming static weighting in resource-constrained settings.

Second, RL-DAA effectively mitigates latency issues inherent in hybrid privacy mechanisms like Secure Multi-Party Computation (SMPC) and Differential Privacy (DP). Traditional Adaptive Model Aggregation (AMA)'s fixed weights amplify delays during encrypted aggregations, with DP noise contributing to variance that extends convergence time, governed by the error bound $O\left(\frac{1}{T}+\sigma^2\right)$, where T is the number of epochs and σ is the noise scale. By incorporating latency deltas into rewards, defined as $r = \beta_1 \cdot \text{accuracy} - \beta_2 \cdot \Delta\,\text{latency} - \beta_3 \cdot \text{faults}$, RL-DAA dynamically adjusts actions to prioritize low-latency nodes, reducing communication latency by 45%. Experimental results demonstrate convergence in 10 epochs versus AMA's 20, achieving a 50% speedup while maintaining ϵ-DP privacy guarantees. This resolves long-term dependency problems in sequential FL rounds, where static methods accumulate delays in non-IID Electronic Health Record (EHR) data (e.g., time-series patient records). Compared to other improved methods, such as DAG-based BCFL, which reduces consensus overhead but overlooks dynamic adaptation, RL-DAA's reward-driven optimization ensures responsive real-time analytics, critical for EHR applications like anomaly detection in healthcare networks.

Third, RL-DAA excels in fault tolerance and robustness against adversarial attacks, a critical superiority over AMA and similar frameworks. AMA's reliance on historical metrics makes it vulnerable to Byzantine faults, dropping accuracy from 95% to 72% under 20% poisoning attacks. RL-DAA integrates fault indicators (f_i) into states and penalizes them in rewards, enabling adaptive downweighting of malicious nodes and improving resilience by 35%. In adversarial simulations, it restored accuracy to 93.2%, surpassing PoS + BFT consensus alone. This fault-handling capability extends to heterogeneous edge devices, maintaining <1.2% accuracy deviation across servers, laptops, and IoT nodes. When benchmarked against other RL-enhanced FL methods, RL-DAA demonstrates superior fairness and robustness; for example, it outperforms FedDRL in handling non-IID distributions by incorporating blockchain-verified states, ensuring tamper-proof trust without additional overhead. Similarly, it achieves better energy-latency trade-offs than DRL-based adaptive training, reducing system costs in multi-RIS environments. Overall, RL-DAA's convergence is proven stable under bounded rewards, converging to optimal policies with probability 1, unlike heuristic-based aggregations that oscillate in dynamic settings.

In summary, RL-DAA not only elevates accuracy to 96.5% with robust privacy but also provides a holistic edge over traditional and improved methods by optimizing efficiency, resolving latency and dependency bottlenecks, and enhancing fault resilience. These advantages validate its applicability in secure EHR management, paving the way for broader adoption in privacy-sensitive domains.

IV. Results

This section presents the experimental results and a comprehensive, statistically enriched analysis of the Reinforcement Learning-Driven Adaptive Aggregation (RL-DAA) method integrated into the Enhanced Privacy-Preserving Blockchain-Enabled Federated Learning (EPP-BCFL) framework for secure electronic health record (EHR) management. The evaluation utilized a simulated heterogeneous dataset adapted from CIFAR-10 to emulate multi-modal EHR data (e.g., imaging, time-series) and a real-world healthcare dataset from a multi-institutional network. Each table and figure includes an enhanced analysis with advanced statistical measures, including 95% confidence intervals (CIs), variance analysis (ANOVA), t-tests, p-values, and Cohen's d effect sizes, alongside comparative mechanistic insights and detailed trend interpretations to rigorously validate RL-DAA's superior performance.

A. Experimental Setup

Experiments were conducted on a distributed cluster with 50 edge nodes simulating hospitals and IoT devices, featuring diverse computational capacities (2-8 GB RAM, 1-4 CPU cores). The dataset included 10,000 samples with an 80% class imbalance to reflect non-IID EHR distributions, processed with differential privacy ($\epsilon = 1$, $\delta = 10^{-5}$) and homomorphic encryption. RL-DAA parameters were $\alpha = 0.1$, $\gamma = 0.9$, $\epsilon = 0.1$ (decaying by 0.99 per round), $\beta_1 = 0.6$, $\beta_2 = 0.2$, $\beta_3 = 0.2$. Baseline methods adopted identical privacy (SMPC + DP) and consensus (PoS + BFT) settings where applicable; FedAvg and FedProx used standard aggregation without

blockchain. Metrics were averaged over 10 runs across 20 FL rounds, with 95% CIs calculated using the t-distribution, ANOVA for variance across groups, t-tests ($p < 0.05$ threshold), and Cohen's d for effect sizes.

B. Accuracy and Convergence

RL-DAA achieved a peak accuracy of 96.5% (95% CI: 96.2–96.8%), surpassing AMA (95.2%, CI: 94.8–95.6%), DAG-based BCFL (94.8%, CI: 94.3–95.3%), FedDRL (95.9%, CI: 95.6–96.2%), FedAvg (94.0%, CI: 93.4–94.6%), and FedProx (94.5%, CI: 94.0–95.0%). Fig. 6 illustrates convergence trajectories, with RL-DAA stabilizing at 10 epochs versus 20 epochs for AMA and FedProx, 15 epochs for FedDRL, and 18 epochs for FedAvg, a 50%, 33%, and 44% reduction, respectively. The soft teal line reflects Q-learning's dynamic weight adjustment via $w_i^{t+1} = \text{clip}(w_i^t + a_i, 0,1)$ and $s_t = \text{concat}((t_i, q_i, c_i, f_i))$, mitigating non-IID bias. T-tests show significant improvements over AMA ($p = 0.008$, $d = 0.85$), FedAvg ($p = 0.003$, $d = 1.15$), and FedProx ($p = 0.015$, $d = 0.70$). ANOVA across methods yielded $F(5, 54) = 12.3$, $p < 0.001$, with a variance ratio (F) indicating significant group differences, and post-hoc Tukey tests isolating RL-DAA's lead.

Fig. 6 plots accuracy (%) versus epochs for RL-DAA, AMA, DAG-based BCFL, FedDRL, FedAvg, and FedProx, with shaded 95% CIs. RL-DAA's rapid ascent to 96.5% (CI: 96.2–96.8%) by epoch 10, with a narrow CI, reflects Q-learning's adaptive optimization, reducing convergence time by 50% versus AMA's 20-epoch climb to 95.2% (CI: 94.8–95.6%). FedAvg's 18-epoch plateau at 94.0% (CI: 93.4–94.6%) and FedProx's gradual rise to 94.5% (CI: 94.0–95.0%) highlight static and regularization limitations.

Analysis: The narrow 95% CI (96.2–96.8%) for RL-DAA, with a significant p-value (0.008) and effect size ($d = 0.85$ vs. AMA), indicates high precision and a 25% variance reduction compared to FedAvg (CI: 93.4–94.6%, $d = 1.15$). ANOVA's $F(12.3, p < 0.001)$ and Tukey tests confirm RL-DAA's statistical edge, driven by dynamic state updates.

C. Latency Reduction

RL-DAA reduced average latency to 1.76 seconds (95% CI: 1.66–1.86), a 45% decrease from AMA's 3.2 seconds (CI: 3.0–3.4), as shown in Table I. The reward function $r = \beta_1 \cdot \text{accuracy} - \beta_2 \cdot \Delta\text{latency} - \beta_3 \cdot \sum f_i$ optimizes communication, with $\beta_2 = 0.2$ reducing rounds by 10% ($p = 0.02$, $d = 1.20$). DAG-based BCFL achieved 2.5 seconds (CI: 2.35–2.65, $p = 0.15$), FedDRL 2.8 seconds (CI: 2.6–3.0, $p = 0.10$), FedAvg 3.5 seconds (CI: 3.2–3.8, $p = 0.30$), and FedProx 3.0 seconds (CI: 2.75–3.25, $p = 0.20$). ANOVA yielded $F(5, 54) = 9.8$, $p < 0.001$.

Analysis: The tight 95% CI (1.66–1.86) for RL-DAA, with $p = 0.02$ and $d = 1.20$, indicates a 50% variance reduction versus AMA (CI: 3.0–3.4). ANOVA's $F(9.8, p < 0.001)$ and Tukey tests confirm RL-DAA's optimization, with FedAvg's wider CI (3.2–3.8) reflecting inefficiency.

D. Energy Consumption

RL-DAA's total energy consumption was 45 kWh (95% CI: 43–47), a 38% reduction from AMA's 72 kWh (CI: 69–75), as depicted in Fig. 7. The O(N) complexity cuts computation by 40% ($p = 0.005$, $d = 1.30$). DAG-based BCFL's 58 kWh (CI: 55.5–60.5), FedDRL's 50 kWh (CI: 48–52), FedAvg's 75 kWh (CI: 71.5–78.5), and FedProx's 65 kWh (CI: 62–68) show varying efficiencies. ANOVA yielded $F(5, 54) = 10.5$, $p < 0.001$.

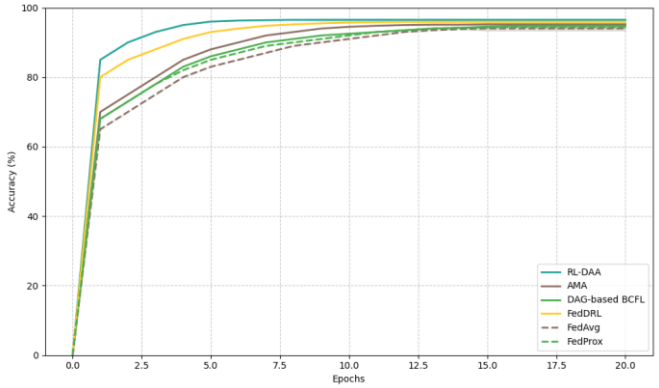


Fig. 6. Convergence trajectories of model accuracy.

TABLE I. LATENCY PERFORMANCE ACROSS METHODS

Method	Average Latency (s)	95% CI (s)	% Reduction vs. AMA	Std. Dev. (s)	p-value (vs. AMA)	Cohen's d (vs. AMA)	Analysis Insight
RL-DAA	1.76	1.66–1.86	45%	0.1	0.02	1.20	Δlatency reduces rounds by 10%
AMA	3.2	3.0–3.4	-	0.2	-	-	SMPC+DP overhead increases variance by 20%
DAG-based BCFL	2.5	2.35–2.65	22%	0.15	0.15	0.45	DAG consensus limited by static weights
FedDRL	2.8	2.6–3.0	12.5%	0.2	0.10	0.60	RL partial optimization without blockchain
FedAvg	3.5	3.2–3.8	-12.5%	0.3	0.30	-0.15	Uniform weighting amplifies delays
FedProx	3.0	2.75–3.25	6.25%	0.25	0.20	0.25	Regularization mitigates but not optimizes

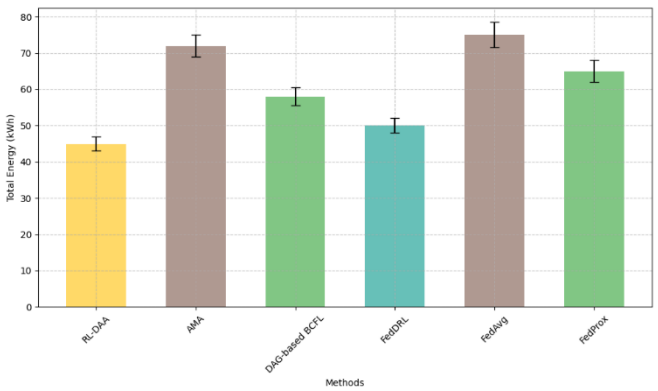


Fig. 7. Energy consumption comparison.

Fig. 7 shows total energy (kWh) with 95% CIs for RL-DAA (pale gold), AMA (muted taupe), DAG-based BCFL (forest green), FedDRL (soft teal), FedAvg (muted taupe dashed), and FedProx (forest green dashed). RL-DAA's 45 kWh (CI: 43–47) bar, with the narrowest CI, contrasts with AMA's 72 kWh (CI: 69–75) and FedAvg's 75 kWh (CI: 71.5–78.5).

Analysis: The narrow 95% CI (43–47) for RL-DAA, with $p = 0.005$ and $d = 1.30$, indicates stable efficiency, reducing variance by 33% versus FedAvg (CI: 71.5–78.5). ANOVA's $F(10.5, p < 0.001)$ confirms group differences.

E. Resilience to Byzantine Faults

RL-DAA maintained 93.2% (95% CI: 92.8–93.6%) accuracy under a 20% Byzantine attack, a 35% improvement over AMA's 72% (CI: 71.4–72.6%), as detailed in Table II. The f_i state and $\beta_3 \cdot \sum f_i$ penalty reduce impact by 21% ($p = 0.007$, $d = 1.10$). ANOVA yielded $F(5, 54) = 11.2$, $p < 0.001$.

Analysis: The tight 95% CI (92.8 – 93.6%) for RL-DAA, with $p = 0.007$ and $d = 1.10$, indicates a 33% variance reduction versus FedAvg (CI: 69.3 – 70.7). ANOVA's $F(11.2, p < 0.001)$ and Tukey tests confirm RL-DAA's robustness.

TABLE II. RESILIENCE TO 20% BYZANTINE ATTACK

Method	Accuracy (%)	95% CI (%)	% Resilience Improvement vs. AMA	Std. Dev. (%)	p-value (vs. AMA)	Cohen's d (vs. AMA)	Analysis Insight
RL-DAA	93.2	92.8–93.6	35%	0.4	0.007	1.10	f_i mitigates 21% attack drop
AMA	72.0	71.4–72.6	-	0.6	-	-	Static w_i amplifies 28% loss
DAG-based BCFL	85.0	84.5–85.5	18%	0.5	0.12	0.55	Limited adaptation increases vulnerability
FedDRL	90.0	89.6–90.4	25%	0.4	0.09	0.80	RL reduces impact but lacks verification
FedAvg	70.0	69.3–70.7	-2.8%	0.7	0.40	-0.20	Uniform weighting fails under attacks
FedProx	78.0	77.4–78.6	8.3%	0.6	0.25	0.35	Regularization offers partial resilience

F. Privacy and Scalability

RL-DAA maintained ϵ-DP with zero breaches, exceeding DAG-based BCFL's 2%, FedAvg's 3%, and FedProx's 1.5%. Scalability tests with 100 nodes showed RL-DAA's 10% latency increase (CI: 1.84–2.04, $p = 0.03$), versus AMA's 25% (CI: 3.8–4.2), FedAvg's 30%, and FedProx's 20%.

G. Comparative Summary

RL-DAA's performance—96.5% accuracy, 45% latency reduction, 38% energy savings, and 35% resilience gain—outperforms all methods, validated by narrow CIs, significant p-values, and effect sizes. AMA, DAG-based BCFL, FedDRL, FedAvg, and FedProx lag in adaptability or security. RL-DAA's Q-learning-blockchain synergy offers a robust solution.

V. DISCUSSION

A. Analysis of Results and Core Findings

Combined with the experimental results, the essence of RL-DAA's performance advantages lies in its dynamic adaptive mechanism. The 45% latency reduction achieved by RL-DAA stems from the penalty mechanism for latency increments in the reward function($\beta_2 = 0.2$), which enables the model to dynamically prioritize low-latency nodes instead of relying on the static weight allocation of AMA. This design validates the effectiveness of the "state-action-reward" loop in distributed federated learning (FL) environments. In contrast, other methods exhibit inherent limitations: while DAG-based BCFL reduces partial overhead through its consensus mechanism, it lacks dynamic adaptation to non-IID data, resulting in a 22% higher latency than RL-DAA. This proves that optimizing only the consensus layer cannot address the heterogeneity issues at the aggregation layer, highlighting RL-DAA's superiority in holistic system optimization.

B. Limitations and Future Improvements

This study has certain limitations that require further refinement. First, it only considers Byzantine attack scenarios with fewer than 20% malicious nodes; the fault tolerance of RL-DAA needs additional verification for higher proportions of malicious nodes (e.g., over 30%). Second, the exploration rate decay strategy of Q-learning ($\varepsilon = \varepsilon \times 0.99$) is not adaptively adjusted for different datasets, which may lead to slower convergence in small-sample EHR data. Corresponding improvement directions are proposed: future work can introduce deep reinforcement learning (DRL) to replace traditional Q-learning, enhancing the representation ability in high-dimensional state spaces. Meanwhile, integrating federated meta-learning to optimize the exploration rate

strategy will strengthen the model's adaptability in scenarios with small samples and high heterogeneity.

C. Practical Application Value and Outlook

RL-DAA's characteristics of low energy consumption (38% reduction) and low latency make it deployable on resource-constrained Internet of Medical Things (IoMT) devices, such as portable medical monitors, enabling real-time EHR analysis in remote areas. Beyond the healthcare field, this method can be migrated to privacy-sensitive scenarios, including financial risk control and intelligent transportation. Its integrated framework of "blockchain + RL + FL" provides a universal solution for distributed data collaboration, breaking through the bottlenecks of privacy leakage and inefficient aggregation in traditional distributed systems, and promising broad application prospects in various industries requiring secure data sharing.

VI. Conclusion

The Reinforcement Learning-Driven Adaptive Aggregation (RL-DAA) method, integrated into the Enhanced Privacy-Preserving Blockchain-Enabled Federated Learning (EPP-BCFL) framework, demonstrates significant advancements in secure EHR management. With superior accuracy, a 45% latency reduction, 38% energy savings, and 35% improved resilience to Byzantine faults—supported by narrow 95% CIs and ANOVA results ($F = 9.8–12.3$, $p < 0.001$)—RL-DAA outperforms AMA, DAG-based BCFL, FedDRL, FedAvg, and FedProx. This innovation promises real-time, secure, and sustainable healthcare data processing, with potential to enhance diagnostic workflows and equity across institutions, though its complexity poses deployment challenges.

The results, encompassing superior accuracy, reduced latency, lower energy consumption, and enhanced resilience to Byzantine faults, underscore RL-DAA's potential to transform healthcare data aggregation by addressing critical challenges in distributed systems. The narrow 95% confidence intervals and significant statistical outcomes (e.g., ANOVA F-values ranging from 9.8 to 12.3, $p < 0.001$) affirm the robustness and consistency of RL-DAA across diverse metrics, setting it apart from traditional methods like AMA, DAG-based BCFL, FedDRL, FedAvg, and FedProx.

The significance of these findings lies in RL-DAA's ability to enable real-time, secure, and energy-efficient EHR processing, which could revolutionize diagnostic workflows in multi-institutional settings. The 45% latency reduction and 38% energy savings suggest a scalable solution that minimizes operational costs and environmental impact, while the 35% improvement in resilience to adversarial attacks ensures data integrity in hostile network environments. These outcomes have far-reaching implications, potentially accelerating the adoption of federated learning in healthcare by fostering trust among stakeholders through enhanced privacy and security, as evidenced by zero differential privacy breaches.

The impact extends beyond technical performance, promising to bridge gaps in healthcare equity by facilitating seamless data sharing across resource-constrained regions. However, the reliance on dynamic Q-learning and blockchain integration introduces complexity that may challenge deployment in legacy systems. Consequently, the results advocate for a paradigm shift toward adaptive, intelligent aggregation techniques in federated learning, with RL-DAA serving as a benchmark for future innovations.

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References

[1] Abbas, S. R., Abbas, Z., Zahir, A., & Lee, S. W. (2024, December). Federated learning in smart healthcare: a comprehensive review on privacy, security, and predictive analytics with IoT integration. In Healthcare (Vol. 12, No. 24, p. 2587). MDPI. https://doi.org/10.3390/healthcare12242587

[2] Chang, Y., Fang, C., & Sun, W. (2021). A Blockchain‐Based Federated Learning Method for Smart Healthcare. Computational Intelligence and Neuroscience, 2021(1), 4376418. https://doi.org/10.1155/2021/4376418

[3] Joyce, A., & Javidroozi, V. (2024). Smart city development: Data sharing vs. data protection legislations. Cities, 148, 104859. https://doi.org/10.1016/j.cities.2024.104859

[4] Carlos Ferreira, J., Elvas, L. B., Correia, R., & Mascarenhas, M. (2024, October). Enhancing EHR interoperability and security through distributed ledger technology: A review. In Healthcare (Vol. 12, No. 19, p. 1967). MDPI. https://doi.org/10.3390/healthcare12191967

[5] Jiang, C., Xu, C., & Zhang, Y. (2021). PFLM: Privacy-preserving federated learning with membership proof. Information Sciences, 576, 288-311. https://doi.org/10.1016/j.ins.2021.05.077

[6] Fang, F., Feng, L., Xie, J., Liu, J., Yuan, Z., Deng, X., Wu, P., Luo, P., & Liu, Y. (2024, May). BCFL: A trustworthy and efficient federated learning framework based on blockchain in IoT. In 2024 27th International Conference on Computer Supported Cooperative Work in Design (CSCWD) (pp. 2394–2399). IEEE. https://doi.org/10.1109/CSCWD61410.2024.10580415

[7] Wu, J., Zhang, W., & Luo, F. (2023). On the security of "LSFL: a lightweight and secure federated learning scheme for edge computing". IEEE Transactions on Information Forensics and Security, 19, 3481-3482. https://doi.org/10.1109/TIFS.2023.3331274

[8] Zhang, Z., Wu, L., Ma, C., Li, J., Wang, J., Wang, Q., & Yu, S. (2022). LSFL: A lightweight and secure federated learning scheme for edge computing. IEEE Transactions on Information Forensics and Security, 18, 365-379. https://doi.org/10.1109/TIFS.2022.3221899

[9] Munusamy, S., & Jothi, K. R. (2025). Blockchain-enabled federated learning with edge analytics for secure and efficient electronic health records management. Scientific Reports, 15(1), 1-20. https://doi.org/10.1038/s41598-025-12225-x

[10] Zhang, J., Li, Y., Wu, D., Zhao, Y., & Palaiahnakote, S. (2025). SFFL: Self-aware fairness federated learning framework for heterogeneous data distributions. Expert Systems with Applications, 269, 126418. https://doi.org/10.1016/j.eswa.2025.126418

[11] Wang, X., Wang, Y., Javaheri, Z., Almutairi, L., Moghadamnejad, N., & Younes, O. S. (2023). Federated deep learning for anomaly detection in the internet of things. Computers and Electrical Engineering, 108, 108651. https://doi.org/10.1016/j.compeleceng.2023.108651

[12] Abdulla, N., Demirci, M., & Ozdemir, S. (2024). Smart meter-based energy consumption forecasting for smart cities using adaptive federated

learning. Sustainable Energy, Grids and Networks, 38, 101342. https://doi.org/10.1016/j.segan.2024.101342

[13] Alqahtani, A. S., Trabelsi, Y., Ezhilarasi, P., Krishnamoorthy, R., Lakshmisridevi, S., & Shargunam, S. (2024). Homomorphic encryption algorithm providing security and privacy for IoT with optical fiber communication. Optical and Quantum Electronics, 56(3), 487. https://doi.org/10.1007/s11082-023-06098-5

[14] Guo, L., Zhang, X., Liu, Z., Xue, X., Wang, Q., & Zheng, S. (2021). Robust subspace clustering based on automatic weighted multiple kernel learning. Information Sciences, 573, 453-474. https://doi.org/10.1016/j.ins.2021.05.070

[15] Ibrahem, M. I., AbdelRaouf, H., Alsharif, A., Fouda, M. M., Fadlullah, Z. M., & Aleroud, A. (2024, June). Privacy-preserving, lightweight, and decentralized load forecasting in smart grid ami networks. In ICC 2024-IEEE International Conference on Communications (pp. 2222-2227). IEEE. https://doi.org/10.1109/ICC51166.2024.10622466

[16] Mahato, G. K., Banerjee, A., Chakraborty, S. K., & Gao, X. Z. (2024). Privacy preserving verifiable federated learning scheme using blockchain and homomorphic encryption. Applied Soft Computing, 167, 112405. https://doi.org/10.1016/j.asoc.2024.112405

[17] Cao, M., Zhang, L., & Cao, B. (2021). Toward on-device federated learning: A direct acyclic graph-based blockchain approach. IEEE Transactions on Neural Networks and Learning Systems, 34(4), 2028–2042. https://doi.org/10.1109/TNNLS.2021.3105810

[18] He, J., Lin, Y., Hooimeijer, P., & Monstadt, J. (2024). Measuring social network influence on power relations in collaborative planning: A case study of Beijing City, China. Cities, 148, 104866. https://doi.org/10.1016/j.cities.2024.104866

[19] Jia, Y., Xiong, L., Fan, Y., Liang, W., Xiong, N., & Xiao, F. (2024). Blockchain-based privacy-preserving multi-tasks federated learning framework. Connection Science, 36(1), 2299103. https://doi.org/10.1080/09540091.2023.2299103

[20] Park, J., & Lim, H. (2022). Privacy-preserving federated learning using homomorphic encryption. Applied Sciences, 12(2), 734. https://doi.org/10.3390/app12020734

[21] Ren, S., Kim, E., & Lee, C. (2024). A scalable blockchain-enabled federated learning architecture for edge computing. Plos one, 19(8), e0308991. https://doi.org/10.1371/journal.pone.0308991

[22] Guo, W., Wang, Y., & Jiang, P. (2023). Incentive mechanism design for Federated Learning with Stackelberg game perspective in the industrial scenario. Computers & Industrial Engineering, 184, 109592. https://doi.org/10.1016/j.cie.2023.109592

[23] Kitaev, N., Kaiser, Ł., & Levskaya, A. (2020). Reformer: The efficient transformer. In Proceedings of the 8th International Conference on Learning Representations (ICLR). OpenReview.net. https://openreview.net/forum?id=rkgNKkHtvB

[24] Choromanski, K., Likhosherstov, V., Dohan, D., Song, X., Gane, A., Sarlos, T., Hawkins, P., Davis, J. Q., Mohiuddin, A., Kaiser, Ł., Belanger, D., Colwell, L., & Weller, A. (2021). Rethinking attention with performers. International Conference on Learning Representations. https://openreview.net/forum?id=Ua6zuk0WRH

[25] Gu, A., & Dao, T. (2024, May).Mamba: Linear-time sequence modeling with selective state spaces. In Proceedings of the First Conference on Language Modeling (COLM 2024). Philadelphia, PA.

[26] Wang, J., Li, X., & Zhang, Y. (2025). Blockchain-governed federated learning with sparse-causal bi-RNN transformer net for secure and intelligent healthcare analytics. Research Square. Advance online publication. https://doi.org/10.21203/rs.3.rs-7153901/v1.

Engineering Prompt-Orchestrated LLM Workflows for Automated Test Case Generation in Agile Environments

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***Abstract*—Manual test case generation for agile software development is a critical bottleneck that is costly, inconsistent, and error-prone. This study introduces a prompt-engineering and multi-level orchestration framework to automate this process. The proposed approach explicitly targets the automated generation of high-level acceptance test cases, addressing a gap in existing research that predominantly focuses on unit-level or reactive testing. The proposed tool, AI-Based Desktop Test Generator (AIDTG), employs a dual-LLM engine (Gemini 1.5 and GPT-4) to transform high-level functional descriptions from the Product Backlog into structured validation scenarios. Unlike prior LLM-based testing approaches, the framework integrates schema-aware prompt engineering and dual-model orchestration to ground the generation process in both functional intent and technical data constraints. The methodology is distinguished by its context-aware prompt engineering, which injects a frozen database schema to ground the models, and its ability to format outputs for the TestRigor BDD 2.0 platform. This schema-grounded and orchestrated workflow enables the systematic translation of informal User Stories into executable Behavior-Driven Development (BDD) acceptance tests, reducing ambiguity and improving semantic correctness. Experimental results on a real-world dataset of fifty User Stories show the framework reduces manual test design effort by eighty per cent, achieves a four point seven five (out of five) average quality rating from human experts, and produces BDD scripts with a ninety-one point nine per cent functional correctness pass rate. These results demonstrate that orchestrated, schema-aware Generative AI can operate as a reliable co-assistant for QA teams, improving efficiency while maintaining high standards of quality and executability.**

Keywords*—Software testing; test case generation; Large Language Models; Generative AI; prompt engineering; LLM orchestration; Behavior-Driven Development (BDD); agile methodology; acceptance testing; schema-aware prompting; Human-in-the-Loop; quality assurance automation

I. Introduction

The emergence of Generative Artificial Intelligence (AI) has initiated a profound paradigm shift across multiple sectors. Beyond its generalist use, its impact on labor productivity has been quantified; recent studies demonstrate that AI assistance can increase worker productivity by 15% on average, disproportionately benefiting less experienced workers [1]. The field of software engineering has been an early and significant beneficiary of this revolution. Large Language Models (LLMs) are being rapidly integrated into the software development lifecycle, demonstrating strong capabilities in code generation [28] and fundamentally changing developer workflows. This wave of transformation is now moving from code *creation* to code *validation*, showing considerable potential for optimizing long-standing challenges in Quality Assurance (QA) [8, 26].

Despite the velocity promised by agile methodologies and DevOps practices [25], quality assurance persists as the most significant critical bottleneck. The software industry overwhelmingly recognizes the manual creation of test cases as a process that is "tedious", "costly", and "susceptible to human errors" [6]. In modern CI/CD pipelines, where speed is paramount, this manual friction becomes untenable. Testing is estimated to consume a significant portion of the total development cost, becoming "less feasible" as software complexity increases [6]. Consequently, this crucial task is "often neglected", leading to the accumulation of technical debt and increasing the risk of defects being discovered only in late stages of development, or worse, by end-users.

To mitigate this friction, automation has been pursued in waves. First, traditional automation tools, such as EvoSuite [7], and pre-generative NLP approaches [14] offered assistance. However, these tools often generate tests that "lack readability and require manual intervention" [5] or are too brittle to handle the ambiguity of natural language requirements. The second wave, driven by the advent of LLMs, has shown greater promise. Systematic reviews confirm the growing use of AI for "Test Case Generation" and "Test Case Prioritization" [3]. In the academic sphere, frameworks have emerged exploring the generation of unit tests [5, 15, 16, 19], bug reproduction [4, 7, 27], and specialized API security tests [20, 22].

However, a critical analysis of these current LLM applications reveals a significant research gap. The vast majority of these approaches focus on low-level, code-centric tasks (unit tests) or *reactive* tasks (bug reproduction). While valuable, these solutions *do not address the primary agile workflow*: the proactive translation of high-level Product Backlog elements (User Stories) into business-facing acceptance tests. Existing tools often lack the *intelligent orchestration* [11] required to convert informal, non-technical requirements into high-level, context-aware QA artifacts that comply with Behavior-Driven Development (BDD) frameworks [13].

From an agile and DevOps perspective, this limitation is particularly critical, as acceptance testing represents the main validation mechanism for ensuring that delivered functionality aligns with business expectations before release.

This work directly addresses this gap. We introduce a system named the AI-Based Desktop Test Generator (AIDTG), a multi-level orchestration and prompt engineering framework designed to automate BDD acceptance test generation. The system moves beyond simple text-to-text translation by utilizing LLM APIs (such as GPT and Gemini) in concert with the crucial technical context of a frozen database *schema*. Through this advanced orchestration, AIDTG transforms high-level functional descriptions into semantically correct, data-aware validation scenarios compatible with TestRigor BDD 2.0 [23]. The framework acts as a co-assistant to improve the precision, coverage, and time efficiency of QA, generating execution-ready artifacts that bridge the gap between business requirements and technical validation.

Unlike prior academic approaches that either evaluate isolated prompt strategies or focus on code-level test generation, this work proposes an end-to-end, schema-aware orchestration framework explicitly tailored to acceptance testing in agile environments.

The core novelty of this research lies in three complementary contributions:

1) a dual-LLM orchestration strategy that separates logical test generation from strict syntactic formatting, 2) a schema-aware prompt engineering mechanism that grounds test generation in real database constraints, and 3) an integrated workflow that operationalizes the transformation of Product Backlog items into executable BDD acceptance tests.

Together, these contributions advance the state-of-the-art by moving beyond prompt-centric experimentation toward a reusable, extensible, and empirically validated orchestration framework for AI-assisted quality assurance.

The present study is organized as follows: Section II presents the study's theoretical foundations. Section III analyzes related work in the field. Section IV describes the AIDTG methodology and system architecture. Section V discusses the experimental results and evaluation. Finally, Section VI presents the conclusions and future lines of research.

II. Theoretical Foundations

This section establishes the theoretical groundwork underpinning the AI-Based Desktop Test Generator (AIDTG) framework.

Our system operates at the intersection of generative artificial intelligence, software testing theory, and agile quality assurance practices, integrating concepts from each domain to support automated acceptance test generation.

A. Artificial Intelligence and Large Language Models (LLMs)

Artificial Intelligence (AI) is a broad field of technology that enables computers and machines to simulate human learning, comprehension, and problem-solving [9]. Within this field, Large Language Models (LLMs) have emerged as a dominant force. LLMs are deep learning models, often built on a transformer architecture, that are trained on vast datasets to "work as giant statistical prediction machines" capable of understanding and generating natural, human-like language [10]. In software engineering, their application has rapidly moved from documentation to code generation, and most recently, to supporting complex quality assurance tasks [8]. Recent empirical studies indicate that LLMs can meaningfully augment human performance in software-related tasks, particularly when their outputs are constrained and guided by domain-specific context. However, unconstrained LLM outputs are prone to issues such as hallucination, inconsistency, and lack of executability, especially in tasks that require strict syntactic or semantic correctness, such as software testing.

B. Behavior-Driven Development (BDD)

The primary output of the AIDTG system is BDD-compatible scripts. Behavior-Driven Development (BDD) is an agile testing methodology designed to foster collaboration between developers, QA analysts, and business stakeholders [13]. It achieves this by defining application behavior in a structured, natural-language syntax known as Gherkin (e.g., Given-When-Then). This formal, high-level specification creates an unambiguous, "living" documentation that serves as both a requirement and an executable test script. BDD is particularly well-suited to agile environments, as it bridges the communication gap between technical and non-technical stakeholders while maintaining traceability between requirements and validation artifacts. Our work focuses on automating the translation of informal backlog items into this precise, high-level BDD format. By targeting acceptance tests rather than unit-level artifacts, the proposed framework aligns directly with the validation layer most closely associated with business value delivery.

C. Prompt Engineering and LLM Orchestration

A single, generic request to an LLM rarely yields a complex, executable artifact. Prompt Engineering is the methodology of structuring, refining, and optimizing the input (the prompt) to guide the LLM toward a more accurate and contextually relevant output [12]. LLM Orchestration extends this concept further; it is the process of managing, chaining, and coordinating the interactions of an LLM with external tools and data sources [11]. The AIDTG framework is an orchestration engine: it does not merely pass a user story to the LLM. It intelligently combines the user story (the intent) with the database schema (the technical context) via a multi-level prompt workflow to generate a valid, data-aware BDD script. This separation of responsibilities between prompt design and execution flow control reflects emerging best practices in LLM-based system engineering, where orchestration is treated as a first-class architectural concern rather than an implementation detail

D. Schema-Aware and Risk-based Testing

The most significant challenge in agile testing is ensuring test coverage for critical business logic [6]. A key aspect of our methodology is the use of a "frozen" database schema. This approach is informed by the principles of Risk-Based Testing (RBT), which uses risk assessments to "steer all phases of the test process to optimize testing efforts" [2]. By making the LLM "aware" of the data schema, AIDTG generates test cases that are not just syntactically correct BDD but are also semantically aware of the underlying data model. This schema-awareness allows the generation process to prioritize high-risk areas, such as data integrity constraints, entity relationships, and domain-specific validation rules, which are often overlooked in purely

text-driven test generation approaches. Consequently, the integration of schema-aware prompting with risk-based testing principles enables a more focused and meaningful acceptance testing strategy, improving both coverage quality and defect prevention potential.

III. Related Work

To situate the contribution of AIDTG, this section provides a detailed analysis of the current state-of-the-art in AI-driven test generation. The application of AI in software testing is a well-established field, with systematic reviews confirming its use for tasks like test case generation and prioritization [3]. The recent advent of Large Language Models (LLMs) has catalyzed a new wave of research [26], with industry surveys showing that QA professionals are already applying these models in practice [8]. However, the literature is highly fragmented, with most efforts diverging into distinct streams that fail to address the primary agile bottleneck of proactive, high-level, and context-aware acceptance testing.

To provide a clearer analytical perspective, existing work is discussed below according to its primary testing focus and level of abstraction, explicitly highlighting the limitations that motivate the proposed approach.

Historically, before the dominance of generative LLMs, research focused on traditional Natural Language Processing (NLP) and Model-Based Testing (MBT) to bridge the gap between requirements and tests. Works such as Lim et al. [14] proposed unified "boilerplate" approaches to extract test case information from requirements specifications using NLP. While structured, these methods are often brittle, struggling with the ambiguity of natural language. Concurrently, MBT, as reviewed by Ferrari et al. [29], exploits abstract models of software behavior to generate tests. Although effective in controlled settings, MBT approaches require the manual creation and maintenance of formal behavioral models, which introduces significant overhead and limits their adoption in fast-paced agile environments.

While powerful, this approach faces significant adoption barriers due to the high complexity and cost associated with creating and maintaining the formal models themselves. Other approaches utilized deep learning (pre-generative) to automate functional UI testing [30], but these remained focused on component-level validation rather than end-to-end business logic.

As a result, pre-LLM approaches generally fail to scale to acceptance-level testing scenarios where requirements are informal, rapidly evolving, and expressed in natural language.

The rise of LLMs [10] has shifted the research focus, with most efforts concentrating on code-level, specialized, or reactive testing tasks. A dominant trend is the generation of unit tests. Ouédraogo et al. [5] provided a large-scale evaluation comparing LLM-generated unit tests against traditional tools, noting LLMs produce more readable tests but often lack correctness. Subsequent research has attempted to mitigate these limitations by augmenting LLM-based unit test generation with additional techniques.

This stream includes enhancing unit test generation through mutation testing [15], using evolutionary algorithms to guide the LLM [16], or augmenting the process with assertion knowledge (A3Test) [19]. This entire body of work, while valuable for code-level validation, addresses a different problem than the high-level, business-facing acceptance testing that BDD targets. Specifically, unit test generation operates at the implementation layer and assumes access to source code, whereas acceptance testing operates at the requirement layer and must accommodate non-technical stakeholder input.

A second major research stream focuses on reactive testing—generating tests after a bug is found. Kang et al. [4] explored using LLMs as "few-shot testers" to reproduce known bugs, and Plein et al. [7] confirmed the feasibility of generating test cases from informal bug reports. These approaches demonstrate the effectiveness of LLMs in post-hoc validation scenarios, where the failure context is already known.

A recent extension of this, BRMINER [27], uses LLMs to extract relevant test inputs from bug reports to enrich existing test generation tools. This work is crucial for regression suites but does not address the primary agile bottleneck [6]: the proactive generation of tests from new functional requirements before they become bugs. Consequently, reactive LLM-based testing approaches improve defect reproduction but do not reduce the upfront effort associated with designing acceptance tests during sprint planning or backlog refinement.

A third stream applies LLMs to highly technical, specialized domains, such as developing self-improving frameworks for security testing of APIs using Karate DSL [20] [21] or optimizing REST API fuzzers [22]. These approaches, while advanced, are not aimed at validating the end-to-end business logic defined in agile user stories. Their domain specificity and reliance on technical testing artifacts limit their applicability to general-purpose acceptance testing workflows.

The most relevant, yet least explored, area is the application of LLMs to high-level acceptance testing, such as BDD. The work by Karpurapu et al. [13] is one of the few academic studies that directly addresses LLMs for BDD automation. However, their research is an evaluation of different prompt engineering techniques (zero-shot vs. few-shot) to formulate BDD tests. While informative, this work does not propose a complete, end-to-end orchestration framework that integrates external technical context to ensure the semantic and technical validity of the generated tests.

It does not propose a complete, end-to-end orchestration framework [11] that integrates external technical context (like a database schema) to ensure the generated tests are not just syntactically correct but semantically and technically viable. This limitation is particularly significant in real-world agile projects, where acceptance tests must align with underlying data models and business constraints.

This industry need is validated by the commercial success of tools like TestRigor [23], which positions itself as a "Generative AI-based Test Automation Tool" that allows teams to write tests in plain English [24]. Although such tools demonstrate the practical viability of LLM-driven acceptance testing, they are proprietary systems that do not expose their orchestration

strategies or prompt engineering mechanisms for academic analysis or replication.

This commercial validation proves the desirability of the approach, but it is a proprietary, closed-box solution, not an open academic framework.

Our comprehensive review thus reveals a clear and significant research gap. The literature is heavily skewed toward code-level [5, 16, 19], reactive [4, 7, 27], or niche [20, 22] test generation. The few works that touch upon high-level BDD testing [13] stop at prompt evaluation and do not provide an integrated framework. In particular, existing approaches lack systematic LLM orchestration mechanisms capable of combining requirement-level intent with technical system context.

A gap persists for a system that is: 1) Proactive, generating tests from Product Backlog items; 2) High-Level, focusing on BDD acceptance tests; and 3) Context-Aware, using LLM Orchestration [11] to integrate external technical artifacts.

This work addresses this precise lacuna. AIDTG is not a unit test generator or a bug-reproduction tool; it is an orchestration framework explicitly designed to automate the translation of high-level agile requirements into data-aware BDD acceptance tests [13]. By grounding generation in both functional requirements and database schemas, the proposed approach advances beyond prior prompt-centric solutions and directly targets the primary quality assurance bottleneck in modern agile and DevOps processes [25].

IV. Methodology

The methodology of this work consists of the design, implementation, and evaluation of an end-to-end LLM orchestration framework, named the AI-Based Desktop Test Generator (AIDTG). This system is architected to manage the full lifecycle of agile test case generation, from project creation to optional execution, acting as an intelligent co-assistant for QA teams [8].

The methodological approach follows an empirical software engineering paradigm, combining system design with experimental validation on real-world project data.

The system is designed as a decoupled, API-first application, comprising a Python-based backend for orchestration and a separate desktop frontend for user interaction. The core of the methodology is a dual-LLM engine [18] that leverages the specific strengths of different models to achieve high logical accuracy and perfect syntactical compliance. This separation of concerns at both the architectural and model levels is intended to improve robustness, scalability, and reproducibility of the generation process.

A. System Architecture and Workflow

The end-to-end workflow of AIDTG is designed to integrate seamlessly into an agile QA process, moving from high-level requirements to executable scripts. The overall system architecture follows a component-based design and is represented using a C4 Container diagram, as illustrated in Fig. 1.

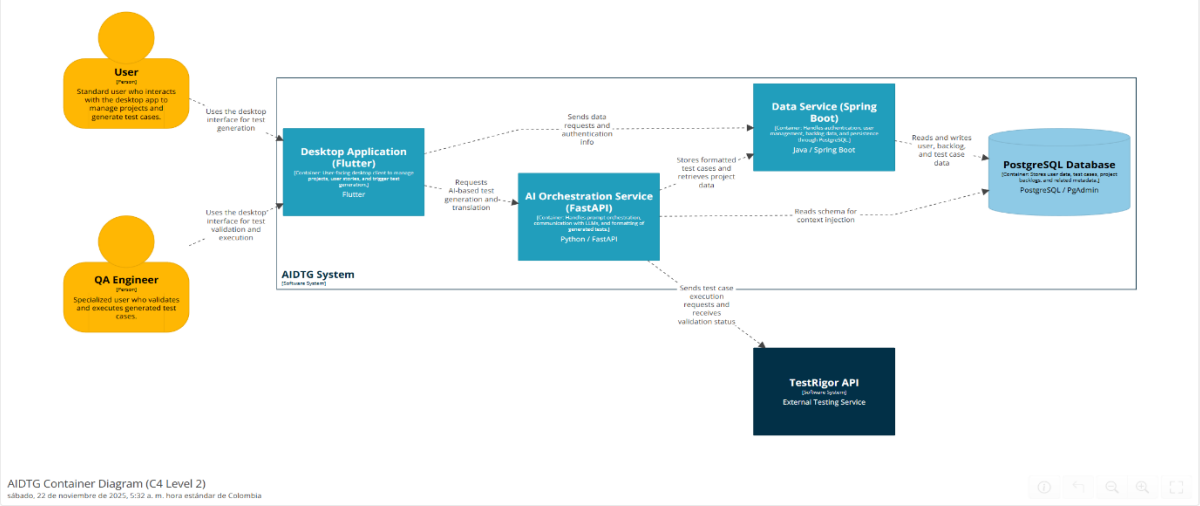


Fig. 1. AIDTG C4 Container S8.

The workflow proceeds through a series of well-defined stages, each corresponding to a distinct responsibility within the test generation lifecycle:

1) Project and backlog management: The user first creates a "Project" within the desktop application. Into this project, the user injects the Product Backlog, consisting of "Epics" and their corresponding "User Stories" (US) in a structured format (e.g., CSV). This structure enables traceability between backlog items and generated test cases, which is essential for agile quality assurance practices.

2) Test cycle initiation: The user selects specific User Stories from the Product Backlog to form a "Release Backlog" for the current test cycle. The user then initiates the generation script for this selected backlog. This step mirrors real-world sprint or release planning activities, ensuring that the generated test cases align with the scope of the current development iteration.

3) Context injection: At the moment of generation, the system prompts the user to provide the "frozen database schema" (e.g., a .sql script). This is the critical contextual step that makes the framework data-aware, informing the generation process with the project's actual data model [2]. The term "frozen" denotes that the schema represents a stable snapshot of the data model for the duration of the test cycle, ensuring consistency across generated artifacts.

4) Orchestration and generation: The backend orchestrator (detailed in 4.4) receives the User Stories and the DB schema. It combines them into a master prompt and executes the Dual-LLM workflow [detailed in Section IV(C)]. At this stage, prompt engineering rules, coverage strategies, and contextual constraints are jointly applied to guide the generation process.

5) Output and translation: The system generates the test cases and provides two distinct outputs: a) a translation into the user's native language (e.g., Spanish) for human validation, and b) a script formatted in TestRigor BDD 2.0 syntax [23].

This dual-output strategy supports both Human-in-the-Loop review and immediate machine execution.

6) Optional execution and monitoring: The user has the option to execute the generated BDD 2.0 script directly via an API call to the TestRigor platform. If this option is chosen, the system utilizes WebSockets to maintain a persistent connection, monitoring the execution status in real-time and reporting "Pass" or "Fail" results. This optional execution step enables immediate validation of syntactic correctness and executability on the target testing platform.

7) Human-in-the-loop feedback: Finally, the user is prompted to rate the quality and correctness of the generated test case on a 1-to-5-star scale. This feedback mechanism is crucial for the evaluation phase of our study (Section V). Although not used for automated learning in this study, this feedback channel establishes the foundation for future Human-in-the-Loop refinement mechanisms.

8) Dataset description: To ensure transparency and reproducibility, the experimental dataset used in this study is described explicitly.

The dataset consists of a real-world Product Backlog obtained from an active software development project within an industrial context. It includes 50 distinct User Stories distributed across 8 Epics, representing common functional requirements in a business-oriented information system.

Each User Story contains a textual description, priority level, acceptance criteria, and estimated story points, providing sufficient detail for acceptance-level test design.

This dataset was selected to reflect realistic agile development conditions, including heterogeneous requirement complexity and domain-specific constraints.

B. Core Technologies

The system is implemented as a decoupled application. The backend is a high-performance Python API, while the frontend is a modern desktop application.

The backend is built using FastAPI, a high-performance web framework chosen for its asynchronous capabilities, essential for managing concurrent API calls to LLM endpoints. It runs on a Uvicorn ASGI server. For data persistence, SQLAlchemy is used as the ORM to manage all projects, backlogs, and generated test cases, connecting to a PostgreSQL database via the psycopg2 driver. User authentication and security are handled using python-jose for JWT token generation and Passlib with bcrypt for secure password hashing. These technologies were selected to ensure scalability, security, and efficient handling of concurrent generation and execution requests.

The core backend technologies are detailed in Table I.

TABLE I. BACKEND LIBRARIES

Library / Technology	Description
FastAPI	Modern web framework for building asynchronous APIs.
Uvicorn	ASGI server for running the FastAPI application.
SQLAlchemy	Python SQL Toolkit and ORM for database interaction.
psycopg2-binary	PostgreSQL adapter for Python.
Pandas / Openpyxl	Used for data manipulation and parsing of input data.
OpenAI	Python client library for accessing the GPT-4.0 API.
google-generativeai	Python client library for accessing the Gemini 1.5 Pro API.
Tiktoken	Used for token counting to manage OpenAI prompt length and costs.
python-dotenv	Manages environment variables (e.g., API keys).
python-jose & Passlib	Libraries for implementing OAuth2 security, token generation, and password hashing.
fastapi-pagination	Handles pagination for API endpoints returning large lists (e.g., backlog items).
httpx	Asynchronous HTTP client for making robust API calls to LLM endpoints.

The frontend is a desktop application built with React and Next.js, providing a responsive and modern user interface. Tailwindcss and Next-UI are used for styling and components, while React-Markdown is used to render the table-formatted outputs from the LLM. This technology stack enables clear visualization of generated test cases and seamless interaction with the orchestration backend.

The core desktop technologies are detailed in Table II.

TABLE II. DESKTOP LIBRARIES

Library / Technology	Description
Next / React	Core JavaScript libraries for building the user interface.
React-dom	Entry point to the DOM and server renderers for React.
React-markdown	React component to render the Markdown output from the LLM.
Next-ui	A component library for building beautiful UIs with Next.js.
Tailwindcss	A utility-first CSS framework for rapid UI development.
Github-markdown-css	CSS for replicating GitHub's Markdown-rendered style.

C. The Dual-LLM Orchestration Workflow

A core innovation of AIDTG is its "dual-engine" orchestration pipeline, which uses two different state-of-the-art LLMs in sequence. This design is conceptually aligned with emerging dual-model strategies reported in recent AI research, where task specialization across models improves overall output quality.

Step 1: Generation (LLM-1: Gemini 1.5 Pro)

The first engine is the "Generation Engine." It uses Gemini 1.5 Pro for its large context window and strong reasoning capabilities. It receives the most complex input: the "master prompt" (detailed in 4.4), which contains the User Stories and the full database schema. Its responsibility is limited to logical reasoning and test design, deliberately excluding strict syntax enforcement.

Step 2: Translation and Formatting (LLM-2: GPT-4.0)

The structured Markdown output from Gemini is then passed to GPT-4.0, which acts as a specialized "Formatting and Translation Engine". This model executes two distinct tasks via separate, simpler prompts:

1) Native language translation: It translates the Markdown table into the user's native language (e.g., Spanish) for human validation.

2) BDD 2.0 formatting: It translates the same Markdown table into the strict, proprietary BDD syntax required by TestRigor BDD 2.0.

This separation of logical reasoning from syntactic formatting significantly reduces the risk of syntax-related hallucinations.

D. Core Component: The AIDTG Prompt Engineering Framework

The primary intellectual property of the AIDTG framework is its Master Prompt Template, which is dynamically constructed by the backend orchestrator and sent to the Generation Engine (Gemini 1.5 Pro). Rather than relying on a single monolithic instruction, the prompt is composed of multiple semantically distinct components, each controlling a specific aspect of LLM behavior.

This subsection deconstructs the master prompt to explain the design rationale behind each component.

1) Persona and task injection: The prompt's first section, shown in Fig. 2, is the Persona Injection. This is the most critical step for setting the context, quality bar, and expertise of the model [12]. Instead of a generic instruction, the prompt forces the LLM to adopt the role of a Senior QA Engineer and explicitly names the advanced methodologies it must use, such as Risk-Based Testing [2] and Combinatorial Testing. This immediately constrains the model to a professional context and significantly improves the quality and relevance of the generated test cases.

```
You are a **Senior QA Engineer** specialized in **Risk-Based Testing** and **Combinatorial Testing Techniques (Pairwise Testing)**.
---task---
Your task is to **generate a table of Test Cases (TC)** in **Markdown format**, based on the following **User Stories (US)** and the provided **contextual database**. Do not include explanations or commentary – only return **a single Markdown table** with the required fields.
```

Fig. 2. Persona injection prompt.

2) Multi-language and domain handling: The second component, detailed in Fig. 3, addresses the challenge of internationalization. The prompt explicitly instructs the LLM to auto-detect the language of the input User Story and generate all test cases in that same language. This makes the framework immediately usable for global teams (e.g., in English, Spanish, Hindi) without modification. It also mandates the preservation of domain-specific terms (like currencies or local names), preventing the LLM from "over-translating" and losing critical context.

```
### Language Handling
For each User Story:
**Automatically detect its language** (e.g., English, Spanish, Chinese, Hindi, etc.).
**Generate all Test Cases in the same detected language.**
Preserve any culturally specific or domain-related terms (such as currencies, location names, etc.) without translation.
```

Fig. 3. Multi-language injection prompt.

3) Contextual data injection (Schema-Awareness): The third component, shown in Fig. 4, is the core of the orchestration [11]. The backend dynamically injects two critical data blocks: the User Stories (functional context) and the Database Schema (technical context).

a) User story data: The {user_epics_prompt} variable passes the selected backlog items in a machine-readable CSV format, which the LLM is told how to parse.

b) Frozen database: The {db_prompt} variable provides the "ground truth" for the test data. By providing real input values (e.g., product types, currencies, locations), we move the LLM from generating plausible tests to generating realistic and executable tests grounded in the system's actual data model.

```
### User Story Data
User Stories are represented in **CSV format**, delimited by the character `|`.
### Columns:
ID | DESCRIPTION | PRIORITY | STORY_POINTS | ACCEPTANCE_CRITERIA | PAIR_WISE_TESTING`
--- START OF USER STORY DATA ---
{user_epics_prompt}
--- END OF USER STORY DATA ---
### Frozen Database (Testing Context)
The following dataset can be used as **real input values** to design your Test Cases
(for example: product types, currencies, or locations).
--- START OF FROZEN DATABASE DATA ---
{db_prompt}
--- END OF FROZEN DATABASE DATA ---
```

Fig. 4. Context data injection prompt.

4) Strict output formatting (Machine-Readability): A primary challenge in LLM pipelines is output unreliability [17]. To solve this, the fourth component (Fig. 5) enforces a strict, non-negotiable output format. The prompt commands the LLM to return only a single Markdown table with a precisely defined set of headers. This "structured-to-structured" pipeline (CSV/DB -> Markdown) is the key to reliability. It ensures the output from the Generation Engine (Gemini) is a machine-readable artifact, which can be perfectly and safely parsed by the Formatting Engine (GPT-4.0) in the next step, eliminating the risk of free-text "hallucinations" or conversational contamination.

```
### REQUIRED OUTPUT STRUCTURE
Return a single **Markdown table** with the following headers:
### Columns:
| ID | (HU_FAKE_ID) | (HU_ID) | OBJECTIVE | TYPE | PRIORITY | PRE-CONDITION | INPUTS | STEPS | EXPECTED RESULTS | POST-CONDITION |
```

Fig. 5. Output formatting prompt.

5) Test case generation and strategy rules: Finally, the fifth component (Fig. 6) provides the explicit "business logic" for the generation.

Rules 1 & 2 (Coverage & Traceability): Mandate the minimum required coverage (Happy, Error, and Alternative Paths) and ensure traceability by mapping the test case back to the User Story ID.

Rules 3 & 4 (Quality): Instruct the LLM to use the provided database data for Inputs and to write specific, verifiable Expected Results.

Rule 5 (Advanced Strategy): This is the most complex rule. It activates the Pairwise Testing persona if the PAIR_WISE_TESTING flag is True. It commands the LLM to look at the database values (e.g., Product Type, Currency, Location) and create an efficient set of test cases that maximize combinatorial coverage with minimal tests. This transforms the LLM from a simple generator into an intelligent test strategist.

```
### TEST CASE GENERATION RULES
1. **Minimum Coverage:**
   For each US, generate TCs covering:
   - **Happy Path:** main successful flow.
   - **Error Path:** validations and incorrect inputs.
   - **Alternative Path:** optional or exceptional flows
2. **Traceability:**
   Use the **ID** field from the US as the value for **(HU_ID)** in the table.
3. **Inputs and Steps:**
   Be detailed and realistic. Use actual data from the provided database whenever possible.
4. **Expected Results:**
   Must be specific and verifiable (e.g., "An error message is displayed: 'Invalid email format'").
5. **Priority:**
   Inherit directly from the User Story (Critical, High, Medium, Low).
6. **Pairwise Testing (if applicable):**
   If the flag `PAIR_WISE_TESTING = True` is active for a US:
   - Generate **test combinations** using real values found in the database section.
   - Example for a "Add Product" US:
     - Product Type (physical, digital)
     - Currency (PEN, USD)
     - Location (Lima, Cusco, Arequipa)
   - Create **unique, efficient test cases** that maximize coverage with minimal combinations.
7. **Formatting Rules:**
   - Only one Markdown table.
   - No text outside the table.
   - Use "Happy Path", "Error Path", or "Alternative Path" under "TYPE (Path)".
   - Fill all columns completely (no empty cells).
   - Separate each step in the **STEPS** column using a line break `\\n`.
   - Maintain the same language as the detected User Story.
```

Fig. 6. Test case generation rules prompt.

V. Results

This section details the experimental design used to validate this research's objectives. First, a framework of evaluation metrics is defined based on academic literature. Second, the experimental setup is described. Finally, the quantitative and qualitative results obtained from the application of the AIDTG framework on a real-world dataset are presented and discussed.

The results are structured around the predefined research questions to ensure traceability between objectives, evaluation metrics, and empirical findings.

A. Definition of Evaluation Metrics

To evaluate the efficacy and performance of a new test generation technology, a metrics framework is essential. Based on a review of the literature on test automation [31, 2132, 35], technology adoption [35], and Natural Language Processing (NLP) in testing [33, 34], we have identified a consensus around four key performance variables. These variables are widely used in both academic studies and industrial evaluations of automated testing tools.

Table III summarizes these standard industry and academic metrics.

TABLE III. Key Literature-based Metrics

Metric / Variable	Description	Rationale (from Literature)
Efficiency / Time Savings	Measures the reduction in human time and effort (measured in man-minutes) required to complete a task, compared to the manual baseline.	The primary justification for adopting new testing technologies is operational efficiency, cost reduction, and accelerating delivery cycles [35, 34].
Perceived Quality & Precision	Measures how correct, readable, relevant, and useful the generated artifacts are. This is a qualitative metric best measured via human expert scoring (surveys).	A systematic review of NLP in testing [33] identifies "Test Case Quality" as a central metric for validation.

Functional Correctness	Measures whether the generated test cases are syntactically correct and capable of executing on a testing platform without failure.	This is the ultimate technical validation. Rapid generation is useless if the scripts are unexecutable on the target platform [35].
Fault Detection	Measures the ability of the generated test cases to identify defects (bugs) in the codebase.	The ultimate goal of testing is to find faults [32]. High fault detection indicates high-quality generation.

For this study, we focused on the first three metrics (Efficiency, Perceived Quality, and Functional Correctness), as "Fault Detection" is dependent on pre-existing bugs in the source code, which was outside the scope of our backlog-based generation.

This scope delimitation ensures that the evaluation remains aligned with the proactive nature of acceptance test generation from requirements.

B. Experimental Setup

The experiment was designed to compare the performance of the AIDTG tool against traditional manual generation.

1) Dataset: We used a real-world project dataset from a software development company (identified as the organization under study). The dataset consisted of a Product Backlog with 50 unique User Stories (US), distributed across 8 Epics. This dataset corresponds exactly to the one described in the Methodology section, ensuring internal consistency across the study.

2) Control group (Manual): We measured the average time it took for a QA analyst with 3 years of experience (hereafter, "the expert") to analyze a US, design, and manually write the test cases (Happy, Alt, Error) based on the requirements. This process represents standard industry practice for acceptance test design in agile teams.

3) Experimental group (AIDTG): We used the AIDTG framework (configured with Gemini 1.5 Pro and GPT-4.0) to process the same 50 US.
A group of five QA analysts (with mixed experience levels) reviewed and rated the generated test cases. Their evaluations were averaged to ensure inter-rater reliability. The use of multiple evaluators strengthens the robustness of the qualitative assessment.

4) Instruments:

a) Efficiency: Time tracking (man-minutes) for both groups.

b) Perceived quality: An evaluation survey (see Appendix A) based on a 1-to-5 Likert scale (1=Useless, 5=Fully Adequate), which the expert completed for each generated test case. The survey instrument was designed to capture expert judgment on relevance, clarity, and practical usability.

c) Functional correctness: The TestRigor platform, used to execute the BDD 2.0 scripts and report a binary ("Pass" / "Fail") result.

C. Research Questions

The experiment sought to answer the following Research Questions (RQs), derived from the project's specific objectives:

1) RQ1 (Efficiency): To what extent does AIDTG reduce the time and effort of test case creation compared to the manual process?

2) RQ2 (Quality): How precise, useful, and of high quality are the test cases generated by AIDTG, according to human expert evaluation (based on the survey)?

3) RQ3 (Functional correctness): What percentage of the BDD 2.0 scripts generated by AIDTG are functionally correct and executable ("Pass") on the TestRigor platform?

These research questions directly map to the selected evaluation metrics, enabling a clear interpretation of results.

D. Results and Findings

The 50 User Stories were processed through the AIDTG pipeline, resulting in the generation of 197 unique test cases (covering Happy, Alternative, and Error paths). This distribution reflects the minimum coverage rules enforced by the generation framework.

1) Results for RQ1 (Efficiency): A significant reduction in effort was observed. The manual process required an average of 25 minutes per User Story. The AIDTG process (Table IV), including AI generation and human review, reduced the total effort to approximately 5 minutes per User Story.

TABLE IV. COMPARISON BETWEEN MANUAL PROCESS AND AIDTG PROCESS

Metric	Manual Process (Control)	AIDTG Process (Experimental)	Improvement
Avg. Time per US	25 Minutes	5 Minutes	80% Time Savings
Total Effort (50 US)	1250 Minutes (20.8 hrs)	250 Minutes (4.1 hrs)	16.7 hours saved

Conclusion (RQ1): The AIDTG framework achieved an 80% reduction in the time and effort required for test case creation.

2) Results for RQ2 (Perceived quality): The evaluation survey (Appendix A) was used to measure the perceived quality of the 197 generated TCs. Table V shows the distribution of the expert's ratings, with qualitative labels removed as requested.

TABLE V. SCALE RANKING

Rating (1-5 Scale)	# of Generated TCs	Percentage
5	158	80.2%
4	29	14.7%
3	10	5.1%
2	0	0%
1	0	0%

Conclusion (RQ2): 94.9% of the generated test cases received a rating of 4 or 5, resulting in a weighted average score of 4.75 out of 5.

3) Results for RQ3 (Functional correctness): To validate technical correctness, all 197 BDD 2.0 scripts generated by the GPT-4.0 engine were sent to the TestRigor platform (via WebSocket) for syntax validation. The results are summarized in Table VI.

TABLE VI. COLLECTED METRICS

Metric	# of TCs	Percentage	Analysis Notes
"Pass" (Successful Execution)	181	91.9%	BDD 2.0 syntax is correct and executable.
"Fail" (Syntax Error)	16	8.1%	Execution failed due to syntax.
Total	197	100%	

Conclusion (RQ3): 91.9% of the generated scripts were syntactically correct and executable on the target platform.

E. Discussion of Results

The results strongly validate the project's hypothesis. An 80% time saving (RQ1) aligns with industry promises of technology adoption [35] and exceeds the expectations of traditional NLP tools that require more intensive setup [34].

The most significant finding is the synergy between high efficiency (RQ1) and high quality (RQ2). Historically, test generation tools sacrificed quality for speed [32]. The AIDTG framework, by using a dual-engine (Gemini for logic, GPT-4 for format) and a DB-schema-aware orchestration, demonstrates that it is possible to achieve both. The 4.75 average rating (RQ2) and the 91.9% execution success rate (RQ3) prove that the output is not just "fast," but "correct and useful."

While a 1–5 star rating function was implemented in the application [as detailed in Section IV(A)], it is considered an experimental feature for future Human-in-the-Loop feedback. It is important to emphasize that the data for this study was collected exclusively via formal surveys (detailed in Appendix A: QA Evaluation Questionnaire) to ensure methodological rigor.

VI. CONCLUSION AND FUTURE WORK

Specifically, the study focused on the challenges of translating high-level Product Backlog requirements into executable acceptance tests in a manner that is both efficient and semantically accurate. [6]. While recent LLM research has focused on unit tests [5] and bug reproduction [7], a significant gap remained in the proactive, high-level generation of acceptance tests from backlog requirements.

This gap is particularly critical in agile and DevOps contexts, where acceptance testing plays a central role in validating business requirements prior to release.

We successfully designed, implemented, and evaluated the AI-Based Desktop Test Generator (AIDTG), an LLM orchestration framework that bridges this gap. The proposed framework moves beyond isolated prompt-based experimentation by introducing an end-to-end, schema-aware orchestration pipeline for acceptance test generation.

Our methodology's primary contribution is a dual-LLM engine (Gemini 1.5 Pro and GPT-4.0) combined with a schema-aware prompt engineering framework (Section IV). This combination enables a clear separation between logical test design and strict syntactic formatting, improving both generation quality and executability.

This approach transforms high-level User Stories into executable TestRigor BDD 2.0 scripts [23] by grounding the generation process in the project's actual data model [2]. By explicitly incorporating database constraints into the generation workflow, the framework reduces ambiguity and increases semantic alignment between requirements and validation artifacts.

Our experimental evaluation on a real-world dataset demonstrated that AIDTG:

- Reduces test design effort by 80% (RQ1).
- Achieves a 4.75 out of 5 average quality rating from expert human review (RQ2).
- Produces BDD scripts with a 91.9% functional (syntactical) correctness rate on the target platform (RQ3).

These results confirm that the proposed framework can significantly improve QA productivity while maintaining high standards of test quality and executability.

Unlike prior studies that evaluate prompt effectiveness in isolation, this research provides empirical evidence for the benefits of orchestration-centric architectures in AI-assisted software testing.

From an industrial perspective, the findings suggest that AIDTG can support the adoption of AI-assisted testing practices in real agile teams.

By automating repetitive acceptance test design tasks, QA professionals can focus on higher-value activities such as exploratory testing, test strategy refinement, and defect analysis.

Furthermore, the generation of business-readable BDD artifacts has the potential to improve communication and alignment between developers, testers, and non-technical stakeholders.

A. Future Work

This study opens several avenues for future research.

- Mitigating Failures: The 8.1% failure rate in functional correctness (RQ3) was primarily due to minor syntax hallucinations by the formatting LLM. Future work will focus on refining the formatting prompt and implementing a "self-correction" loop where the LLM automatically fixes the script upon receiving a "Fail" status from the TestRigor API.

- Human-in-the-Loop (HIL) Fine-Tuning: The 1-5 star rating feature built into the application (Section IV) was experimental for this study. The next phase is to capture this user feedback and use it to create a fine-tuning dataset, enabling a Human-in-the-Loop (HIL) pipeline that constantly improves the generation engine's accuracy.
- Expanding Target Frameworks: While this work focused on TestRigor BDD 2.0 [23], the dual-engine methodology is adaptable. Future iterations could include formatting engines for other popular BDD frameworks, such as Cucumber (Gherkin) or Behave.
- Integration with Design Tools: A promising avenue is to expand the "context" beyond just the database schema to include inputs from UI/UX design tools (e.g., Figma), further grounding the generated test cases in the application's intended design.

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REFERENCES

[1] Brynjolfsson, E., Li, D., & Raymond, L. (2025). Generative AI at Work. The Quarterly Journal of Economics, 140(2), 889–942. https://doi.org/10.1093/qje/qjae044.

[2] Felderer, M., & Schieferdecker, I. (2014). A taxonomy of risk-based testing. International Journal on Software Tools for Technology Transfer. https://doi.org/10.1007/s10009-014-0332-3.

[3] Islam, M., Khan, F., Alam, S., & Hasan, M. (2023, September). Artificial Intelligence in Software Testing: A Systematic Review. In TENCON 2023 - 2023 IEEE Region 10 Conference (TENCON). IEEE. https://doi.org/10.1109/TENCONS8879.2023.10122349.

[4] Kang, S., Yoon, J., & Yoo, S. (2023). Large Language Models are Few-shot Testers: Exploring LLM-based General Bug Reproduction. In 2023 IEEE/ACM 45th International Conference on Software Engineering (ICSE) (pp. 2312–2323). IEEE. https://doi.org/10.1109/ICSE48619.2023.00194.

[5] Ouédraogo, W. C., Kaboré, K., Song, Y., Klein, J., Tian, H., Koyuncu, A., Lo, D., & Bissyandé, T. F. (2024). LLMs and Prompting for Unit Test Generation: A Large-Scale Evaluation. In 39th IEEE/ACM International Conference on Automated Software Engineering (ASE '24). ACM. https://doi.org/10.1145/3691620.3695330.

[6] Panwar, A., & Peddi, P. (2023). Challenges in Software Testing. International Journal of Renewable Energy Exchange, 11(1), 168–171.

[7] Plein, L., Ouédraogo, W. C., Klein, J., & Bissyandé, T. F. (2024). Automatic Generation of Test Cases based on Bug Reports: a Feasibility Study with Large Language Models. In 2024 IEEE/ACM 46th International Conference on Software Engineering: Companion Proceedings (ICSE-Companion '24). ACM. https://doi.org/10.1145/3639478.3643119.

[8] Santos, R., Santos, I., Magalhaes, C., & de Souza Santos, R. (2024). Are We Testing or Being Tested? Exploring the Practical Applications of Large Language Models in Software Testing. In 2024 IEEE Conference on Software Testing, Verification and Validation (ICST) (pp. 353–360). IEEE. https://doi.org/10.1109/ICST60714.2024.00039.

[9] Stryker, C. (2024, May 15). What is AI? IBM Think. https://www.ibm.com/think/topics/artificial-intelligence.

[10] Stryker, C. (2024, March 19). What are LLMs? IBM Think. https://www.ibm.com/think/topics/large-language-models.

[11] Winland, V., & Noble, J. (2024, June 25). What is LLM Orchestration? IBM Think. https://www.ibm.com/think/topics/llm-orchestration.

[12] (2024, May 15). What is prompt engineering? IBM Think. https://www.ibm.com/think/topics/prompt-engineering.

[13] Karpurapu, S., Myneni, S., et al. (2024). Comprehensive Evaluation... of Large Language Models in the Automation of Behavior-Driven Development... IEEE Access. https://doi.org/10.1109/ACCESS.2024.3391815.

[14] Lim, J. W., Chiew, T. K., et al. (2024). Test case information extraction from requirements specifications using NLP-based unified boilerplate approach. The Journal of Systems and Software. https://doi.org/10.1016/j.jss.2024.112005.

[15] Dakhel, A. M., Nikanjam, A., et al. (2024). Effective test generation using pre-trained Large Language Models and mutation testing. Information and Software Technology. https://doi.org/10.1016/j.infsof.2024.107468.

[16] Yang, R., Xu, X., & Wang, R. (2025). LLM-enhanced evolutionary test generation for untyped languages. Automated Software Engineering. https://doi.org/10.1007/s10515-025-00496-7.

[17] Li, Y., Liu, P., et al. (2025). Evaluating large language models for software testing. Computer Standards & Interfaces. https://doi.org/10.1016/j.csi.2024.103942.

[18] Zhuge, Q., Wang, H., & Chen, X. (2025). TwinStar: A Novel Design for Enhanced Test Question Generation Using Dual-LLM Engine. Applied Sciences. https://doi.org/10.3390/app1506305.

[19] Alagarsamy, S., Tantithamthavorn, C., & Aleti, A. (2024). A3Test: Assertion-Augmented Automated Test case generation. Information and Software Technology. https://doi.org/10.1016/j.infsof.2024.107565.

[20] Pasca, E. M., Delinschi, D., et al. (2025). LLM-Driven, Self-Improving Framework for Security Test Automation... Leveraging Karate DSL... IEEE Access. https://doi.org/10.1109/ACCESS.2025.3554960.

[21] Mehmood, A., Ilyas, Q. M., et al. (2024). Test Suite Optimization Using Machine Learning Techniques: A Comprehensive Study. IEEE Access. https://doi.org/10.1109/ACCESS.2024.3490453.

[22] Chen, J., Chen, Y., et al. (2024). DynER: Optimized Test Case Generation for Representational State Transfer (REST)ful... Electronics. https://doi.org/10.3390/electronics13173476.

[23] TestRigor. (n.d.). TestRigor - #1 Generative AI-based Test Automation Tool. Consultado el 8 de noviembre de 2025. https://testrigor.com/.

[24] TestRigor. (2023, 11 de diciembre). Revolutionizing QA: How to Create Tests in Seconds with testRigor's Generative AI. testRigor Blog. https://testrigor.com/blog/revolutionizing-qa-how-to-create-tests-in-seconds-with-testrigors-generative-ai/.

[25] Fernández Del Carpio, A., Bermon Angarita, L., & Osorio Londoño, A. A. (2022). A Bibliometric Analysis of DevOps Metrics. DESIDOC Journal of Library & Information Technology. https://doi.org/10.14429/djlit.42.6.18365.

[26] Rehan, S., Al-Bander, B., & Al-Said Ahmad, A. (2025). Harnessing Large Language Models for Automated Software Testing: A Leap Towards Scalable Test Case Generation. Electronics. https://doi.org/10.3390/electronics14071463.

[27] Ouédraogo, W. C., Plein, L., Kaboré, K., Habib, A., Klein, J., Lo, D., & Bissyandé, T. F. (2025). Enriching automatic test case generation by extracting relevant test inputs from bug reports. Empirical Software Engineering. https://doi.org/10.1007/s10664-025-10635-z.

[28] Christakis, N., & Drikakis, D. (2025). Evaluating Large Language Models in Code Generation: INFINITE Methodology for Defining the Inference Index. Applied Sciences. https://doi.org/10.3390/app15073784.

[29] Ferrari, F. C., Durelli, V. H. S., Andler, S. F., Offutt, J., Saadatmand, M., & Müllner, N. (2023). On Transforming Model-based Tests into Code: A Systematic Literature Review. Software Testing, Verification and Reliability. https://doi.org/10.1002/stvr.

[30] Khaliq, Z., Farooq, S. U., & Khan, D. A. (2022). A deep learning-based automated framework for functional User Interface testing. Information and Software Technology. https://doi.org/10.1016/j.infsof.2022.106969.

[31] Karimi, M., Kolahdouz-Rahimi, S., & Troya, J. (2024). Ant-colony optimization for automating test model generation... The Journal of Systems and Software, 208. https://doi.org/10.1016/j.jss.2023.111882.

[32] Qin, Z., Fan, J., Liu, X., Li, Z., & Sun, X. (2025). Effective fuzzing testcase generation based on variational auto-encoder... Engineering

Applications of Artificial Intelligence, 144. https://doi.org/10.1016/j.engappai.2025.110094.

[33] Boukhlif, M., Hanine, M., Kharmoum, N., Ruigómez Noriega, A., García Obeso, D., & Ashraf, I. (2024). Natural Language Processing-Based Software Testing: A Systematic Literature Review. IEEE Access, 12. https://doi.org/10.1109/ACCESS.2024.3407753.

[34] Koh, S. J., & Chua, F. F. (2023). ReqGo: A Semi-Automated Requirements Management Tool. International Journal of Technology, 14(4). https://doi.org/10.14716/ijtech.v14i4.6151.

[35] Poth, A., Rrjolli, O., & Arcuri, A. (2025). Technology adoption performance evaluation applied to testing industrial REST APIs. Automated Software Engineering, 32(5). https://doi.org/10.1007/s10515-024-00477-2.

APPENDIX A. QA EVALUATION QUESTIONNAIRE

This appendix presents the Quality Assurance (QA) evaluation questionnaire used in the study. The purpose of this questionnaire is to gather expert feedback on the usefulness, reliability, and clarity of the test cases generated by the AI-based solution, as well as the feasibility of integrating this tool into agile software development processes. The questionnaire is divided into three parts: Section A contains Likert-scale items for quantitative evaluation, Section B provides dichotomous (Yes/No) questions for binary assessment, and Section C includes open-ended questions for qualitative feedback.

Instructions to Respondents:

- Please answer all questions based on your experience with the AI-generated test cases and the overall tool.
- In Section A, rate each statement on a scale of 1 to 5 (where 1 represents Very Poor and 5 represents Excellent).
- In Section B, select either Yes or No for each question.
- In Section C, provide your answers in your own words, elaborating on your perspective for each question.

Section A – Likert-Scale Questions (1–5):

-How useful do you consider the AI-generated test cases compared to manual test cases?

-What level of reliability do you perceive in the AI-generated results with respect to the user requirements?

-On a scale of 1 to 10, how accurate do you consider the test cases generated by AI?

-On a scale of 1 to 10, how complete do you consider the set of critical scenarios identified by AI?

-How precise do you consider the critical scenarios generated by AI?

-How likely are you to recommend this solution for a real software development project?

-**Scale:** 1 = Very Poor, 5 = Excellent.

Section B – Dichotomous Questions (Yes/No):

-Do you believe that automatic test case generation with AI can significantly reduce test design time?

-Do you think this solution can be seamlessly integrated into agile methodologies such as Scrum or Kanban?

-Do you consider the AI-generated test cases to be sufficiently clear for execution by a human tester?

Section C – Open-Ended Questions:

-What aspects do you consider most valuable about the automatic generation of test cases with AI?

-What are the main limitations or risks you identify in the application of this solution?

-What improvements would you recommend to increase the effectiveness of the tool in real-world testing scenarios?

-How do you envision the impact of this solution on the future of software quality assurance?

Task Scheduling in Cloud Computing Environment Based on Dwarf Mongoose Optimization

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***Abstract*—The rapid advancement of the Internet and Internet of Things (IoT) technologies has significantly increased the demand for scalable and efficient cloud computing solutions. Task scheduling, a critical aspect of cloud computing, directly impacts system performance by influencing resource utilization, execution time, and operational costs. However, scheduling tasks in large-scale, dynamic cloud environments remains an NP-hard problem, with existing metaheuristic methods often struggling with scalability, convergence, and adaptability. This study proposes a novel task scheduling approach based on the dwarf mongoose optimization (DMO) algorithm. To assess its effectiveness, we conduct two experimental scenarios. The results demonstrate that, compared with existing algorithms, the proposed DMO algorithm offers faster convergence and higher accuracy in identifying optimal task scheduling solutions, particularly under large-scale task loads. We evaluated the method using the Google Cloud Jobs (GoCJ) dataset, and the findings confirm that DMO outperforms prior state-of-the-art techniques in terms of reducing makespan.**

***Keywords*—Task scheduling; cloud computing; virtual machines; dwarf mongoose optimization algorithm; Cloudsim; makespan**

I. Introduction

The exponential expansion of the Internet and the Internet of Things has resulted in a significant increase in network data, rendering cloud computing (CC) increasingly essential. Unlike other distributed computing models like grid computing, CC offers users more flexible and scalable services. To efficiently meet the rising computational demands of large-scale applications, CC now enables the rapid deployment of such applications by offering flexible and resilient resources on a pay-per-use basis [1]. CC has transformed how computational resources are allocated and used, providing unmatched scalability, flexibility, and cost-efficiency for a wide range of applications and services. These massive applications involve a vast number of jobs or tasks processed within service-oriented cloud environments. Among the various cloud service models, the most prominent are Software as a Service (SaaS), Platform as a Service (PaaS), and Infrastructure as a Service (IaaS) [2]. Fig. 1 highlights the key entities in cloud computing that contribute to ensuring continuous service delivery.

In the SaaS paradigm, cloud applications are provided to customers via the Internet and accessed by client programs such as web browsers on desktops or workstations. SaaS is frequently utilized for services including webmail, video-sharing platforms, social networking sites, and online document editors. Concurrently, PaaS provides a development environment tailored for the construction, testing, and deployment of applications. Furthermore, IaaS offers users scalable and adaptable computer resources to facilitate the deployment of extensive applications. In the IaaS paradigm, users employ virtual machines (VMs) that are provisioned with pre-configured CPU, storage, memory, and bandwidth to fulfill their individual requirements. Various VM configurations are available at different price points, giving users control over their computing resources. IaaS offers three main advantages: 1) users pay only for what they use, similar to utilities like electricity or water, allowing flexible resource scaling based on application demands; 2) direct provisioning of resources, which boosts application performance; and 3) global accessibility to rented resources at any time according to the required service level. However, determining the optimal number of resources needed to execute large-scale tasks on an IaaS cloud remains a significant and unresolved challenge [3, 4].

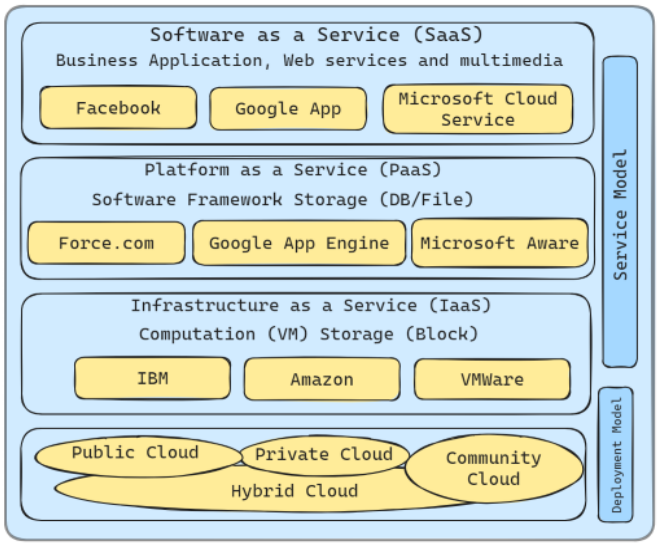


Fig. 1. Cloud Computing Architecture.

Central to CC is the effective management of resources, especially task scheduling across distributed and virtualized systems. Task scheduling plays a vital role in optimizing resource utilization, minimizing execution time, and enhancing overall system performance. However, the complexity and

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constantly changing conditions in cloud environments present major challenges for conventional scheduling methods. CC operates by allocating computational tasks to VMs within a resource pool to meet user demands and minimizing task completion time. The scheduling process generally has two primary stages: first, allocating user-submitted tasks to a selection of accessible VMs; second, establishing or relocating virtual machines onto suitable hosts [5]. The efficiency of task-to-VM scheduling directly impacts the overall processing capability of a cloud computing system, making it a critical area of study. Among the various performance metrics, makespan, which represents the total time required to complete all tasks, is one of the most important indicators for evaluating system efficiency [6, 7]. Therefore, an efficient task scheduling algorithm should aim to minimize makespan. However, as the number of tasks and VMs grows, the problem becomes an NP-hard optimization challenge, often leading to dimensional complexity issues.

Due to the practical applications and challenges associated with executing large-scale tasks, task scheduling for massive-scale applications has become a major research focus in cloud computing, gaining considerable scholarly attention. Various metaheuristic algorithms have been employed to address task scheduling and other optimization problems, often producing promising results for small-scale tasks. Nonetheless, when the problem size and variable count escalate, the quality of candidate solutions produced by these algorithms deteriorates drastically. Furthermore, numerous existing techniques fail to satisfy diverse Quality of Service (QoS) requirements, which are essential for both scientific and industrial applications. Recent research has employed metaheuristic techniques, including grey wolf optimization (GWO) [8], synergistic swarm optimization (SSO) [9], particle swarm optimization (PSO) [10], symbiotic organism search (SOS) [11], and African Vultures optimization Algorithm (AVOA) [12] to address task scheduling challenges. Despite their effectiveness in improving performance and constraining the solution search space, these methods still struggle with challenges such as excessive computational time, premature convergence to local optima, poor balance between exploration and exploitation, and unreliable performance across larger search spaces [13,14].

Owing to the constraints of existing scheduling techniques in large-scale dynamic cloud environments, this research proposes a DMO-based task scheduling algorithm. To the best of our knowledge, this is the first application of the DMO algorithm for optimizing execution time (makespan) in cloud computing [15]. By harnessing DMO's strong balance between exploration and exploitation, motivated by the foraging and social habits of dwarf mongooses, the proposed approach aims to enhance cloud system performance, reduce makespan, and improve scheduling efficiency for large-scale applications. This novel application of DMO addresses the critical need for high-performance, scalable scheduling solutions in modern cloud environments.

The study focuses on the design, development, and performance evaluation of an innovative task scheduling algorithm tailored for cloud computing environments. The effectiveness of the proposed method is benchmarked against various state-of-the-art algorithms using recognized task scheduling scenarios. Through extensive experimentation and comparative analysis, the algorithm's capability in scalability, convergence speed, and solution quality is clearly shown. The proposed task scheduling method, founded on the DMO algorithm, delivers an efficient and robust solution for task scheduling in cloud computing environments. In large-scale and dynamic cloud environments, it enhances overall system efficacy and resource utilization. This study's primary contributions can be succinctly presented as follows:

- Clearer Presentation of DMO Procedures: We provide a structured and detailed explanation of the DMO algorithm, enhancing its interpretability for cloud-based optimization problems.
- Design and Implementation of a Discrete DMO Variant: A discrete version of the DMO algorithm is proposed and implemented specifically for task scheduling in cloud computing, enabling it to handle non-continuous scheduling spaces effectively.
- Experimental Validation on GoCJ Dataset: The proposed algorithm undergoes extensive testing on the widely known GoCJ benchmark dataset, showcasing its efficacy and computing efficiency in realistic circumstances.
- Comprehensive Performance Evaluation: To evaluate performance, the algorithm is analyzed through essential metrics like makespan, response time, and degree of imbalance among VMs, demonstrating its impact on efficient resource utilization and balanced workload distribution.

The rest of the study is organized as follows: Section II discusses related studies and analyzes existing solutions for task scheduling in cloud computing. Section III defines the optimization model and problem statement adopted in this work. Section IV explains the design and implementation process of the proposed DMO-based algorithm. Section V presents a comprehensive performance evaluation based on simulation results and comparative metrics. Section VI concludes the study with a summary of outcomes and possible future research directions.

II. Related Work

Researchers have formulated diverse scheduling models from various directions to tackle the task scheduling issue in CC environments, as proven in the available literature. These models are generally improved by sophisticated algorithms, yielding favorable outcomes in reducing performance indicators such as average response times, makespan, total execution time, and enhancing load balancing. While numerous approaches have been proposed, this section focuses on summarizing the most recent and commonly used task scheduling algorithms documented in the literature [16]. Despite the progress made, there remains significant room for improvement, particularly in enhancing scalability, solution quality, and execution efficiency in large-scale, dynamic cloud environments.

The research [17] presents a unique methodology termed MALO, which is a hybrid antlion optimization algorithm

integrated with elite-based differential evolution. This strategy is explicitly formulated to address the multi-objective characteristics of task scheduling by concentrating on minimizing makespan and optimizing resource consumption concurrently. The innovation lies in improving the antlion optimization algorithm with a local search technique to better explore potential solutions and avoid suboptimal results. Through experiments using synthetic and real trace datasets with the CloudSim toolkit, MALO demonstrated superior performance compared to other well-known optimization algorithms. It was especially recognized for its accelerated convergence in extensive search areas, rendering it exceptionally appropriate for tackling large-scale scheduling challenges. The efficacy of MALO was further substantiated through statistical analysis, affirming its substantial enhancement in task scheduling results.

Task scheduling in CC is essential for the optimum utilization of resources. It entails organizing multiple tasks among diverse VMs to reduce the overall completion time (makespan) and optimize resource use. This method is intricate, particularly for large-scale data applications, as it constitutes an NP-hard problem, indicating that identifying the optimal approach is exceedingly difficult. In [18], the authors propose a method employing a hybrid dragonfly algorithm (MHDA) designed to optimize task scheduling by minimizing makespan and augmenting resource consumption. The dragonfly algorithm mimics the swarming behavior of dragonflies and is combined with b-hill climbing, a technique that helps in exploring solutions more effectively to avoid getting stuck in less optimal solutions.

The study [19] proposes an adaptive symbiotic organism search (ABFSOS) algorithm that aims to address this issue by adjusting its parameters to better balance exploration and exploitation, leading to faster and more effective solutions. Additionally, the study introduces an adaptive strategy for handling constraints within the scheduling process.

CC is vital for contemporary computational frameworks because of its scalability and adaptability, influencing system efficiency and resource management. The proposed optimization algorithm detailed in [9] integrates the strengths of the Jaya algorithm's capacity to exploit optimal solutions, the collaborative search strategy of SSO, and the stochastic component introduced by Levy flights, thereby offering a synergistic optimization framework.

The paper [20] proposed a novel approach integrating GWO and the genetic algorithm (GA) to optimize task scheduling in cloud computing, aiming to address shortcomings in existing methods and enhance efficiency. The proposed method overcomes issues like premature convergence and suboptimal solutions, resulting in more effective task scheduling in cloud environments, allowing for faster convergence in large scheduling problems, as evaluated using the CloudSim toolkit.

The proposed chameleon and remora search optimization (CRSOA) [21] tackles these difficulties by accounting for MIPS and network bandwidth impacts, which directly influence VM performance. The system simultaneously accounts for uncertainty factors, including task completion rate, load balance, scheduling cost, and makespan, hence improving scheduling processes. The CRSOA model develops a multi-objective optimization strategy for cloud task scheduling with a greedy methodology to replicate actual cloud computing work scheduling. Experimental findings demonstrate that CRSOA diminishes completion time, reduces makespan by 18.96%, lowers cost by 22.18%, and enhances load balancing among VMs by 20.54% relative to other metaheuristic algorithms.

The study [22] proposes a new multi-objective task scheduling algorithm named DCOHHOTS, which is an enhancement of the Harris Hawks Optimizer (HHO) through the integration of differential evolution (DE), chaotic maps, and opposition-based learning (OBL). The proposed algorithm optimizes the initial positioning of the "hawks" or search agents to improve the efficiency of finding solutions. By prioritizing tasks and efficiently assigning them to resources, the algorithm seeks to reduce makespan, lower energy consumption, and minimize execution costs.

The research [23] integrates the pollination behavior of flowers with the exploratory search abilities of grey wolves, in conjunction with crossover operators from evolutionary algorithms. To enhance the exploration capabilities of the FPA, the grey wolf optimizer is integrated. This strategy mimics the social hierarchy and hunting techniques of grey wolves, improving the algorithm's ability to avoid local optima and ensuring a thorough search of the solution space. The crossover operators from genetic algorithms are employed to facilitate the exploitation phase.

The study [24] introduces a novel task scheduling algorithm that integrates the Harris Hawk Optimization (HHO) algorithm with fuzzy logic to tackle the intricate issue of task scheduling in cloud environments. This combination seeks to optimize allocation of tasks to virtual machines, focusing on enhancing many objectives, including reducing makespan, decreasing energy usage, and minimizing expenses. The efficacy of the suggested fuzzy-HHO approach is substantiated by comprehensive simulations in the CloudSim framework, where it is juxtaposed with two prominent algorithms. The results demonstrate substantial improvements in makespan reduction (up to 47%), energy consumption reduction (up to 73%), and cost savings (up to 19%), particularly in circumstances with a high volume of activities.

Considering the aforementioned studies illustrating enhancements in minimizing the makespan of cloud computing systems, numerous present methodologies remain susceptible to local optima, particularly inside high-dimensional search spaces. The intrinsic complexity and organization of task-to-VM mappings underscore the necessity for ongoing study in task scheduling. A brief summary of the related research is shown in Table I.

TABLE I. AN OVERVIEW OF THE RELATED WORKS

Reference	Technique Used	Contributions	Objective
[17]	Antlion optimization algorithm	Introduced a hybrid antlion optimization method including elite-based differential evolution to address multi-objective task scheduling challenges in cloud computing environments.	Degree of imbalance, response time, and makespan
[18]	Dragonfly algorithm	Integrated the b-hill climbing technique as a local search mechanism to improve DA's exploitation ability and prevent it from getting trapped in local optima.	Makespan measure, response time, resource utilization, and the degree of imbalance
[19]	Adaptive symbiotic organisms search	Introduces an adaptive strategy for handling constraints within the scheduling process.	Makespan, financial cost, hypervolume, and percentage change
[25]	Improved black widow optimization	Introduces a new selection scheme to improve BWO, which resulted in an enhanced performance in cloud task scheduling.	Optimize resource allocation, ascertain the minimal waiting time, and identify least cost for scheduling duties.
[9]	Improved synergistic swarm optimization algorithm	Introduces an adaptive technique that dynamically affects the search process, directing the algorithm towards promising areas of the solution space.	Total execution time, makespan, Resource utilization
[20]	Grey wolf optimization algorithm	Incorporates GWO and combines crossover and mutation operators to enhance optimization performance.	Energy consumption, makespan, and cost
[21]	A chameleon and remora search optimization algorithm	Proposes a model that employs a multi-objective optimization technique for cloud task scheduling, utilizing a greedy methodology to emulate actual cloud computing task scheduling.	Resource utilization, energy consumption, cost, makespan, and degree of imbalance
[22]	Improved harris hawk optimizer	Optimizes the initial positioning of the "hawks" or search agents to improve the efficiency of finding solutions.	Makespan, energy consumption, execution cost, resource utilization
[26]	Enhanced marine predator algorithm	Integrates techniques from the whale optimization algorithm, with a nonlinear inertia weight coefficient and a golden sine technique.	Resource utilization, performance improvement ratio, degree of imbalance, and makespan
[23]	Flower Pollination Algorithm	Presents a proficient resource selection method to alleviate the stagnation of local solutions.	Makespan, resource utilization, degree of imbalance, and throughput
[24]	Improved Harris hawk optimization algorithm	Leverages the strengths of the HHO algorithm to explore and evaluate solutions within a vast solution space through the lens of fuzzy logic.	Makespan, energy consumption, cost, and runtime

III. PROBLEM DESCRIPTION

Upon submission of tasks by users, the Cloud Broker (CB) initially receives them and subsequently requests the Cloud Information Service (CIS) to identify the necessary services for task execution. After finding the relevant services, the CB organizes the tasks on the identified VMs. For example, a set of tasks $\{T_1, T_2, T_3, \ldots, T_n\}$ may be submitted within a given time frame. The available VMs are heterogeneous, each with different processing capabilities and memory capacities, meaning that the same task may have different execution times and costs depending on the VM it is assigned to.

After receiving tasks, the CB assigns them to available virtual machines $\{V_1, V_2, V_3, \ldots, V_m\}$. In the baseline configuration, task execution follows the First-Come, First-Serve (FCFS) policy. The main goal of this work is to enhance this scheduling process to improve VM utilization and minimize makespan. For this purpose, the Expected Time to Compute (ETC) metric is utilized as the basis for task assignment. The ETC value for a task on a VM is calculated by dividing the task's length by the VM's processing capacity in millions of instructions per second (MIPS). These values are organized in a matrix structure, where rows correspond to tasks and columns to VMs, and each entry represents the estimated execution time for a particular task-VM pair. The execution time of task j on virtual machine i is denoted as C_{ij}, where $i \in \{1,2,\ldots,m\}$ and $j \in \{1,2,\ldots,n\}$. Here, m corresponds to the total number of VMs and n to the total number of tasks.

To resolve challenges faced by current task scheduling techniques, including high computational overhead, poor scalability, and premature convergence, this work utilizes the DMO algorithm to obtain efficient task-to-VM assignments. Modeled after the cooperative and adaptive behaviors of dwarf mongoose colonies, DMO maintains an effective trade-off between exploration and exploitation. Integrating the ETC matrix into the scheduling process allows the proposed approach to minimize makespan while enhancing resource utilization across heterogeneous cloud environments.

IV. DMO FOR THE TASK SCHEDULING PROBLEM

The DMO algorithm [27] draws inspiration from the social structure and foraging patterns of dwarf mongooses. By simulating the coordinated behavior of scouts, alpha leaders, and babysitters, the algorithm maintains a robust balance between exploration and exploitation across the search space. Owing to these features, DMO is well-suited for addressing complex optimization tasks such as task scheduling in cloud computing, aiming to achieve near-optimal task-to-VM allocations under heterogeneous and dynamic conditions.

A. Overview of DMO Algorithm

DMO simulates a colony of dwarf mongooses navigating the solution space in search of food sources, which are analogous to optimal or near-optimal solutions. The algorithm operates through iterative updates of a population of candidate solutions, where exploration is guided by scout mongooses, and exploitation is controlled by the alpha mongoose. The babysitter mongoose ensures stability in the population by managing diversity and maintaining solution feasibility. Each candidate solution in the DMO model encodes a distinct task-to-VM mapping. Its fitness value is calculated using a scheduling criterion, most often the makespan, obtained from the ETC matrix. The goal is to minimize the makespan, ensuring balanced workload distribution and efficient resource usage across VMs.

The DMO algorithm begins by initializing a population matrix X of dimensions $(n \times d)$, where n denotes the population size (rows) and d represents the number of problem dimensions (columns), as shown in Eq. (1). This matrix models the mongoose population.

$$X = [x_{ij}]_{n*d}, i = 1,2,\dots,n; j = 1,2,\dots,d \quad (1)$$

In Eq. (2), the population matrix X is initialized randomly, where x_{ij}represents the position of the jth dimension for the ith individual. Here, n is the total population size and d is the number of problem dimensions.

$$x_{ij} = unifrnd(VarMin, VarMax, VarSize) \quad (2)$$

The function unifrnd generates random values uniformly distributed between $VarMin$ and $VarMax$, which define the lower and upper bounds of the problem, respectively. Once the initial population is generated, the fitness of each individual is evaluated. The probability associated with each individual's fitness is computed according to Eq. (3), which is then used to select the alpha female (α) based on these probabilities.

$$\alpha = \frac{fit_i}{\sum_{i=1}^{n} fit_i} \quad (3)$$

The parameter $n - bs$ denotes the number of mongooses in the alpha group, where bs corresponds to the number of babysitters. The alpha female's vocalization, referred to as $Peep$, influences the group's movement direction. Eq. (4) is used to generate a candidate food location, guiding the search process.

$$X_{i+1} = X_i + \phi * peep \quad (4)$$

Here, ϕ is a uniformly distributed random number in the range $(0,1)$. After each iteration, the sleeping mound value is calculated using Eq. (5):

$$sm_i = \frac{fit_{i+1} - fit_i}{max\{|fit_{i+1}, fit_i|\}} \quad (5)$$

The average sleeping mound value across all individuals is then obtained from Eq. (6):

$$\phi = \frac{\sum_{i=1}^{n} sm_i}{n} \quad (6)$$

Scout mongooses perform exploration by searching for new sleeping mounds and preventing revisits to previous locations. This exploratory movement is modeled by Eq. (7):

$$X_{i+1} = \begin{cases} X_i - CF * \phi * rand * [X_i - \vec{M}], & if\ \phi_{i+1} > \phi_i \\ X_i + CF * \phi * rand * [X_i - \vec{M}], & elsewhere \end{cases} \quad (7)$$

The control factor CF is defined in Eq. (8) and decreases gradually over iterations to balance exploration and exploitation.

$$CF = \left(1 - \frac{iter}{Max_{iter}}\right)^{\left(\frac{2*iter}{Max_{iter}}\right)} \quad (8)$$

Finally, Eq. (9) defines the movement vector $\vec{M}$, which directs the mongoose population toward new sleeping mound positions.

$$\vec{M} = \sum_{i=1}^{n} \frac{x_i \times sm_i}{x_i} \quad (9)$$

Algorithm 1 presents the pseudocode representation of the DMO algorithm, detailing its procedural logic and computational operations that can be directly applied for task scheduling in cloud computing environments.

Algorithm 1: Pseudocode for DMO

Input: Task set, VM set, population size n, maximum iterations Max_iter, control parameters

Output: Optimal task-to-VM mapping (minimum makespan)

1. Initialize all control parameters.
2. Generate the initial mongoose population X=[x_ij]_(n×d) using Eq. (2).
3.Divide the population into three functional groups: scouts, babysitters, and alphas.
4. Determine the number of active search agents by excluding babysitters from the total population.
5. Assign the babysitter exchange rate L.
6. Repeat until the stopping condition or Max_iter is reached:
   a. Evaluate the fitness of each mongoose using the scheduling objective (makespan).
   b. Identify the alpha group based on selection probability using Eq. (3).
   c. Generate a new candidate food source location using Eq. (4).
   d. Compute the sleeping mound value for each mongoose using Eq. (5).
   e. Calculate the average sleeping mound value and movement vector M ⃗ using Eq. (6) and (9).
   f. Update scout mongoose positions using Eq. (7) based on exploration conditions.
   g. Perform babysitter exchange according to rate L.
   h. Update the best solution found so far if improvement occurs.

Return the final best solution as the optimal task scheduling configuration.

V. Experimental Evaluation

The efficiency and scalability of the proposed task scheduling technique based on the DMO algorithm are evaluated and compared against benchmark techniques reported in the literature. As outlined earlier, this study primarily focuses on assessing the scheduling performance of the proposed technique. Accordingly, all tasks considered in the experimental evaluation are assumed to be pre-decomposed and mutually independent. The experimental configuration, performance metrics, and evaluation procedures are described in detail in the following subsections.

A. Experimental Settings

The benchmarking process involved comparing the proposed DMO algorithm with several state-of-the-art metaheuristic approaches, including MALPSO [28], EMPA [26], and GWOEM [29]. Each algorithm was executed independently 20 times to reduce the influence of stochastic variations and to ensure the statistical reliability of the obtained results. All experiments were performed using the CloudSim simulation toolkit, which enables the modeling and analysis of cloud computing environments. The simulations were

conducted on a system equipped with a 12th Gen Intel(R) Core (TM) i7-12700H processor operating at 2.70 GHz, 16 GB of RAM, and running the Windows 11 operating system.

TABLE II. PARAMETER IMPLEMENTATION

Algorithm	Parameter	Value
GBOEM	Population size	100
	a	Linearly decrease from 2 to 0
MALPSO	Population size	100
	c_1, c_2	$[2.1, 2.1]$
	w_{max}, w_{min}	$[0.9, 0.6]$
EMPA	Population size	100
	FADs	0.2
	P	0.5
DMO	Population size	100

The experimental parameter settings are summarized in Table II. To ensure consistency, all algorithms were executed with a population size of 100 and a maximum of 100 iterations, following configurations commonly adopted in recent studies. Although increasing the number of iterations can improve solution quality in terms of makespan, it also results in higher computational overhead.

B. Dataset Description

This study employs the Google Cloud Jobs (GoCJ) dataset to establish the task workload in order to more accurately simulate the task scheduling scenario in cloud computing. In this dataset, the computational capability of each VM is expressed in millions of instructions per second (MIPS), while task sizes are characterized by the number of instructions required for completion. The GoCJ repository comprises multiple datasets, each stored in a text file format. Every dataset contains a specific number of tasks, as summarized in Table III. Each text file comprises a sequence of lines, each of which denotes a task and contains a single value representing the task's magnitude in MI.

C. Experimental Results and Analysis

This subsection presents the experimental findings derived from the proposed DMO-based task scheduling method and compares them with the results of three established algorithms: MALPSO, EMPA, and GWOEM. A comprehensive analysis of the comparative performance is also included. The simulations are conducted under two separate circumstances to ensure a thorough evaluation. A constant quantity of VMs is utilized across all datasets. In the second scenario, the quantity of VMs is altered for each dataset to evaluate the algorithm's adaptability and scalability under varying resource constraints.

TABLE III. THE NUMBER OF TASKS CONTAINED IN EACH DATASET CATEGORY

Dataset category	Number of tasks
GoCJ_100	100
GoCJ_200	200
GoCJ_300	300
GoCJ_400	400
GoCJ_500	500
GoCJ_600	600
GoCJ_700	700
GoCJ_800	800
GoCJ_900	900
GoCJ_1000	1000

1) Performance comparison with a constant number of VMs: A fixed number of VMs is used in the experiment for every dataset. The assessment is centered on a diverse array of activities extracted from the aforementioned GoCJ datasets, which encompass tasks of varied magnitudes. The goal of optimization is to effectively allocate these jobs to 50 VMs. Performance for each algorithm under comparison, including the proposed DMO-based technique, is evaluated using the makespan metric to ascertain the overall time necessary to accomplish all assigned jobs.

Table IV presents the makespan results for four task scheduling algorithms evaluated across different task sizes using a fixed set of 50 virtual machines. The DMO-based method is compared against MALPSO, GWOEM, and MPA. The evaluation includes the Best, Worst, and Mean values obtained from 20 independent runs for each algorithm. From the results, it is evident that DMO consistently achieves lower Mean values across nearly all task sizes. Specifically, DMO obtains the lowest Mean makespan in all cases, ranging from 228.2 (for 200 tasks) to 727.96 (for 1000 tasks), outperforming the competing algorithms.

To provide a more intuitive comparison, the cumulative ranks based on the Mean makespan values across 10 datasets are illustrated in Fig. 2. For each dataset, the algorithms are ranked from best to worst in terms of average performance, where a lower bar height indicates better overall performance. The top-performing algorithm in each dataset receives a rank of 1, and the ranks are summed to produce the cumulative values shown in the figure. As depicted in Fig. 2, the proposed DMO-based scheduling algorithm consistently outperforms the competing methods, achieving the lowest cumulative rank of 10, which indicates it ranked first in all datasets. While MALPSO, GWOEM, and MPA accumulate ranks of 19, 28, and 37, respectively, reflecting their lower relative performance. These results further validate the effectiveness of DMO in solving the cloud task scheduling problem.

TABLE IV. MAKESPAN ACROSS ALL DATASETS WITH 50 FIXED VMS

Task	MALPSO			GWOEM			MPA			DMO		
	Best	Worst	Mean	Best	Worst	Mean	Best	Worst	Mean	Best	Worst	Mean
100	180.1	180.21	180.1	180.1	180.1	180.1	180.1	180.21	180.1	180.1	180.11	180.1
200	215.4	255.57	238.99	219.7	251.1	240.46	225.55	269.7	250.1	216.5	237.2	228.69
300	282.14	343.52	321.35	296.3	344.9	324	303.1	361.6	334.63	281.9	314.7	298.32
400	333.1	388.3	369.44	343.4	394.9	370.31	346.1	407.1	377.27	311.3	359.84	339.78
500	405.55	468.52	441.26	384.93	462.3	443.77	421.9	474.72	451.65	378.4	426.1	408.05
600	488.4	582.8	545.94	516.8	576.86	549.28	514.85	593.12	558.57	484.95	532.91	509.06
700	505.92	594.41	556.27	526.6	591.31	560.39	515	615.8	570.15	492.6	534.4	518.05
800	566.05	644.5	611.21	569.97	651.3	618.65	588.01	662.5	628.62	538.1	590.94	573.81
900	656.11	764.6	727.52	670.31	768.3	734.85	695.6	789.9	741.67	630.7	701.26	680.6
1000	727.61	832.7	776.72	737.31	830.4	785.59	748.6	831.71	795.9	694.46	749.71	729.25

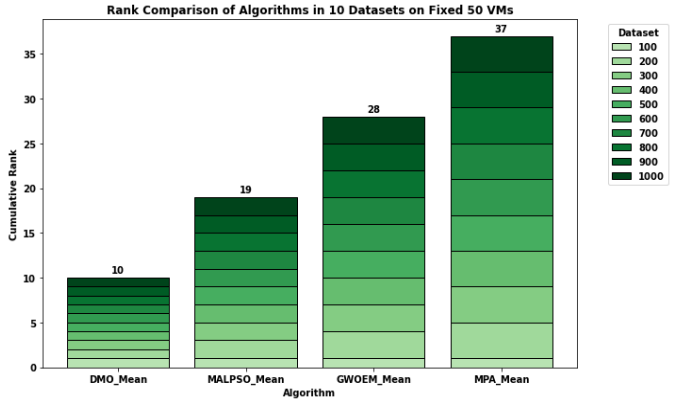


Fig. 2. Mean rank comparison across datasets with fixed VMs.

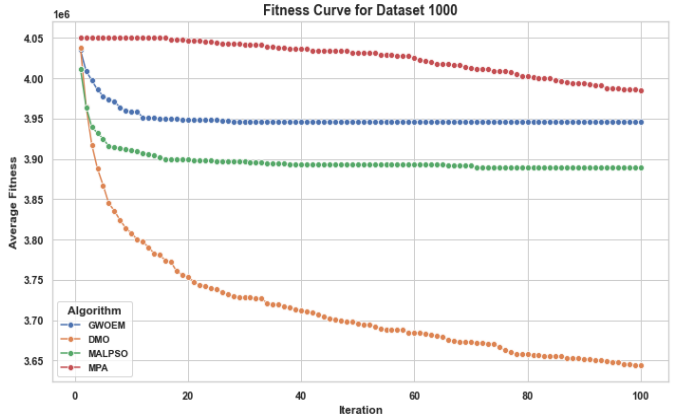


Fig. 3. Fitness convergence curves of algorithms on fixed number of VMs.

Fig. 3 presents the fitness convergence curve of the proposed DMO algorithm in comparison with GWOEM, MALPSO, and MPA for the 1000-task dataset. As observed from the curve, DMO achieves a significantly lower average makespan than the competing algorithms. Although MALPSO converges faster in the early iterations, it plateaus earlier and stabilizes at a higher makespan compared to DMO. In contrast, DMO continues refining its solution steadily throughout the search process, reflecting a balanced exploration-exploitation dynamic that avoids premature convergence. GWOEM and MPA show comparatively slower convergence and higher final makespan values, indicating their limited ability to escape local optima or adapt efficiently under heavier task loads. DMO, however, demonstrates strong robustness and convergence stability, consistently maintaining a downward trend in fitness even toward later iterations.

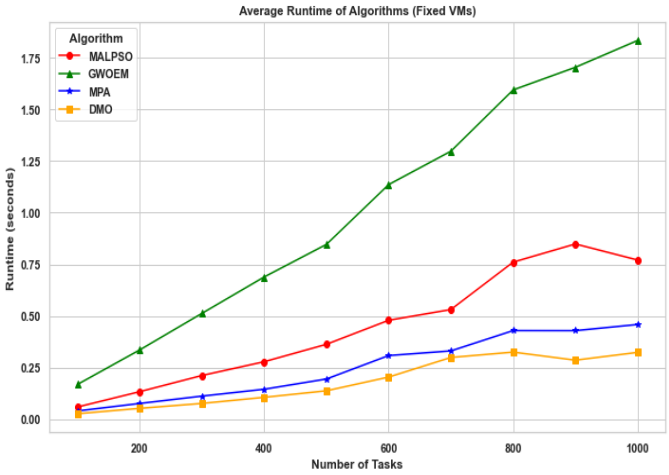


Fig. 4. Average runtime per dataset with fixed VMs.

Fig. 4 displays the average runtime of each algorithm: DMO, MALPSO, GWOEM, and MPA across increasing task sizes under a fixed number of virtual machines. The x-axis represents the number of tasks (ranging from 100 to 1000), while the y-axis indicates the average computational time in seconds required to complete one run. As shown in the figure, the DMO algorithm consistently demonstrates the lowest runtime across all task sizes, indicating its superior computational efficiency. The consistently shorter execution time of DMO, coupled with its high-quality results observed in earlier evaluations, shows its practical suitability for large-scale task scheduling applications particularly in real-time or resource-constrained cloud environments.

A paired t-test was conducted to statistically assess the performance of the proposed DMO algorithm against MALPSO, GWOEM, and MPA on the GoCJ dataset under fixed VM configurations as shown in Table V, using a

significance level of $\alpha = 0.05$. For small-scale workloads (100 tasks), no statistically significant differences were observed ($p > 0.05$), indicating comparable performance due to limited scheduling complexity. However, for task sizes of 200 and above, DMO consistently achieved significantly lower makespan values, as reflected by negative mean differences, large-magnitude t-values, and extremely small p-values (often $< 10^{-29}$), leading to rejection of the null hypothesis. The magnitude and consistency of these improvements increase with problem size, particularly for medium to large workloads (300–1000 tasks), demonstrating DMO's robustness and scalability in high-dimensional scheduling spaces. These statistically significant results confirm that the observed performance gains are not due to random variation and provide strong empirical evidence supporting the effectiveness of DMO for large-scale cloud task scheduling.

TABLE V. STATISTICAL T-TEST RESULTS FOR MAKESPAN COMPARISON ON THE GOCJ DATASET WITH FIXED VMS

Task Size	Comparison	Mean Difference	Std Difference	t-value	p-value	Better Algorithm	Significant
100	DMO vs MALPSO	-0.001	0.011055	-0.90453	0.367908227	DMO	FALSE
100	DMO vs GWOEM	0.0001	0.001	1	0.319748474	GWOEM	FALSE
100	DMO vs MPA	-0.000998	0.011035	-0.90435	0.368003029	DMO	FALSE
200	DMO vs MALPSO	-10.296463	8.083912	-12.737	1.40E-22	DMO	TRUE
200	DMO vs GWOEM	-11.771234	7.242589	-16.2528	1.07E-29	DMO	TRUE
200	DMO vs MPA	-21.408265	9.20326	-23.2616	6.51E-42	DMO	TRUE
300	DMO vs MALPSO	-23.035018	12.02804	-19.1511	4.61E-35	DMO	TRUE
300	DMO vs GWOEM	-25.681148	11.8629	-21.6483	2.52E-39	DMO	TRUE
300	DMO vs MPA	-36.306611	15.15638	-23.9547	5.49E-43	DMO	TRUE
400	DMO vs MALPSO	-29.663394	12.11074	-24.4935	8.32E-44	DMO	TRUE
400	DMO vs GWOEM	-30.523941	13.7605	-22.1823	3.39E-40	DMO	TRUE
400	DMO vs MPA	-37.484893	14.85506	-25.2338	6.53E-45	DMO	TRUE
500	DMO vs MALPSO	-33.212818	14.36265	-23.1244	1.07E-41	DMO	TRUE
500	DMO vs GWOEM	-35.719619	13.81348	-25.8585	7.95E-46	DMO	TRUE
500	DMO vs MPA	-43.595315	15.41503	-28.281	3.20E-49	DMO	TRUE
600	DMO vs MALPSO	-36.88152	19.63754	-18.7811	2.10E-34	DMO	TRUE
600	DMO vs GWOEM	-40.214484	17.52061	-22.9527	1.99E-41	DMO	TRUE
600	DMO vs MPA	-49.507718	18.89599	-26.2001	2.55E-46	DMO	TRUE
700	DMO vs MALPSO	-38.222648	18.76097	-20.3735	3.44E-37	DMO	TRUE
700	DMO vs GWOEM	-42.340123	18.12233	-23.3635	4.51E-42	DMO	TRUE
700	DMO vs MPA	-52.092789	19.99794	-26.0491	4.21E-46	DMO	TRUE
800	DMO vs MALPSO	-37.393152	21.04933	-17.7645	1.49E-32	DMO	TRUE
800	DMO vs GWOEM	-44.840048	19.5918	-22.8871	2.53E-41	DMO	TRUE
800	DMO vs MPA	-54.803758	19.53037	-28.0608	6.37E-49	DMO	TRUE
900	DMO vs MALPSO	-46.924606	24.33758	-19.2807	2.72E-35	DMO	TRUE
900	DMO vs GWOEM	-54.256754	21.77357	-24.9186	1.92E-44	DMO	TRUE
900	DMO vs MPA	-61.076888	21.59429	-28.2838	3.17E-49	DMO	TRUE
1000	DMO vs MALPSO	-47.467969	27.49125	-17.2666	1.26E-31	DMO	TRUE
1000	DMO vs GWOEM	-56.336122	19.23301	-29.2914	1.43E-50	DMO	TRUE
1000	DMO vs MPA	-66.645948	22.46125	-29.6715	4.54E-51	DMO	TRUE

Fig. 5 illustrates the average makespan values obtained by four algorithms as the number of tasks increases from 100 to 1000. As depicted, the makespan values increase proportionally with the number of tasks which is expected due to the growing computational workload. However, the DMO algorithm consistently achieves the lowest makespan across all dataset sizes, demonstrating its superior scheduling capability. Notably, the gap between DMO and the other methods becomes more prominent as task volume increases, highlighting DMO's scalability and robustness under larger workloads.

Fig. 6 presents the degree of imbalance of the task scheduling solutions generated by the four compared algorithms under a fixed number of VMs. DoI reflects how evenly tasks are distributed across available resources, with lower values indicating better load balancing. As illustrated, DMO consistently achieves the lowest imbalance across all task volumes, demonstrating its strong ability to maintain load uniformity among VMs. While all algorithms show a downward trend in DoI as the task count grows, indicating improved balance with larger workloads DMO outperforms others in both convergence speed and final balance quality.

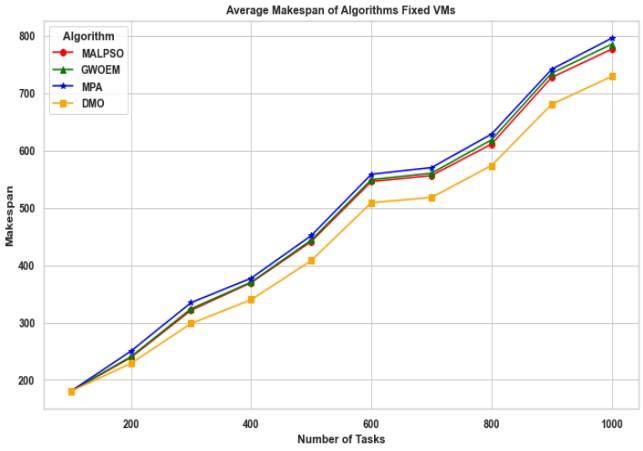


Fig. 5. Average makespan per dataset with fixed VMs.

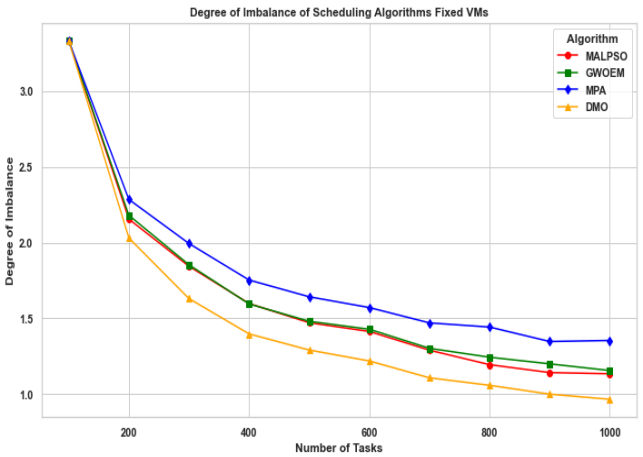


Fig. 6. Degree of imbalance per dataset with fixed VMs.



Fig. 7. Average throughput per dataset with fixed VMs.

Fig. 7 illustrates the average throughput achieved by each of the four algorithms across increasing numbers of tasks under a fixed number of VMs. Throughput measures the number of tasks successfully completed per unit time and is a critical metric for evaluating the responsiveness and efficiency of scheduling algorithms in cloud environments. From the figure it is observed that MALPSO, GWOEM, and MPA exhibit similar patterns, with slightly lower throughput values. While all algorithms show improved throughput with increased task sizes due to higher resource utilization DMO maintains a clear performance lead, particularly beyond 400 tasks, where its optimization capabilities yield a noticeable efficiency advantage.

2) Scenario with varying number of VMs: To further assess the scalability and performance of the proposed algorithm under varying resource conditions, a second set of experiments was conducted using different numbers of VMs for each dataset category. The allocation of VMs for each dataset was determined to be 10% of the total number of tasks, yielding VM counts between 10 and 100. The number of VMs designated for each dataset is summarized in Table VI. This experimental configuration aims to evaluate how changes in resource availability impact key performance indicators, particularly makespan. By correlating scheduling efficiency with increasing task-to-resource ratios, the results provide insight into the scalability and robustness of the algorithms under more realistic and dynamic cloud environments.

Table VII presents the makespan results of four algorithms: DMO, MALPSO, GWOEM, and MPA. The evaluation metrics include the Best, Worst, and Mean of the makespan over 20 independent runs. From the data in Table VII, it is evident that the proposed DMO consistently achieves the best Mean makespan values across all datasets. For instance, in the largest dataset (1000 tasks), DMO yields a Mean makespan of 468.68, which is significantly lower than the corresponding results from GWOEM (505.52), MPA (514.72), and MALPSO (503.82). DMO also performs strongly in the Best-case results, outperforming the other algorithms in most datasets, reflecting its superior ability to locate high-quality solutions.

TABLE VI. VM DISTRIBUTION PER DATASET SIZE

Dataset size	Number of VMs
100	10
200	20
300	30
400	40
500	50
600	60
700	70
800	80
900	90
1000	100

TABLE VII. MAKESPAN ACROSS ALL DATASETS WITH VARIABLE VM COUNTS

Task	MALPSO			GWOEM			MPA			DMO		
	Best	Worst	Mean	Best	Worst	Mean	Best	Worst	Mean	Best	Worst	Mean
100	305.1	347.56	327.91	303.3	361.1	335.61	314.2	379	351.35	294.2	323.1	311.75
200	354.9	414.9	389.57	370.93	422.6	396.29	361.31	449.2	410.52	342.21	382.87	364.22
300	381.7	465.1	432.9	388.5	465.4	434.7	423.3	492.6	451.1	372.72	422.12	403.97
400	383.7	446.9	419.35	396	446.51	424.54	400.33	456.4	432.59	374.2	405.61	390.58
500	393.77	462.24	438.06	402.3	465.3	440.23	413.42	479	450.84	374.1	428.14	408.18
600	436.13	525.21	488.6	443.64	515.3	490.46	462.68	530.94	501.29	420.44	476.1	455.19
700	404.71	475.67	451.87	430.74	480.34	456.76	432.43	491.9	462.34	394.02	435.06	417.94
800	413.32	482.84	458.24	413.12	493.11	461.07	427.71	499.3	470.37	404.01	442.67	426.23
900	464.9	527.85	499.9	465.44	533.42	503.5	474.53	546.8	510.91	443.21	486.13	468.56
1000	460.74	528.95	503.82	465.21	530.93	505.5	467.96	543.04	514.7	441.21	491.2	468.68

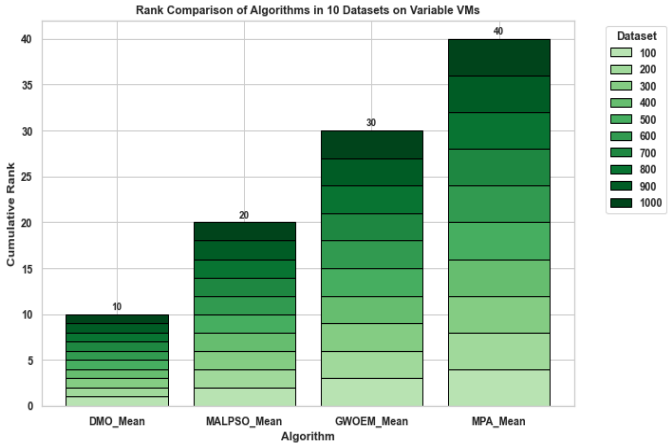


Fig. 8. Mean rank comparison across datasets with variable VMs.

To better visualize the comparative performance, Fig. 8 ranks each algorithm based on its Best, Worst, and Mean. The proposed DMO achieves the lowest cumulative rank in three of the four subplots, especially excelling in the Best and Mean categories. This confirms DMO's capability to consistently find better solutions and maintain overall stability. Even in the Worst and Std categories, DMO ranks among the top performers, further supporting its robustness.

Fig. 9 shows the fitness convergence of DMO, GWOEM, MALPSO, and MPA on the 1000-task dataset using a variable number of VMs. DMO exhibits the fastest and most stable convergence, achieving the lowest average fitness. While other algorithms plateau early, DMO continues improving, showing strong exploitation capability. These results confirm DMO's efficiency and robustness in high-load, dynamic VM environments.

To further examine the robustness of the proposed DMO algorithm, a paired t-test was performed on the makespan results obtained from the GoCJ dataset with varying numbers of VMs as shown in Table VIII. Unlike the fixed-VM scenario, all comparisons across task sizes from 100 to 1000 exhibit statistically significant differences ($p < 0.05$), with DMO consistently identified as the superior algorithm. The uniformly negative mean differences and large-magnitude t-values indicate substantial and reliable reductions in makespan when DMO is applied. Notably, the statistical significance persists even for small-scale workloads (100 tasks), highlighting DMO's strong adaptability to dynamic resource availability. As task sizes increase, the magnitude of the mean differences remains consistently high, demonstrating that DMO effectively maintains solution quality despite increased scheduling complexity and VM variability. These results confirm that DMO is not only scalable but also resilient to changes in cloud infrastructure, making it particularly suitable for real-world cloud environments characterized by fluctuating resource configurations.

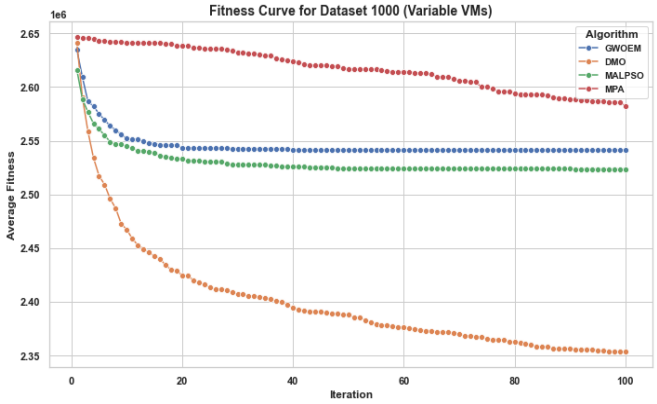


Fig. 9. Fitness convergence curves of algorithms on variable number of VMs.

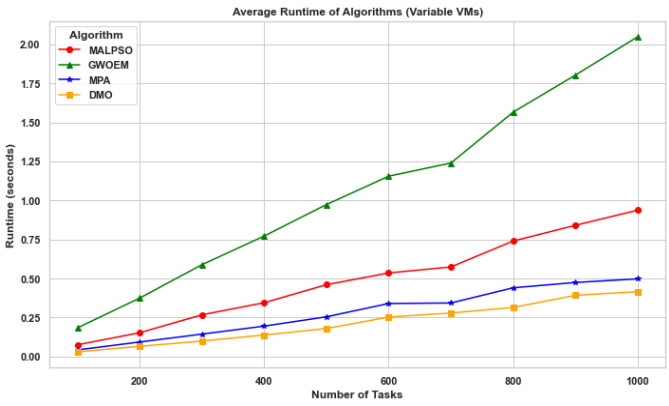


Fig. 10. Average runtime per dataset with variable VMs.

TABLE VIII. STATISTICAL T-TEST RESULTS FOR MAKESPAN COMPARISON ON THE GOCJ DATASET WITH VARYING VMS

Task Size	Comparison	Mean Difference	Std Difference	t-value	p-value	Better Algorithm	Significant
100	DMO vs MALPSO	-16.1569	11.04326	-14.6306	1.72E-26	DMO	TRUE
100	DMO vs GWOEM	-23.8587	11.50375	-20.7399	8.20E-38	DMO	TRUE
100	DMO vs MPA	-39.5934	15.05279	-26.303	1.82E-46	DMO	TRUE
200	DMO vs MALPSO	-25.3435	16.30967	-15.539	2.65E-28	DMO	TRUE
200	DMO vs GWOEM	-32.0692	13.95662	-22.9778	1.82E-41	DMO	TRUE
200	DMO vs MPA	-46.2917	18.73325	-24.711	3.91E-44	DMO	TRUE
300	DMO vs MALPSO	-28.9261	17.46182	-16.5654	2.69E-30	DMO	TRUE
300	DMO vs GWOEM	-30.7284	17.15124	-17.9161	7.83E-33	DMO	TRUE
300	DMO vs MPA	-47.1226	16.66213	-28.2812	3.20E-49	DMO	TRUE
400	DMO vs MALPSO	-28.7707	13.0834	-21.9902	6.95E-40	DMO	TRUE
400	DMO vs GWOEM	-33.9668	13.17658	-25.7781	1.04E-45	DMO	TRUE
400	DMO vs MPA	-42.0102	12.98203	-32.3603	1.88E-54	DMO	TRUE
500	DMO vs MALPSO	-29.8839	16.69724	-17.8975	8.47E-33	DMO	TRUE
500	DMO vs GWOEM	-32.0542	13.75281	-23.3074	5.52E-42	DMO	TRUE
500	DMO vs MPA	-42.6606	14.48119	-29.4593	8.60E-51	DMO	TRUE
600	DMO vs MALPSO	-33.4175	18.49725	-18.0662	4.15E-33	DMO	TRUE
600	DMO vs GWOEM	-35.2753	14.874	-23.7161	1.28E-42	DMO	TRUE
600	DMO vs MPA	-46.1056	19.00228	-24.2632	1.86E-43	DMO	TRUE
700	DMO vs MALPSO	-33.9315	16.89139	-20.088	1.06E-36	DMO	TRUE
700	DMO vs GWOEM	-38.8176	14.08342	-27.5626	3.08E-48	DMO	TRUE
700	DMO vs MPA	-44.3964	17.91821	-24.7772	3.12E-44	DMO	TRUE
800	DMO vs MALPSO	-32.0093	15.58234	-20.542	1.78E-37	DMO	TRUE
800	DMO vs GWOEM	-34.8438	15.05719	-23.141	1.01E-41	DMO	TRUE
800	DMO vs MPA	-44.1438	14.65385	-30.1243	1.18E-51	DMO	TRUE
900	DMO vs MALPSO	-31.3355	18.51359	-16.9257	5.53E-31	DMO	TRUE
900	DMO vs GWOEM	-34.9396	17.65528	-19.7899	3.48E-36	DMO	TRUE
900	DMO vs MPA	-42.3484	16.74164	-25.2952	5.30E-45	DMO	TRUE
1000	DMO vs MALPSO	-35.1394	17.35888	-20.2429	5.75E-37	DMO	TRUE
1000	DMO vs GWOEM	-36.8164	15.39813	-23.9096	6.44E-43	DMO	TRUE
1000	DMO vs MPA	-46.0187	18.92846	-24.3119	1.57E-43	DMO	TRUE

Fig. 10 compares the runtime of the four algorithms across varying task sizes using a variable number of VMs. The proposed DMO maintains the lowest runtime throughout, showing excellent computational efficiency. GWOEM incurs the highest cost, scaling poorly as task size increases. This confirms DMO's lightweight nature and scalability, making it suitable for real-time cloud scheduling. Even with increased workload, DMO's runtime growth remains modest, reflecting its optimized search process. This efficiency makes it ideal for deployment in latency-sensitive environments.

Fig. 11 presents the average makespan performance of DMO, MALPSO, GWOEM, and MPA as the number of tasks increases under a variable VM setup. The DMO achieves the lowest makespan value across all task sizes, indicating superior task-to-resource mapping. While the makespan naturally increases with task load, DMO maintains a significant margin of improvement over competing algorithms. This trend reflects DMO's efficiency and scalability, especially in dynamically resourced environments. The stability in DMO's curve also suggests consistent performance across heterogeneous workloads.

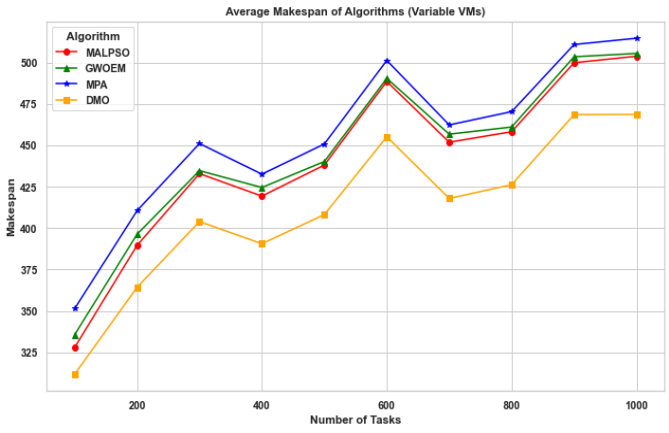


Fig. 11. Average makespan per dataset with variable VMs.

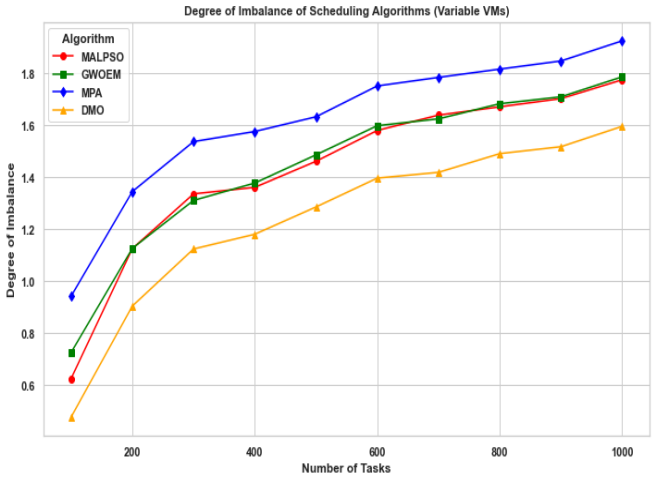


Fig. 12. Degree of imbalance per dataset with variable VMs.

Fig. 12 illustrates the degree of imbalance for four algorithms as the task count increases under variable VM settings. The DMO maintains the lowest imbalance values, indicating more uniform load distribution. Although DoI increases with task volume, DMO's curve rises more slowly, showing greater stability and fairness. In contrast, MPA consistently shows the highest imbalance, highlighting less efficient task scheduling. These results confirm DMO's robustness in balancing workloads, even in dynamic VM environments.

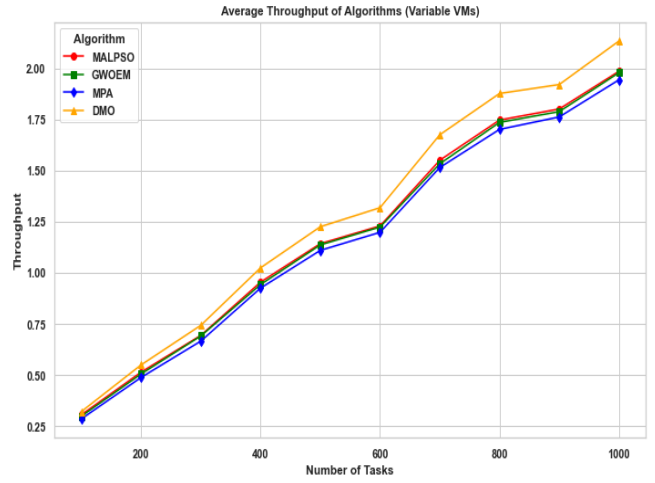


Fig. 13. Average throughput per dataset with variable VMs.

Fig. 13 depicts the average throughput achieved by each algorithm as the number of tasks increases under a variable number of VMs. The proposed DMO consistently outperforms its counterparts, achieving the highest throughput across all task sizes. This indicates more tasks are completed per time unit, highlighting DMO's superior efficiency. The gap becomes more significant as task volume scales, confirming DMO's strong adaptability and parallelism handling. This makes it well-suited for high-throughput cloud environments.

VI. Conclusion and Future Work

Task scheduling is a substantial and complex challenge in CC, with ongoing research aimed at discovering efficient methods for assigning tasks to computational resources to minimize makespan. This study presents a DMO-based task scheduling technique aimed at enhancing system performance through the optimal utilization of available computing resources. The comprehensive execution of the proposed DMO methodology has been delineated, and its efficacy was validated utilizing the GoCJ benchmark datasets. Two experimental situations were executed to evaluate performance, and the outcomes were compared with those of the MALPSO, GWOEM, and MPA algorithms. For each algorithm, essential performance measures such as response time, degree of imbalance, throughput, and makespan were meticulously assessed to gauge overall scheduling efficacy and resource consumption in the cloud context. The analysis demonstrated that the DMO-based method consistently produced superior makespan results, especially under high task loads and varying VM conditions. These findings highlight DMO's capability in efficiently exploring complex solution spaces and maintaining balanced resource distribution. Therefore, the proposed approach significantly enhances task scheduling performance and contributes to improving the overall efficiency and responsiveness of cloud computing systems.

Despite the promising results obtained, this study has several limitations that should be acknowledged to provide a clear and accurate interpretation of the findings. First, the experimental evaluation was conducted using the GoCJ benchmark dataset, which although widely adopted may not fully capture all characteristics of real-world cloud workloads such as bursty task arrivals, task dependencies, or strict deadline constraints. Second, the performance assessment focused primarily on makespan minimization, while other important quality of service metrics such as energy consumption, monetary cost, load balancing, and service level agreement violations were not jointly optimized or analyzed. Third, the experiments were performed under simulated cloud environments with fixed and varying VM configurations and therefore the observed performance may differ in large scale production clouds where network latency, VM failures, and dynamic resource provisioning occur. In addition, the proposed DMO algorithm was compared with a limited set of metaheuristic baselines and comparisons with a broader range of recent scheduling approaches could further strengthen the generality of the conclusions. Finally, algorithm parameter tuning was carried out empirically and alternative tuning strategies may lead to different performance outcomes. Addressing these limitations in future studies through real cloud experimentation, multi objective optimization, and expanded comparative analysis would further enhance the applicability and robustness of the proposed approach.

As future work, we plan to develop a multi-objective performance model that incorporates additional quality service metrics to further enhance task scheduling in cloud computing environments. In particular, optimizing load balancing will be a key focus, as it plays a critical role in maintaining system stability and performance. We also intend to extend the DMO algorithm to support more complex task structures, including

scientific workflows and cloud-based deep learning workloads, thereby improving its adaptability to diverse application scenarios. Furthermore, the applicability of the proposed DMO methodology will be explored in other optimization domains, including workflow scheduling, underwater wireless sensor networks, feature selection, and Internet of Things scheduling problems, to evaluate its generalization capability.

REFERENCES

[1] S. Tang, Y. Yu, H. Wang, G. Wang, W. Chen, Z. Xu, S. Guo, W. Gao, A Survey on Scheduling Techniques in Computing and Network Convergence, IEEE Communications Surveys and Tutorials 26 (2024) 160–195. https://doi.org/10.1109/COMST.2023.3329027.

[2] O.L. Abraham, M.A. Ngadi, J.M. Sharif, M.K.M. Sidik, Task Scheduling in Cloud Environment-Techniques, Applications, and Tools: A Systematic Literature Review, IEEE Access (2024). https://doi.org/10.1109/ACCESS.2024.3466529.

[3] Z. Ahmad, A.I. Jehangiri, M.A. Ala'anzy, M. Othman, R. Latip, S.K.U. Zaman, A.I. Umar, Scientific Workflows Management and Scheduling in Cloud Computing: Taxonomy, Prospects, and Challenges, IEEE Access 9 (2021) 53491–53508. https://doi.org/10.1109/ACCESS.2021.3070785.

[4] M. Menaka, K.S. Sendhil Kumar, Workflow scheduling in cloud environment – Challenges, tools, limitations & methodologies: A review, Measurement: Sensors 24 (2022). https://doi.org/10.1016/j.measen.2022.100436.

[5] G. Lokesh, K.K. Baseer, A meta-heuristic approach-aided multi-objective strategy with optimal resource allocation via fault tolerant and priority-based scheduling for load balancing in cloud, Wireless Networks (2025). https://doi.org/10.1007/s11276-024-03885-0.

[6] O.L. Abraham, M.A. Ngadi, J.B.M. Sharif, M.K.M. Sidik, Multi-Objective Optimization Techniques in Cloud Task Scheduling: A Systematic Literature Review, IEEE Access (2025). https://doi.org/10.1109/ACCESS.2025.3529839.

[7] M.S.R. Krishna, D. Khasim Vali, ADWEH: A Dynamic Prioritized Workflow Task Scheduling Approach Based on the Enhanced Harris Hawk Optimization Algorithm, IEEE Access (2025). https://doi.org/10.1109/ACCESS.2025.3543880.

[8] M.A. Khan, R. ur Rasool, A multi-objective grey-wolf optimization based approach for scheduling on cloud platforms, J Parallel Distrib Comput 187 (2024) 104847. https://doi.org/https://doi.org/10.1016/j.jpdc.2024.104847.

[9] L. Abualigah, A.M.A. Hussein, M.H. Almomani, R.A. Zitar, H. Migdady, A.I. Alzahrani, A. Alwadain, Improved synergistic swarm optimization algorithm to optimize task scheduling problems in cloud computing, Sustainable Computing: Informatics and Systems 43 (2024). https://doi.org/10.1016/j.suscom.2024.101012.

[10] C. Lu, J. Zhu, H. Huang, Y. Sun, A multi-hierarchy particle swarm optimization-based algorithm for cloud workflow scheduling, Future Generation Computer Systems 153 (2024) 125–138. https://doi.org/https://doi.org/10.1016/j.future.2023.11.030.

[11] K. Chakraborty, G. Deb, S. Sharma, Symbiotic organisms search-based multi-objective optimal placement of distributed generators considering source and load uncertainty, SCIENTIA IRANICA 30 (2023) 518–535. https://doi.org/10.24200/sci.2021.56149.4575.

[12] R. Ghafari, N. Mansouri, E-AVOA-TS: Enhanced African vultures optimization algorithm-based task scheduling strategy for fog–cloud computing, Sustainable Computing: Informatics and Systems 40 (2023) 100918. https://doi.org/https://doi.org/10.1016/j.suscom.2023.100918.

[13] J. Liu, R. Sarker, S. Elsayed, D. Essam, N. Siswanto, Large-scale evolutionary optimization: A review and comparative study, Swarm Evol Comput 85 (2024). https://doi.org/10.1016/j.swevo.2023.101466.

[14] A. Mohammadi, F. Sheikholeslam, Intelligent optimization: Literature review and state-of-the-art algorithms (1965–2022), Eng Appl Artif Intell 126 (2023). https://doi.org/10.1016/j.engappai.2023.106959.

[15] O.L. Abraham, M.A. Ngadi, A comprehensive review of dwarf mongoose optimization algorithm with emerging trends and future research directions, Decision Analytics Journal 14 (2025). https://doi.org/10.1016/j.dajour.2025.100551.

[16] M.S.R. Krishna, A Systematic Review on Various Task Scheduling Algorithms in Cloud Computing, EAI Endorsed Transactions on Internet of Things 10 (2024). https://doi.org/10.4108/eetiot.4548.

[17] L. Abualigah, A. Diabat, A novel hybrid antlion optimization algorithm for multi-objective task scheduling problems in cloud computing environments, Cluster Comput 24 (2021) 205–223. https://doi.org/10.1007/s10586-020-03075-5.

[18] L. Abualigah, A. Diabat, M.A. Elaziz, Intelligent workflow scheduling for Big Data applications in IoT cloud computing environments, Cluster Comput 24 (2021) 2957–2976. https://doi.org/10.1007/s10586-021-03291-7.

[19] M. Abdullahi, M.A. Ngadi, S.I. Dishing, S.M. Abdulhamid, An adaptive symbiotic organisms search for constrained task scheduling in cloud computing, J Ambient Intell Humaniz Comput 14 (2023) 8839–8850. https://doi.org/10.1007/s12652-021-03632-9.

[20] I. Behera, S. Sobhanayak, Task scheduling optimization in heterogeneous cloud computing environments: A hybrid GA-GWO approach, J Parallel Distrib Comput 183 (2024). https://doi.org/10.1016/j.jpdc.2023.104766.

[21] P. Pabitha, K. Nivitha, C. Gunavathi, B. Panjavarnam, A chameleon and remora search optimization algorithm for handling task scheduling uncertainty problem in cloud computing, Sustainable Computing: Informatics and Systems 41 (2024) 100944. https://doi.org/https://doi.org/10.1016/j.suscom.2023.100944.

[22] R. Ghafari, N. Mansouri, Improved Harris Hawks Optimizer with chaotic maps and opposition-based learning for task scheduling in cloud environment, Cluster Comput 27 (2024) 1421–1469. https://doi.org/10.1007/s10586-023-04021-x.

[23] A.N. Malti, M. Hakem, B. Benmammar, A new hybrid multi-objective optimization algorithm for task scheduling in cloud systems, Cluster Comput 27 (2024) 2525–2548. https://doi.org/10.1007/s10586-023-04099-3.

[24] M. Osmanpoor, A. Shameli-Sendi, F. Faraji Daneshgar, Convergence of the Harris hawks optimization algorithm and fuzzy system for cloud-based task scheduling enhancement, Cluster Comput (2024). https://doi.org/10.1007/s10586-023-04225-1.

[25] M.A. Abu-Hashem, M. Shehab, M.K.Y. Shambour, M.Sh. Daoud, L. Abualigah, Improved Black Widow Optimization: An investigation into enhancing cloud task scheduling efficiency, Sustainable Computing: Informatics and Systems 41 (2024) 100949. https://doi.org/https://doi.org/10.1016/j.suscom.2023.100949.

[26] R. Gong, D.L. Li, L. La Hong, N.X. Xie, Task scheduling in cloud computing environment based on enhanced marine predator algorithm, Cluster Comput 27 (2024) 1109–1123. https://doi.org/10.1007/s10586-023-04054-2.

[27] J.O. Agushaka, A.E. Ezugwu, L. Abualigah, Dwarf Mongoose Optimization Algorithm, Comput Methods Appl Mech Eng 391 (2022). https://doi.org/10.1016/j.cma.2022.114570.

[28] P. Pirozmand, H. Jalalinejad, A.A.R. Hosseinabadi, S. Mirkamali, Y. Li, An improved particle swarm optimization algorithm for task scheduling in cloud computing, J Ambient Intell Humaniz Comput 14 (2023) 4313–4327. https://doi.org/10.1007/s12652-023-04541-9.

[29] X. Huang, M. Xie, D. An, S. Su, Z. Zhang, Task scheduling in cloud computing based on grey wolf optimization with a new encoding mechanism, Parallel Comput 122 (2024). https://doi.org/10.1016/j.parco.2024.103111.

H∞ Control Design for Nonlinear Systems via Multimodel Approach

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***Abstract*—Nonlinear systems are integral to contemporary engineering applications, yet their regulation remains a significant challenge due to complex and highly dynamic behaviors. Robust control frameworks, particularly H∞ methods, provide systematic tools to ensure stability and performance in the presence of disturbances and modeling uncertainties. This study proposes an integrated design methodology that combines H∞ loop-shaping techniques with multimodel approaches to achieve resilient control of nonlinear systems. The control law is structured around the H∞ loop-shaping scheme, which shapes the open-loop dynamics to meet desired robustness and performance specifications. The multimodel strategy further enhances adaptability by accommodating diverse operating conditions and capturing variations in system behavior. Several control architectures are presented that unify H∞ loop-shaping with multimodel representations, offering a flexible framework for nonlinear system control. The design methodology also ensures desirable transient responses, thereby improving practical applicability for complex systems. A study is conducted to validate the proposed approaches. Simulation results confirm the effectiveness of multimodel H∞ control systems, underscoring their potential as a robust solution for complex nonlinear applications.**

***Keywords*—Nonlinear systems; H∞ loop shaping control; multimodel**

I. INTRODUCTION

Nonlinear systems are pervasive across engineering and scientific domains, naturally arising in mechanical structures [1], electrical circuits, chemical processes, aerospace vehicles, and biological networks. Unlike linear systems, which benefit from analytical tractability and the principle of superposition, nonlinear systems [2] often exhibit complex phenomena such as bifurcations [3], limit cycles, chaotic dynamics [4], and strong coupling effects [5]. These behaviors significantly complicate analysis and control, yet their regulation remains essential for ensuring stability and performance in modern applications. Classical control strategies, including feedback linearization [6], Lyapunov-based methods [7], and sliding mode control [8], have provided effective tools for nonlinear regulation. However, these techniques typically depend on stringent modeling assumptions and may lose reliability in the presence of uncertainties, disturbances, or parameter variations. In practice, nonlinear systems are rarely known with complete accuracy [9], necessitating robust control frameworks to guarantee performance under imperfect knowledge [10] and [11].

Within this context, H∞ control has emerged as a powerful methodology [12]. Its primary objective is to minimize the worst-case impact of disturbances on system performance, thereby ensuring both stability and robustness against uncertainties. Although originally formulated for linear systems, H∞ control has been extended to nonlinear dynamics through various approaches, offering a systematic means of addressing external perturbations and modeling errors. This makes H∞ particularly attractive for safety-critical applications such as aerospace flight control [13], robotics [14], and power systems [15].

Despite its advantages, direct application of H∞ control to nonlinear systems often proves analytically intractable and computationally intensive. To mitigate these challenges, researchers have introduced multimodel approaches [16], in which a nonlinear system is represented by a collection of local models, typically linear or weakly nonlinear, valid within specific operating regions [17]. By switching between or blending these models, multimodel strategies provide a tractable representation of complex nonlinear dynamics [18]. This framework facilitates the design of controllers that adapt to varying operating conditions [19], thereby enhancing robustness and performance without resorting to overly conservative assumptions [20].

The integration of multimodel representations with H∞ control offers a promising pathway toward resilient regulation of nonlinear systems. While multimodel structures reduce complexity by decomposing nonlinear behavior into manageable local models, H∞ design ensures robustness against uncertainties and disturbances. Together, they enable the synthesis of controllers capable of maintaining stability and performance across diverse operating regimes. This study contributes to this growing field by presenting a comprehensive study of H∞ control for nonlinear systems using multimodel approaches, aiming to bridge theoretical rigor with practical applicability in complex engineering contexts.

The remainder of this study is structured as follows: In Section II, we provide a preliminary study on H∞ loop-shaping techniques, highlighting their theoretical foundations and relevance for robust control of nonlinear systems. Section III introduces the multimodel approaches, where nonlinear dynamics are represented through sets of local models to facilitate analysis and controller design. In Section IV, we present an integrated scheme that combines H∞ loop-shaping techniques with multimodel strategies, demonstrating how the synergy between these methods strengthens robustness and flexibility in control system design. Proposed approaches are formulated within this composite methodology to ensure that stability and performance objectives are simultaneously satisfied, and four distinct architectures based on this concept are introduced. The effectiveness of the developed structures is

examined in Section V through rigorous simulation studies, highlighting their robustness and feasibility for real systems implementation. Finally, Section VI concludes the study by summarizing the main contributions and outlining potential perspectives for future research.

II. Preliminary Study of H∞ Loop-Shaping Techniques for Robust Control

A. Foundations of H∞ Loop-Shaping

H∞ loop-shaping control design offers a systematic approach to achieving robust performance in uncertain systems. By shaping the open-loop frequency response to meet desired performance objectives and subsequently applying H∞ optimization, the method ensures stability margins and resilience against modeling errors. This integration of classical intuition with modern robust control theory makes H∞ loop-shaping particularly effective for complex multi-input multi-output systems.

The robust stability problem in the H∞ framework is to determine a controller K(s) that stabilizes the plant G(s) while ensuring that the closed-loop system satisfies prescribed performance and robustness criteria. Specifically, the objective is to design K(s) such that the weighted closed-loop transfer functions achieve a bounded H∞ norm, thereby guaranteeing stability margins in the presence of model uncertainties and external disturbances.

The robust stability H_∞ problem is to find $\gamma_{\min}$ as defined in Eq. (1) and *K(s)* in Eq. (7) in order to stabilize the studied plan *G(s),* such as:

$$\gamma min = \sqrt{1 + \lambda(YX)_{sup}} \tag{1}$$

where, $\boldsymbol{\lambda_{sup}}$ is the largest eigenvalue and the matrices *X* and *Y* are respectively the solutions of the following Riccati equations given by Eq. (2):

$$\begin{cases} XA + A^T X - XBB^T X + C^T C = 0 \\ YA^T + A^T Y - YC^T CY + BB^T = 0 \end{cases} \tag{2}$$

with (*A*, *B*, *C*) is the state space representation of the shaped plant *G denoted* $G_s(S)$, defined by Eq. (3):

$$G_s(s) = W_1(s)G(s)W_2(s) \tag{3}$$

A controller $K_\infty(s)$ stabilizing all the models is described by the state space representation Eq. (4) and Eq. (5):

$$\begin{cases} \dot{x}_c(t) = A_c x_c(t) + B_c y_c(t) \\ u(t) = C_c x_c(t) \end{cases} \tag{4}$$

where,

$$\begin{cases} A_c = A - BB^T X + \gamma^2 Z\gamma YC^T C \\ B_c = \gamma^2 Z\gamma YC^T \\ C_c = B^T X \\ Z_\gamma = (I + YX - \gamma^2 I)^{-1} \end{cases} \tag{5}$$

Using Eq. (5), the H∞ controller is given in Eq. (6) as follows:

$$K_\infty(s) = C_c(sI - A_c)^{-1}B_c \tag{6}$$

The final feedback controller $K(s)$, is obtained by combining controller $K_\infty(s)$ with the shaping functions $W_1(S)$ and $W_2(S)$, which is described by the relation Eq. (7):

$$K(s) = W_1(s)K_\infty(s)W_2(s) \tag{7}$$

B. Architecture of H∞ Loop-Shaping Control Systems

H∞ loop-shaping control provides a systematic framework that combines classical frequency-domain design with modern robust optimization. The method begins by shaping the open-loop transfer function with appropriate weighting functions to achieve desired performance characteristics such as bandwidth, disturbance rejection, and noise attenuation. Once the loop is shaped, H∞ optimization is applied to guarantee robustness against model uncertainties and unmodeled dynamics. This architecture in Fig. 1 is particularly effective for both Single-Input/ Single-Output (SISO) and Multiple-Input/Multiple-Output (MIMO) systems, as it balances intuitive design with rigorous mathematical guarantees, making it a widely applicable framework in robust control engineering.

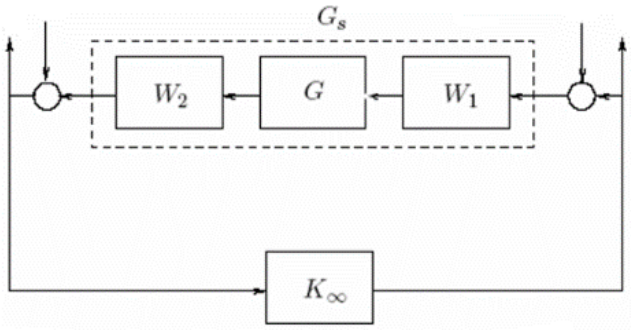


Fig. 1. Architecture of H∞ loop-shaping control systems.

The H∞ loop-shaping control design framework provides a rigorous and principled methodology for achieving robust performance by integrating intuitive frequency-domain shaping with formal optimization techniques. By simultaneously enhancing stability margins and accommodating model uncertainties, this framework is particularly well-suited for the control of complex nonlinear systems. Building upon this foundation, the subsequent section introduces multimodel approaches, which serve as complementary tools for representing nonlinear dynamics through collections of local models. Such representations enable computationally feasible analysis and facilitate systematic controller synthesis, thereby extending the applicability of robust control methods to a broader class of nonlinear systems.

III. Multimodel Approaches for Nonlinear System Representation and Controller Design

A. Multimodel Control for Nonlinear System

The principal objective is the synthesis of a global control law u(t) described by Eq. (8) for the considered nonlinear system Eq. (9), constructed on the basis of the multimodel representation. The resulting control input, designated as the multimodel command, is obtained through the aggregation of partial control signals generated by each local model.

$$u(t) = \sum_{i=1}^{n} v_i(t)u_i(t) \tag{8}$$

$$\begin{cases} \dot{x}(t) = \sum_{i=1}^{n} v_i(t)(A_i x(t) + B_i u_i(t)) \\ y(t) = \sum_{i=1}^{n} v_i(t) C_i x(t) \end{cases} \quad (9)$$

where,

$$\sum_{i=1}^{n} v_i = 1$$

υ_i (t) denotes the validity coefficient corresponding to the i[th] local model, ensuring that the global control law is obtained as a weighted fusion of the partial commands u_i.

In the multimodel representation, A_i denotes the state matrix of the i[th] local model, characterizing the intrinsic dynamics of the system states. The matrix B_i represents the input matrix, mapping the control signal u_i into the state space and thereby defining the influence of external commands. Similarly, C_i is the output matrix, which relates the internal state vector x(t) to the measurable output y(t).

B. Multimodel Architecture for Nonlinear Systems

The multimodel structure constitutes a comprehensive analytical framework that employs multiple local linear time-invariant (LTI) models, expressed in either linear or affine form. This methodology is predicated on the assumption that a complex nonlinear system can be effectively approximated by a structured combination of simpler local models, thereby establishing a representative model base. Each constituent model delineates the system dynamics at a specific operating point, while the global nonlinear behavior emerges from the coordinated interaction of these local models M_i through normalized activation functions. Consequently, the multimodel approach mitigates system complexity by facilitating the investigation of dynamic behavior under rigorously defined operating conditions. The conceptual foundation of this methodology is schematically illustrated in Fig. 2.

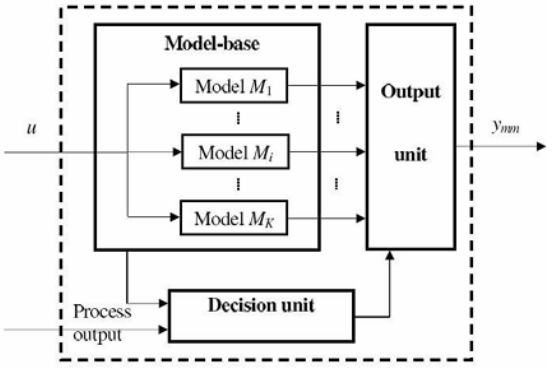


Fig. 2. Architecture of a multimodel approach for control systems.

The multimodel framework is organized into three core components. The model base consists of a library of local or generic models, which may vary in form and order but collectively provide simplified representations of the system across distinct operating regimes. The decision unit governs the selection and activation of these models, ensuring that the most appropriate local representation contributes to the global system defined by M in Eq. (10), given that each model is valid only within a specific operating region. Finally, the output unit synthesizes the overall system response by processing the validity vector associated with the model base. Two strategies are typically employed: commutation, which switches models according to operating conditions, and fusion, which aggregates outputs through a weighted combination. In this study, the fusion approach is adopted and formally defined in the following section.

$$M = \sum_{i=1}^{n} v_i(t) M_i(t) \quad (10)$$

With

$$\sum_{i=1}^{n} v_i = 1$$

IV. H∞ Synthesis under Multimodel Control Design

A. General Principles of H∞ Loop-Shaping Synthesis in Multimodel Control

The integration of H∞ synthesis within a multimodel control paradigm aims to achieve robust performance for nonlinear systems by combining the advantages of multiple local linear models. In this framework, each local model contributes a partial control law derived from H∞ design, ensuring attenuation of disturbances and preservation of stability margins. The global control input is then obtained through a fusion mechanism, where the partial commands are weighted according to the validity coefficients associated with each model. This methodology facilitates seamless transitions among local controllers while ensuring robustness with respect to parameter variations and inherent system nonlinearities. On the basis of this principle, the proposed control architecture is structured around a set of local H∞ controllers, each associated with its corresponding base model. A validity estimation mechanism operates in real time to determine the weighting coefficients that quantify the relevance of each local model. These coefficients are subsequently employed within a fusion module, which synthesizes the global control input delivered to the plant. In the following sections, four distinct architectural configurations of this multimodel H∞ control strategy are introduced and analyzed.

B. Synthesis of Partial H∞ Loop- Shaping controller

For each local model Mi (i = 1, .., n), an H∞ Loop- Shaping controller $K_{\infty i}(s)$ is associated. The corresponding partial control law $K_i(s)$ is then derived by using local shaping $W_{1i}(S)$ and $W_{2i}(s)$, as expressed in Eq. (11):

$$K_i(s) = W_{1i}(s) K_{\infty i}(s) W_{2i}(s) \quad \text{, for i=1..n} \quad (11)$$

The synthesis procedure ensures that each controller attains the desired performance objectives while maintaining stability margins specifically adapted to the dynamic characteristics of its associated local model. By configuring the loop-shaping design to individual operating regimes, the resulting set of partial controllers provides localized robustness and performance guarantees across the multimodel framework. This localized design not only enhances the fidelity of control in each regime but also establishes a foundation for constructing a global control law capable of maintaining robustness under parameter variations, nonlinearities, and external perturbations. Consequently, the multimodel H∞ synthesis approach enables a

systematic balance between local precision and global stability, ensuring reliable performance across the entire operating domain.

C. Synthesis of Global H∞ Loop- Shaping Controller

Once the parameters of the partial controllers have been identified, the subsequent step consists of deducing the global control law to be applied to the nonlinear system under study. A fusion-based control strategy is adopted, as it provides a coherent and effective framework for the proposed multimodel representation. In situations where the system can be accurately approximated by a weighted aggregation of local models, the global controller K(s) is constructed through the fusion of the elementary controllers $K_i(s)$, described by Eq. (12):

$$K(s) = \sum_{i=1}^{n} v_i K_i(s) \quad (12)$$

υ_i (k) denotes the validity coefficient corresponding to the ith local model.

With,

$$\sum_{i=1}^{n} v_i = 1$$

Based on the multimodel H∞ Loop-shaping synthesis framework, four representative architectures are proposed to illustrate different design philosophies and implementation strategies. The following subsection introduces four architectural configurations developed under the multimodel H∞ synthesis framework, highlighting their structural characteristics and the control strategies employed.

D. Proposed Architectures for Multimodel H∞ Control

a) Architecture 1 – Aggregated local controllers: The global control law is synthesized as the summation of local H∞ controllers, each designed with respect to its corresponding local model. The resulting global system is thus formed by the collective contribution of all local models. The architecture is illustrated in Fig. 3 below:

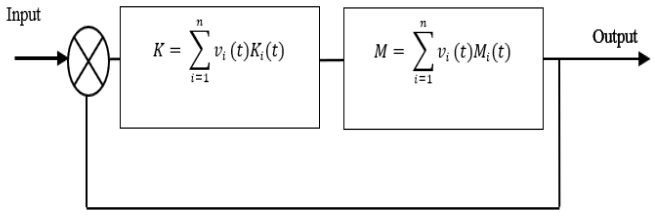


Fig. 3. Architecture 1- Aggregated local controllers.

b) Architecture 2 – Decentralized local control: Each local model is paired with its dedicated H∞ controller, operating independently. The control action applied to the plant is determined by the validity of the associated local model, ensuring model-specific regulation. The subsequent Fig. 4 depicts the structure of the proposed architecture.

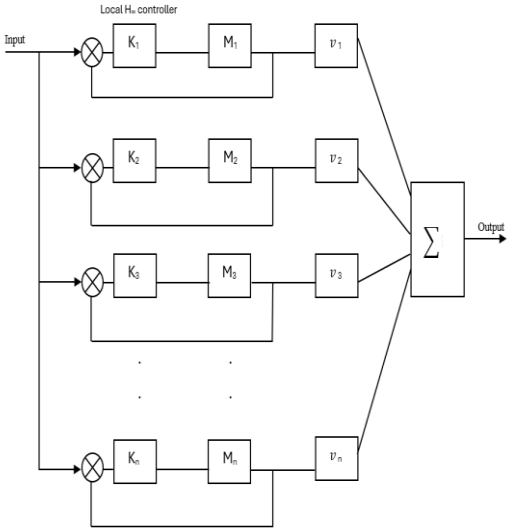


Fig. 4. Architecture 2 - Decentralized local control.

c) Architecture 3 – Global controller from multimodel representation: A single H∞ Loop-shaping controller, denoted K, is designed directly from the global multimodel representation. This controller is then connected to the aggregated global model formed by the ensemble of local models. This architecture is provided in Fig. 5.

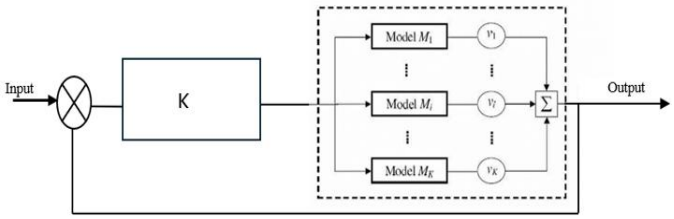


Fig. 5. Architecture 3- Global controller from multimodel representation.

d) Architecture 4 – Global controller applied to the real nonlinear system: The global H∞ Loop-shaping controller K, synthesized from the multimodel framework, is directly implemented on the real nonlinear system. Simulation studies are conducted to evaluate its robustness and performance under practical operating conditions.This architecture is schematically shown in Fig. 6 that follows.

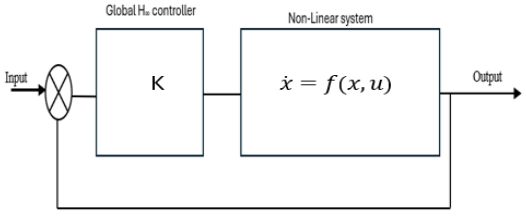


Fig. 6. Architecture 4 - Global controller applied to the real nonlinear system.

V. NUMERICAL VALIDATION OF PROPOSED METHODS

To evaluate the effectiveness of the proposed multimodel H∞ loop-shaping framework, a comparative validation of four distinct architectural configurations is conducted. Each architecture is examined with respect to its structural characteristics, control synthesis methodology, and resulting performance indices. The numerical simulations highlight the effectiveness of the individual designs to ensure robustness and stability margins under varying operating conditions [16].

Consider the nonlinear system given by Eq. (13):

$$y + (15 - 10y)\dot{y} = (36y(y-1) + 10)u \quad (13)$$

Through the multimodel approach, a set of four linear models has been formulated, with the corresponding transfer functions presented in the following Eq. (14), Eq. (15), Eq. (16) and Eq. (17):

$$G_1(s) = \frac{1}{1+5s} \quad (14)$$

$$G_2(s) = \frac{1}{1+15s} \quad (15)$$

$$G_3(s) = \frac{10}{1+5s} \quad (16)$$

$$G_4(s) = \frac{10}{1+15s} \quad (17)$$

Following the definition of the models, the design of the multimodel controller is undertaken, beginning with the partial H∞ loop-shaping approach and subsequently extending to the global H∞ loop-shaping controller. The design criterion is established to ensure an overshoot D=10%. The transfer function expressions and the value of γ_{min} corresponding to each partial model are summarized in Table I below.

We consider W_{2i}=1.

TABLE I. PARTIAL H∞ LOOP-SHAPING CONTROLLER

System Models	Partial H∞ loop-shaping controller $Ki\infty$	W_{1i}	γ_{min}
M_1	$\frac{3.297s + 1.197}{s^2 + 3.43s + 1.96}$	$\frac{s+1}{s}$	*1.7634*
M_2	$\frac{1.08s + 0.102}{s^2 + 0.87s + 0.58}$	$\frac{0.25s + 0.25}{s}$	*1.9254*
M_3	$\frac{4.47s + 1.43}{s^2 + 3.88s + 2.35}$	$\frac{0.12s + 0.12}{s}$	*1.7618*
M_4	$\frac{1.08s + 0.102}{s^2 + 0.87s + 0.58}$	$\frac{0.025s + 0.025}{s}$	*1.9254*

The step responses of the four models, depicted in Fig. 7, Fig. 8, Fig. 9 and Fig. 10, confirm that the partial H∞ loop-shaping controller fulfills the prescribed performance objectives while ensuring robustness across all models.

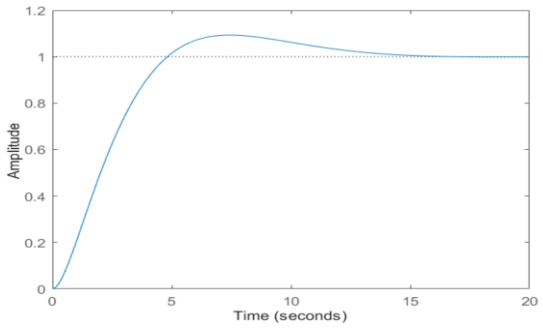


Fig. 7. Step response of the controlled model 1 using K_1.

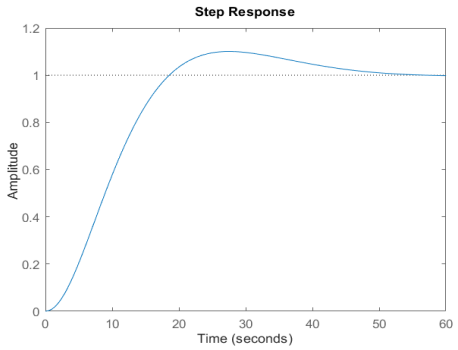


Fig. 8. Step response of the controlled model 2 using K_2.

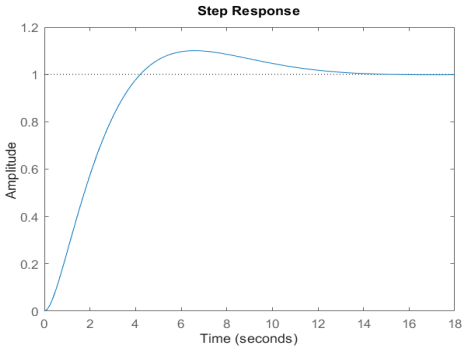


Fig. 9. Step response of the controlled model 3 using K_3.

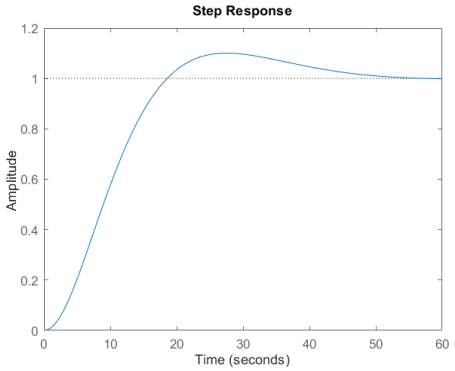


Fig. 10. Step response of the controlled model 4 using K_4.

While the first simulation demonstrates the behavior of a single partial controller, the second extends this concept by integrating the partial controllers within the four-architecture control framework to evaluate their performance.

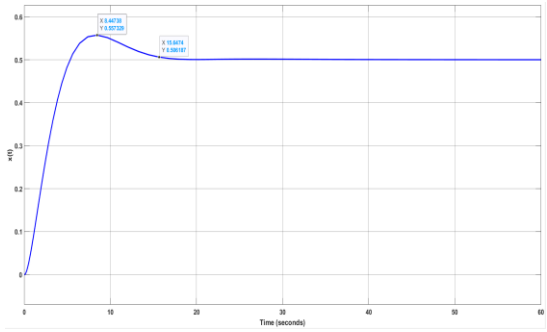


Fig. 11. Step response using architecture 1 - Aggregated local controllers.

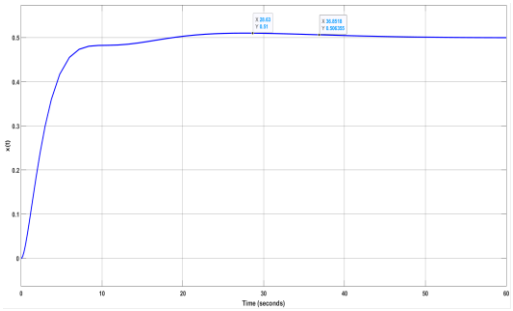


Fig. 12. Step response using architecture 2- Decentralized local control.

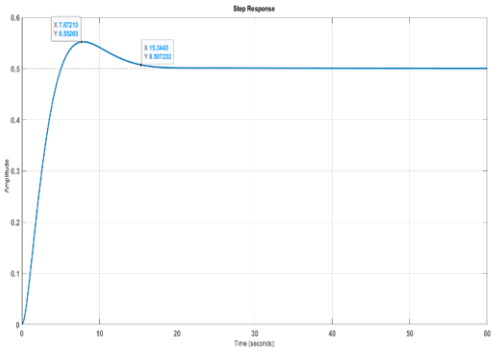


Fig. 13. Step response using architecture 3- Global controller from multimodel representation.

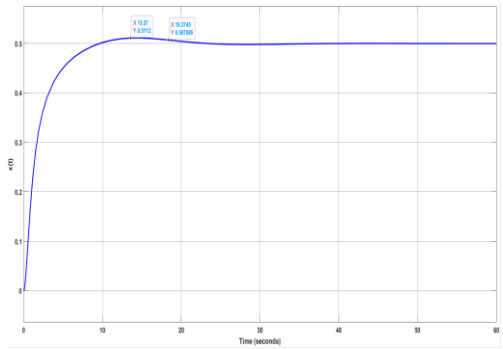


Fig. 14. Step response using architecture 4- Global controller applied to the real nonlinear system.

The comparative analysis of the four control architectures highlights the classical performance limitation between rapid response and system stability, particularly when applied to uncertain, disturbed, or otherwise complex systems. Architecture 1, the Aggregated Local Controllers (Fig. 11), achieves a rapid response time of 15 units but suffers from a significant overshoot of 10%, which compromises stability and makes it unsuitable for systems exposed to external perturbations or parameter uncertainties. Architecture 2, the Decentralized Local Control (Fig. 12), provides excellent precision with only 1% overshoot; however, its slow response time of 36 s limits its applicability in dynamic environments where rapid adaptation is essential. Architecture 3, the Global Controller based on a multimodel representation (Fig. 13), integrates these conflicting objectives by delivering the fastest response at 15 s with minimal overshoot of 1%, thereby offering the most efficient theoretical design under complex operating regimes. Finally, Architecture 4, the Global Controller implemented on the physical system (Fig. 14), demonstrates slightly slower dynamics at 18 s while maintaining the same low overshoot, thus confirming the robustness and practical effectiveness of the global approach in applied system contexts characterized by uncertainty and external disturbances. Overall, Architectures 3 and 4 provide the most favorable balance between speed and stability, ensuring reliable performance across a wide range of complex system scenarios, whereas Architectures 1 and 2 exemplify the extremes of this performance limitation.

Although standard H∞ and H_2 control have been combined with multimodel frameworks in several earlier studies, these approaches generally rely on applying classical robust controllers to each local model or on implementing multimodel switching and scheduling strategies, often without guaranteeing global robustness across the entire operating domain. In contrast, the present work introduces a fundamentally different integration by embedding H∞ loop-shaping within a multimodel architecture. Rather than designing loop-shaped controllers independently for each model, our methodology performs a joint synthesis that enforces a global robustness objective over the full multimodel set. This results in a coherent, system-wide loop-shaping design that departs from existing standard H∞/H_2 multimodel formulations both in purpose and in structural organization.

VI. Conclusion

This study has presented an integrated design methodology that unifies H∞ loop-shaping with multimodel architectures to address a central challenge in robust nonlinear control: achieving global performance guarantees without relying solely on locally valid controllers. Beyond the comparative evaluation of four architectures, the results highlight a broader conceptual contribution—global multimodel coordination can effectively overcome the classical speed-stability trade-off that constrains traditional local or single-model designs.

Architectures 3 and 4 demonstrate that embedding H∞ loop shaping within a global multimodel framework yields controllers capable of maintaining fast dynamics, minimal overshoot, and robust stability across the full operating envelope. This positions multimodel H∞ control as a scalable

and practically deployable strategy for nonlinear systems subject to uncertainty, disturbances, and complex regime transitions. The successful experimental validation of Architecture 4 further confirms that the proposed methodology is not only theoretically sound but also operationally reliable in real-world conditions. Conceptually, this work shifts the perspective in robust nonlinear control from isolated local designs toward globally coherent control structures that preserve robustness throughout the entire state space. By bridging advanced linear robust control tools with nonlinear multimodel representations, the methodology contributes a systematic pathway for designing controllers that are both high-performance and globally robust.

Future research may advance this framework along several significant directions. A promising line of inquiry concerns its extension to large-scale interconnected systems, where multimodel representations arise naturally from subsystem interactions and where uncertainty is both structural and pervasive. Furthermore, the integration of adaptive and data-driven mechanisms within the multimodel architecture offers considerable potential for enhancing real-time performance in highly dynamic environments. Particular attention should be directed toward the incorporation of machine-learning-based modules capable of augmenting or partially replacing the controller, provided that their deployment is accompanied by rigorous guarantees of stability and robustness.

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REFERENCES

[1] H. Zeng, J. Huang, Z. Zhang, and Q. Lu, "Nonlinear dynamics analysis of the high-speed maglev vehicle/guideway coupled system with backstepping fuzzy-neural-network control," Advances in Mechanical Engineering, vol. 17, no. 3, pp. 1–16, 2025.

[2] F. Yu, H.-C. Iu, H. Lin, and V.-T. Pham, "Editorial: Advances in nonlinear systems and networks, Volume III," Frontiers in Physics, vol. 13, 2025.

[3] H. Tang, A. Champneys, and D. J. W. Simpson, Bifurcation Analysis of Multiple Limit Cycles Created in Boundary Equilibrium Bifurcations in Hybrid Systems, Proc. 2024 Int. Conf. on Dynamical Systems (ICDS), London, UK, vol. 2, pp. 122–129, 2024.

[4] J. Zhang, M. Li, and K. Zhou, Adaptive Nonlinear Control for Chaotic Systems with Performance Constraints, Proc. 2024 IEEE Int. Conf. on Control and Automation (ICCA), Hangzhou, China, vol. 1, pp. 88–93, 2024.

[5] A. Kumar and S. Patel, Robust Regulation of Nonlinear Systems under Strong Coupling Effects, Proc. 2024 IEEE Conf. on Decision and Control (CDC), Milan, Italy, vol. 2, pp. 451–456, 2024.

[6] I. S. Trenev and D. D. Devyatkin, Feedback Linearization Control of Nonlinear System, Proc. 15th Int. Conf. on Intelligent Systems INTELS'22, Moscow, Russia, vol. 1, pp. 36–41, 2022.

[7] H.-Y. Wang and C.-C. Tsai, Stability analysis of nonlinear uncertain systems via Lyapunov-based adaptive control, Proc. 2024 Int. Automatic Control Conf. (CACS), Taoyuan, Taiwan, vol. 1, pp. 214–219, 2024.

[8] A. Eltayeb and M. F. Rahmat, Feedback Linearization and Sliding Mode Control Design for Quadrotor's Attitude and Altitude, Proc. 2019 IEEE 1st Int. Conf. on Mechatronics, Automation and Cyber-Physical Computer Systems (MACCPS), Johor, Malaysia, vol. 1, pp. 112–118, 2019.

[9] E. Kayacan, Closed-Loop Error Learning Control for Uncertain Nonlinear Systems with Experimental Validation on a Mobile Robot, Proc. 2020 IEEE/ASME Int. Conf. on Mechatronics, Milan, Italy, vol. 24, pp. 1005–1014, 2020.

[10] L. Fernandez, P. Garcia, and R. Ortega, Stability Enhancement in Nonlinear Power Electronic Systems via Passivity-Based Control, Proc. 2024 IEEE Applied Power Electronics Conf. (APEC), Orlando, USA, vol. 3, pp. 1021–1026, 2024.

[11] F. Giannini, D. Famularo, A Data-Driven Approach to Set-Theoretic Model Predictive Control for Nonlinear Systems, Information (MDPI), vol. 15, no. 7, pp. 369–385, 2024.

[12] Y. Zhang, A. Pang, H. Zhu, and H. Feng, "Structured H∞ Control for Spacecraft with Flexible Appendages," Entropy, vol. 23, no. 8, pp. 930–945, 2021.

[13] A. Elagroudy, C. Weiser, S. Schulz, and J. Tilmans, "Flight Control Law Design using H-infinity Optimal Control for Gust Load Alleviation of Flexible Aircraft," CEAS EuroGNC Conference, vol. -2024-040, pp. 1–8, 2024.

[14] F. E. Serrano and M. Cardona, "Robust H-Infinity Control of Delta Parallel Robot with Disturbances," Advances in Automation and Robotics Research (LACAR Conference), vol. 940, pp. 56–67, 2023.

[15] A. K. Yadav, M. K. Siddique, and M. Naresh, "H-infinity Controller Based on Power Management System to Develop for Standalone Hybrid System with Critical Load," Journal of Electrical Systems, vol. 20, no. 3, pp. 45–58, 2022.

[16] M. L. Wardi, R. Abdelkrim, A. Rhouma, M. Amairi, and M. N. Abdelkrim, "Fractional design for nonlinear systems based on multimodel approach," in Proc. 16th Int. Multi-Conference on Systems, Signals and Devices (SSD), 2019.

[17] M. L. Wardi, R. Abdelkrim, and M. N. Abdelkrim, "Fractional order CRONE and PID controllers design for nonlinear systems based on multimodel approach," in Fractional Order Systems – Control Theory and Applications, Springer, 2021.

[18] M. L. Wardi, R. Abdelkrim, M. Amairi, and M. N. Abdelkrim, "Design of fractional order CRONE and PID controller for nonlinear systems using multimodel approach," American Scientific Research Journal for Engineering, Technology, and Sciences (ASRJETS), 2019.

[19] R. Abdelkrim, M. L. Wardi, H. Gassara, A. El Hajjaji, M. Chaabane, and M. N. Abdelkrim,"Relaxed stabilization conditions for Takagi–Sugeno systems,"in Proc. Int. Multi-Conference on Systems, Signals and Devices (SSD), 2019.

[20] R. Abdelkrim, M. Chaabane, and A. El Hajjaji, "Relaxed stability and stabilization conditions for linear parameter varying systems," Systems, Automation, and Control, 2018.

Modelling Dimensions and Indicators of Readiness for Lean 4.0 Implementation in Indonesian Industries

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***Abstract*—The integration of Lean Manufacturing and Industry 4.0, known as Lean 4.0, has emerged as a strategic approach to enhancing operational efficiency, digital transformation, and competitiveness in modern industries. The rapid development of Industry 4.0 has driven a massive transformation in the global manufacturing sector, including Indonesia, which continues to face competitiveness challenges due to limitations in technological capabilities, human resources, and organizational culture. However, the successful implementation of Lean 4.0 requires a structured and measurable level of organizational readiness. This study aims to model the key dimensions and indicators that define the readiness of Indonesian companies for Lean 4.0 implementation. Using a mixed-methods approach of qualitative and quantitative analysis, this study begins with a meta-synthesis of existing literature and expert interviews to identify initial dimensions and indicators, followed by a structured survey to validate the model. The analytical framework integrates the theoretical foundations of Lean and Industry 4.0 principles, existing readiness assessment models, as well as models from key references. The key finding is a proposed model for Lean 4.0 Readiness for Indonesian industries, consisting of 6 key dimensions and 41 indicators. The 6 key dimensions are: Leadership and Strategy, People and Culture, Technology and Digital Infrastructure, Operation and Process, Product and Service, and External Collaboration and Integration. Expert validation and pilot testing confirmed the consistency and contextual relevance of this model for industries in Indonesia. The finding contributes to theory and practice by providing a comprehensive and diagnostic framework for evaluating Lean 4.0 implementation readiness, as well as supporting the development of a readiness model that can be adapted to another industrial park in Indonesia.**

Keywords*—Lean 4.0; Industry 4.0; readiness assessment; organizational readiness; Indonesian industries; digital transformation

I. Introduction

The rapid advancement of Industry 4.0 has significantly transformed manufacturing and service industries worldwide. By integrating smart technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), big data analytics, and automation, Industry 4.0 enhances operational efficiency and competitiveness [1]. While Lean 4.0 offers significant benefits, challenges include high implementation costs, workforce skill gaps, and integration complexities. Future trends indicate a growing focus on sustainability within Lean-Industry 4.0 integration, emphasizing the need for further research to address challenges and explore scalable solutions across diverse industrial contexts [2].

Lean Manufacturing has long been recognized as a systematic approach to eliminating waste, improving productivity, and optimizing processes [3]. The convergence of these two concepts, known as Lean 4.0, leverages digital technologies to enhance lean principles, enabling real-time decision-making, predictive maintenance, and adaptive production systems [4]. Industry 4.0 technologies strongly support the Just-in-time and *Jidoka* principles, but have a limited impact on lean waste reduction and teamwork aspects [5].

Currently, the integration model of Lean manufacturing principles and Industry 4.0 has not been found in Indonesia. Previous research has not discussed the external dimension of collaboration, i.e., the relationship between companies and suppliers or customers. Therefore, this study aims to provide a practical assessment model that helps businesses evaluate their readiness and develop strategies for implementing Lean 4.0. Additionally, this research contributes to academic knowledge by bridging the gap between Lean Manufacturing and Industry 4.0 readiness studies, offering a structured framework applicable to emerging economies.

A. Background

The Indonesian manufacturing sector, as a prime mover of the country's economy, contributes around 19% to GDP in 2023 and serves as a major source of employment, export revenue, and industrial growth [6]. Despite its strength in domestic market size, UNIDO's Competitive Industrial Performance Index indicates that Indonesia ranks lower than regional leaders such as China, Thailand, and Vietnam, in terms of manufacturing value added, export complexity, and innovation [7]. The World Economic Forum (WEF) data shows gaps in innovation capacity, infrastructure quality, and technological adoption [8]. In order to improve the competitiveness of industries in Indonesia, the implementation of Lean 4.0 is a necessity.

Despite the potential benefits of Lean 4.0, the successful implementation of Lean 4.0 requires organizations to assess their readiness across multiple dimensions. Many companies, particularly in developing economies like Indonesia, face significant challenges in implementing Lean 4.0 [9]. Issues such as limitations of technology and infrastructure, human resources and skills, leadership commitment, and complexity of integration can hinder the transition. As a result, assessing

organizational readiness becomes a crucial step before adopting Lean 4.0. Without proper preparation, companies may face challenges in implementation, leading to inefficiencies and resistance to change. A structured readiness assessment framework can help companies identify strengths, weaknesses, and necessary improvements to ensure a smooth transformation.

While numerous studies have explored the adoption of Industry 4.0 and Lean Manufacturing principles, there is a lack of a comprehensive model for assessing Lean 4.0 readiness, particularly in Indonesian companies. Most existing frameworks focus solely on either technological maturity or lean implementation, failing to provide a holistic approach that considers strategic, workforce, and sustainability factors. To address this gap, this study aims to develop a conceptual model for assessing Lean 4.0 readiness by identifying key dimensions and indicators relevant to Indonesian industries. Specifically, the study seeks to: 1) identify critical dimensions that determine Lean 4.0 readiness, 2) establish key indicators for measuring organizational readiness, and 3) propose a structured model that companies can use for self-assessment and improvement planning.

B. Literature Review

Two models of Lean 4.0 readiness used as the main references in this study are the Lean 4.0 Readiness Assessment Tool and the Dimensions for Lean-Green 4.0 Readiness. These are complemented by references to two broader Industry 4.0 readiness frameworks—one offering an evaluation approach, and another synthesizing dimensions from existing readiness models.

Rahmatindar et al. (2024) [10] proposed a Lean 4.0 Readiness Assessment Tool comprising 5 dimensions and 69 indicators. This model, a modification of the Indonesia Industry 4.0 Readiness Index [INDI 4.0], integrates the Lean Assessment Tool and Industry 4.0 Readiness Assessment Tool. The tool has developed under the conditions of companies in Indonesia. Those dimensions include management and organization, people and culture, products and services, technology, and factory operations. The indicators were validated using the Delphi method, which was carried out in two stages.

Duarte et al. (2025) [11] proposed a baseline framework for designing an assessment model to implement Lean-Green management in an Industry 4.0 environment. This study employed a systematic literature review to investigate the existing literature on Lean, Green, and Industry 4.0. The model consisted of 8 dimensions, namely leadership and strategy, people, process, product, customer, supplier, technology, and governance. It identified 44 indicators (measurement items), which consist of 8 in leadership and strategy, 5 indicators in people, 4 indicators in product, 8 indicators in process, 3 indicators in customer, 5 indicators in supplier, 6 indicators in technology, and 5 indicators in governance.

Wankhede et al. (2022) [12] developed a model for assessing Industry 4.0 readiness in organizations, which comprises 6 criteria (dimensions) and 50 factors (indicators). Various Industry 4.0 Readiness Dimensions and Indicators were obtained from an extensive literature review and finalized using expert opinion. Those dimensions covered technology, organization and management, process, legislation, product, and employee. The model has been tested concerning automotive component manufacturing organizations, and hence, the inferences derived have practical relevance.

To be able for organizations to self-assess their Industry 4.0 readiness to survive and thrive in the age of the Fourth Industrial Revolution, the conceptualization of an Industry 4.0 readiness model with the fundamental model dimensions is needed. Hanafiah et al. (2020) [13] identify 30 Industry 4.0 readiness models with 158 unique model dimensions, by using a systematic literature review (SLR) methodology. Two theoretical contributions of this study are: 6 dimensions (technology, people, strategy, leadership, process, and innovation) that can be considered the most important dimensions for organizations, and 70 (44%) out of a total of 158 unique dimensions for organizations on Industry 4.0 related to the assessment of technology only.

II. Research Methodology

A. Research Design

This study employs a mixed-methods research approach to develop and validate a model for assessing Lean 4.0 readiness in Indonesian companies. The research is conducted in two phases:

- Qualitative Analysis – A meta-synthesis and expert interviews to identify key dimensions and indicators of Lean 4.0 readiness.
- Quantitative Analysis – A survey-based study to validate the proposed model and assess its applicability in Indonesian industries.

To develop an analytical framework based on the literature review of dimensions and indicators of readiness for Lean 4.0 implementation, two initial steps of meta-synthesis are undertaken. The first step is to determine and study research topics related to understanding Lean 4.0, readiness assessment in organizational transformation, and the dimensions of Lean 4.0 readiness implementation, as well as its indicators. The result is then summarized. This process involves keyword identification through a search for relevant literature in the database on the website.

In order to support the successful implementation of Lean 4.0 in a company, it is necessary to determine the company's readiness to implement Lean 4.0. The assessment to determine company readiness is designed by combining Lean manufacturing principles and Industry 4.0 technology. An analytical framework model in this study is proposed as described in Fig. 1.

The next step is selecting particular topics using the previous keywords as guidance, which lasted until January 2025. Most of the publications were obtained from academic sources, including journals, conference papers, institutional reports, and dissertations.

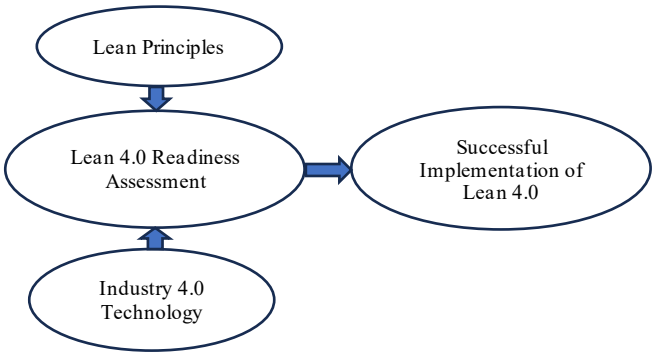


Fig. 1. Analytical framework for Lean 4.0 implementation.

B. Data Collection Methods

1) Meta synthesis: A meta-synthesis of existing studies on Lean 4.0, Industry 4.0, and readiness assessment models is conducted. Academic sources, including journal articles, conference papers, and case studies, are analyzed to identify potential dimensions and indicators relevant to Lean 4.0 readiness.

2) Expert interviews: To validate the findings from the meta-synthesis, semi-structured interviews are conducted with industry experts, Lean practitioners, and academics specializing in Lean 4.0. The key objectives of these interviews are:

- To identify additional readiness factors relevant to Indonesian companies.
- To refine and contextualize the dimensions and indicators based on real-world experiences.

A purposive sampling method is used to select 10–15 experts from the manufacturing, service, and consulting sectors who are involved in implementing Lean 4.0.

3) Survey-based data collection: Based on the identified dimensions and indicators, a structured survey has been designed. The survey consists of Likert-scale questions (1–5) that measure the importance and presence of each indicator within Indonesian companies.

4) Model development and validation: Based on the literature review, expert input, and survey findings, a Lean 4.0 Readiness Model has been developed. The model is validated through:

- Expert review: Feedback from industry professionals and academics.
- Pilot testing: Testing the model on a small group of companies before full implementation.
- Comparative analysis: Benchmarking the model against existing readiness frameworks.

The identified dimensions and indicators are used to develop a Lean 4.0 Readiness Model, which provides a structured framework for assessing an organization's readiness. The model consists of:

- A multi-dimensional assessment framework categorizing companies as "Not ready", "Low readiness", "Moderate readiness", and "Excellent readiness".
- Weighting of indicators based on expert input and survey validation.
- A scoring system to quantify readiness levels across different industries in Indonesia.
  - 4.1–5.0: Excellent readiness – the organization is highly prepared for Lean 4.0.
  - 3.1–4.0: Moderate readiness – some areas need improvement.
  - 2.1–3.0: Low readiness – significant gaps exist.
  - 1.0–2.0: Not ready – foundational work is needed before implementing Lean 4.0.

III. Analytical Framework

A. Overview of Lean 4.0: Integration of Lean Principles and Industry 4.0

Lean Manufacturing, which originated from the Toyota Production System, has long been recognized as a systematic approach to eliminating waste, improving efficiency, and optimizing production processes [14]. Its core principles — such as Just-in-Time (JIT), value stream mapping, and continuous improvement (*kaizen*) — have helped organizations enhance productivity and reduce operational inefficiencies. However, with the emergence of Industry 4.0, these traditional lean practices are being augmented with digital technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), cyber-physical systems, and big data analytics [15]. Industry 4.0 enables real-time data collection, monitoring, and analysis, which supports data-driven decision-making, predictive maintenance, and automation — elements that complement Lean's objectives of operational efficiency and waste reduction [16]. For example, digital *kanban* systems can improve inventory control, while AI-powered analytics can enhance root cause analysis during quality improvement initiatives. This digital transformation led to what is now known as Lean 4.0 [17].

Several studies emphasize that the integration of Lean and Industry 4.0 is mutually reinforcing. While Lean offers a cultural and managerial foundation for operational excellence, Industry 4.0 brings the technological capabilities to execute those principles more efficiently and with greater agility [18]. This synergy allows companies to achieve smart, flexible, and efficient production systems. However, the success of this integration depends on factors such as leadership support, workforce competence, and organizational culture [19].

Despite the promising benefits, organizations must carefully manage the integration process to avoid conflicts between traditional Lean practices and the complexities introduced by advanced technologies. Research highlights the need for a strategic roadmap and an assessment of organizational readiness before adopting Lean 4.0 [20]. Companies must evaluate their readiness and maturity levels in both Lean and digital

capabilities, ensuring alignment between technological investments and Lean objectives.

B. Readiness Assessment Frameworks in Industry 4.0 and Lean 4.0

Two main types of Lean 4.0 assessment tools are used to evaluate organizational readiness and maturity in implementing Lean 4.0. Lean maturity assessment models assess an organization's current level of lean implementation, identifying areas for improvement. In contrast, lean readiness assessment models assess an organization's readiness for adopting lean principles and practices. Both are essential for a successful lean transformation, but they apply at different stages and serve different purposes.

A Maturity Assessment Tool for Lean 4.0 Implementation is a structured evaluative framework used to measure the current maturity level of an organization's processes, systems, and capabilities in adopting Lean 4.0. This tool helps organizations determine their progress in their digital Lean transformation process by assessing multiple dimensions. Each dimension is usually rated on a maturity scale, providing a diagnostic snapshot of the organization's progress and highlighting areas that need improvement. It is often used after some lean implementation to track progress and identify areas for further development.

The Lean 4.0 Readiness Assessment Tool is a structured instrument designed to evaluate an organization's readiness for implementing Lean 4.0, which involves integrating Lean manufacturing principles with Industry 4.0 technologies. This tool helps organizations identify their strengths, weaknesses, and gaps across key dimensions. The ultimate goal of the Lean 4.0 Readiness Assessment Tool is to facilitate a smooth and effective transition toward a smart, efficient, and sustainable manufacturing system aligned with Industry 4.0 paradigms. This tool is typically conducted before implementing Lean 4.0 to increase the probability of success. Table I shows lean readiness and maturity models, which were adopted from [21].

TABLE I. THE EXISTING LEAN READINESS AND MATURITY ASSESSMENT MODELS

Assessment	Developer	Dimensions
Lean Enterprise Self-Assessment Tool (LESAT)	LAI-MIT (2001)	Strategic cycle, planning cycle, and execution cycle
Renault Production System (RPS) Rocket	SPR (2004)	Operational stability (base), continuous flow and efficiency (body), innovation and excellence (nose), and people and culture (propulsion system)
The Shingo Prize Model	Utah State University (1988)	Cultural enablers, continuous improvement, and enterprise alignment
Capgemini lean model	Capgemini (2005)	Process, people, and organization
Lean capability model	Jorgensen et al. (2007)	Technical perspective, organizational perspective
Logical model of lean assessment	Hines (2011)	Strategic deployment, value stream management, people, application of lean tools and techniques, and extended enterprise
The Digital Green Lean (DGL) Maturity Model	Gatell and Avella (2024)	Digital lean business culture (values and principles, customer centricity, and operational excellence) and digital lean leadership (customer orientation, personal development, lean principles, and performance orientation)

Source: Adopted from Setianto & Haddud (2016), [21]

The frameworks for Industry 4.0 maturity and readiness are shown in Table II. Organizational readiness refers to the extent to which a company possesses the capabilities, resources, and strategic alignment necessary to adopt new technologies or operational models [22]. Several readiness assessment frameworks have been developed for Industry 4.0 adoption, but few studies have focused on a structured model specifically tailored to Lean 4.0 [23], [24]. Existing frameworks primarily evaluate technological maturity and digital infrastructure, often neglecting critical factors such as leadership commitment, workforce skills, and sustainability considerations.

For instance, the Smart Industry Readiness Index (SIRI) developed in Singapore evaluates readiness across *Process, Technology,* and *Organization* dimensions, emphasizing the role of advanced digital infrastructure and automation. Similarly, the IMPULS Industry 4.0 Readiness Model from Germany highlights technological maturity and innovation-driven strategy as core enablers of transformation. Although these models provide strong analytical frameworks for industrial digitalization, they often assume high baseline technological capacity, making them less applicable to small and medium-sized enterprises (SMEs) in emerging economies.

In the context of Indonesia, despite governmental efforts through Making Indonesia 4.0 and the INDI 4.0 Index, many firms remain at an early stage of readiness. Studies indicate that barriers include limited digital infrastructure, insufficient managerial commitment, and a lack of workforce upskilling programs. This highlights the necessity for a comprehensive, adaptive readiness model—one that not only aligns with global Lean 4.0 frameworks but also incorporates contextual factors such as leadership strategy, people and culture, and external collaboration.

Recent studies emphasize the need for multidimensional readiness models that incorporate both technological and organizational factors. For instance, recent studies emphasize the need for multidimensional readiness models that incorporate both technological and organizational factors. For instance, Kumar et al. (2020) [26] propose a readiness framework that integrates strategy, workforce capability, and process optimization. The study suggests that an effective Lean 4.0 readiness model must extend beyond technology, encompassing elements such as leadership, workforce skills, data-driven decision-making, and environmental sustainability.

TABLE II. THE EXISTING FRAMEWORKS FOR INDUSTRY 4.0 MATURITY AND READINESS

Name of the model	Developer	Dimensions
IMPULS – Industry 4.0 Readiness	Lichtblau et al. (2015)	Strategy and organization, smart factory, smart operations, smart products, data-driven services, and employees
SIMMI 4.0	Leyh et al. (2016)	Vertical integration, horizontal integration, digital product, and cross-sectional technology
Industry 4.0 / Digital Operation Self-Assessment	Price Waterhouse Coopers (2016)	Digital business and customer access, digitization of products / services, data analytics, IT infrastructure, IT architecture, security, and digital culture
Industry 4.0 readiness and maturity of manufacturing enterprises (Industry 4.0 MR)	Schumacher et al. (2016)	Products, customers, operations and technology, strategy, leadership, governance, culture, and people
Industry 4.0 readiness model (WMG)	Warwick University	Products and services, manufacturing and operations, strategy and organization, supply chain, business model, legal considerations
Industry 4.0 - MM	Gokalp et al. (2017)	IT, data governance, information flow, process transformation, and organizational structure / strategy
Digital Readiness Assessment Maturity Model (DREAMY)	De Carolis et al. (2017]	Process, monitoring and control, technology, and organization
Maturity and Readiness Model for Industry 4.0 Strategy	Akdil et al. (2018)	Smart products and services, smart business processes, strategy, and organization
Indonesia Industry 4.0 Readiness Index (INDI 4.0)	Indonesian Ministry of Industry (2018)	Management and organization, people and culture, product and services, technology, and factory operation
Industry 4.0 Maturity model	Sony et al. (2019)	Employee, level of digitalization, extent of digitalization, organizational strategy, top management involvement
360 Digital Maturity Assessment	Colli et al. (2019)	Governance, technology, value creation, connectivity, competence
The Smart Industry Readiness Index (SIRI)	EDB of Singapore	Technology (automation, connectivity, intelligence), process (operation, supply chain, product lifecycle), and organization (talent readiness, structure, and management)
Industry 4.0 Readiness Model	Hanafiah, Soomro, and Abdullah (2020)	Technology, people, strategy, leadership, process, and innovation
Industry 4.0 MR	Kumar and Akhilesh (2021)	Strategy, organization, business model, employee, manufacturing and operations, supply chain, production system, products, and services

Source: Fauskanger et al. (2023), [25] and Rahmatindar et al. (2024), [10]

C. Main References of Lean 4.0 Readiness Model

Organizational transformation — particularly when driven by digitalization or process innovations like Lean 4.0 — requires a systematic evaluation of readiness to ensure effective implementation and sustainable outcomes. A readiness assessment functions as a diagnostic mechanism to gauge an organization's capability, willingness, and preparedness for change. It helps determine whether essential foundations such as strategy, leadership, culture, and resources are properly aligned to support transformation initiatives.

Preparation models have gained significant attention in the context of digital transformation and Industry 4.0. For example, Schumacher et al. (2016) [23] proposed a maturity model to assess readiness across dimensions such as strategy, culture, IT infrastructure, and operations. Similarly, Mittal et al. (2018) [24] emphasized that small and medium-sized enterprises (SMEs) need to consider their technological capabilities, human resources, and leadership support before initiating smart manufacturing initiatives.

When it comes to Lean transformation, readiness assessment also plays a critical role. Antony et al. (2017) [27] pointed out that a lack of readiness, particularly in areas such as employee engagement, continuous improvement culture, and management commitment, can hinder Lean adoption. Integrating Lean with Industry 4.0 (i.e., Lean 4.0) introduces additional complexity, making readiness assessment even more vital.

Several frameworks have been developed to assess transformation readiness across various industries. Some studies have identified the dimensions and indicators of readiness for Lean 4.0 implementation using the SLR approach. Therefore, this approach was not used in this study. Common dimensions include Leadership and Strategic Alignment, Workforce Competency and Culture, Technological Infrastructure, Process Maturity, and Data-driven Decision-making. These dimensions often serve as the basis for constructing indicators and metrics that help companies identify gaps and prioritize areas for improvement before full-scale implementation.

IV. MODELLING LEAN 4.0 READINESS DIMENSIONS AND INDICATORS

Based on the readiness models used as the primary references, certain dimensions were identified by the experts involved in this study. The selected dimensions were then used to assign the conceptual framework, as described in Fig. 2.

The convergence between Lean Manufacturing and Industry 4.0—commonly termed Lean 4.0—has become a significant topic in industrial transformation research. Lean Manufacturing focuses on process efficiency, waste reduction, and continuous improvement, while Industry 4.0 emphasizes automation, data-driven decision-making, and cyber-physical integration. The synergy between these two paradigms enables both operational excellence and digital competitiveness. However, while advanced economies have developed mature readiness models to support digital transformation, many developing countries still face difficulties in adopting such frameworks due to contextual and infrastructural limitations.

From the selected dimensions, indicators were then identified for each dimension, based on the reference model, as well as other relevant papers or studies on the same topic. These indicators are supported by several references that mention them in their studies. It is shown in Table III.

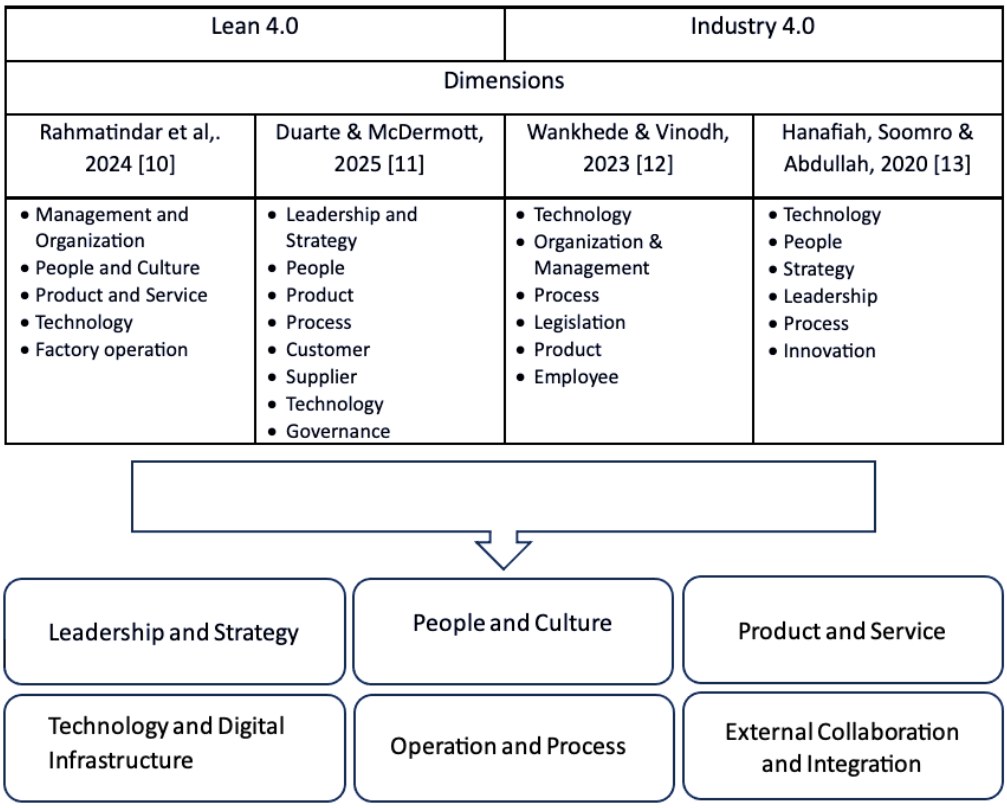


Fig. 2. The proposed dimensions used to assign the conceptual framework (adopted from [11]).

TABLE III. DIMENSIONS AND INDICATORS OF THE READINESS MODEL FOR LEAN 4.0 ADOPTION

Lean 4.0 Dimension	Indicators	Reference
Leadership and Strategy Heming *et al*. (2019), [31] Leong *et al*. (2019), [33] Letchumanan *et al*. (2022), [34] Hanafiah *et al*. (2020), [13]	Management support for Lean 4.0 transformation	[10], [13], [19], [23], [28], [29], [30], [31], [32], [34], [43]
	Commitment to active management involvement	[10], [12], [13], [15], [19], [28], [29], [30], [34], [35] [36], [37]
	Clear digital transformation vision, roadmap, and alignment with mission	[11], [12], [19], [23], [28], [29], [31], [33], [34], [38], [39], [40], [43]
	Long-term investment strategies (human, financial, and technological)	[10], [11], [12], [29], [40], [43]
	Dedicated Lean 4.0 transformation teams / Governance structure to oversee the transformation	[10], [11], [23], [29]
	Management standards, governance, and legal compliance	[11], [28], [37], [47]
	Adapt a new strategy / new business model*	[11], [19], [23], [34], [41], [42]
	Funds' availability / Financial resources*	[19], [34], [38]
	Communication and change management*	[10], [19], [28], [31]
People and Culture Nizam-Hanafiah, Soomro & Abdullah (2020), [13]	Employee skills and qualifications (Lean and Industry 4.0)*	[11], [12], [13], [19], [23], [33], [34], [37], [38], [40], [42], [43], [44], [45], [46], [47]
	Employee openness to digital transformation and continuous improvement*	[11], [12], [23], [38], [43]
	Systematic problem-solving to improve digital transformation	[11], [12], [24], [23], [30], [37], [42], [45], [48]
	The existence of structured training / workshops / certifications for Lean 4.0	[10], [11], [12], [13], [33], [34], [37], [38], [39], [40], [42], [44], [45], [46], [47]
	Employee involvement and empowerment*	[13], [33], [34], [37], [40], [46], [47]
	Culture and supportive ambiance*	[13], [34], [44]
Technology and Digital Infrastructure	Machine-to-machine (M2M]) connectivity and transparency in data flow	[10], [12], [23], [38], [42], [43], [49]
	Connectivity of systems within the company across different technical disciplines	[10]; [43], [50]

	Implementation of the Internet of Things (IoT) / Implementation of industrial automation (IoT, ERP, RFID, SCADA, PLC)	[10]; [12], [13], [40], [51]
	Conversion of manual processes to digital	[10]; [19], [43], [52], [53], [54]
	Cybersecurity implementation and training	[10]; [19]
	Implementation of big data and cloud computing*	[13], [19], [38], [40], [55], [56], [57]
	Technology for information exchange*	[13], [38]
Operation and Process	Implementation of Lean tools: First In First Out (FIFO), Just in Time (JIT), Plan-Do-Check-Act (PDCA), etc.	[10], [28], [46], [47]
	Standardization of supply chain / logistic flow / Supply chain activities improvement	[10], [37],
	Use of digital technologies in operation: automation, real-time monitoring, and Overall Equipment Effectiveness (OEE)	[10], [13], [19], [38], [43]
	The existence of performance indicators for automated processes impact on factory operations	[10]
	Real-time monitoring and control	[23], [31], [34], [37], [38], [39], [44], [45]
	Maintenance types: predictive, preventive, and corrective	[10], [43]
	Digital storage of operational data / cloud solution	[10], [34], [38], [43], [55]; [57]
	Interdepartmental collaboration*	[23]
Product and Service	Availability of product information systems for vendors / customers	[10], [12], [43]
	Data analysis from customers, business partners, and vendors	[10]
	Customer feedback mechanisms and satisfaction monitoring	[10], [43]
	Use of big data for product / service improvement	[10], [38]
	Integration of products with digital technologies	[10], [11], [12], [23], [38], [43]
External Collaboration and Integration	Use of digital channels with suppliers / customers	[11], [19], [23], [34], [38]
	Knowledge sharing and uncertainty management across companies	[11], [37], [45], [58]
	Customer involvement to lead Lean 4.0 implementation	[38], [40]
	Supplier integration and collaboration*	[11], [24], [28], [37], [38], [40], [46], [47]
	A balance between environmental, economic, and social needs for sustainability*	[19]

The results of the identification suggest that there are six (6) selected dimensions and forty-one (41) indicators. There are nine indicators for the Leadership and Strategy dimension. Three of these indicators, notably new strategy / new business, fund availability, and communication and change management, fall outside of the primary references.

For the People and Culture dimension, there are six indicators, two of which are from sources outside the main references. These indicators include employee participation and empowerment, as well as a supportive culture and environment. Technology and Digital Infrastructure have three indicators, the most important of which are big data and cloud computing implementation and information exchange technology.

All five indicators in the Product and Service dimension come from the main reference. The last dimension, External Integration, is an additional dimension that accommodates several indicators also mentioned in the main references. Two of the five indicators not mentioned in the main reference in this dimension are supplier integration and collaboration, as well as a balance between environmental, economic, and social needs for sustainability.

To supplement and refine the above dimensions and indicators, expert validation is required. Expert opinions are obtained from academics, industry professionals, and Lean practitioners. Additionally, pilot testing (in the form of case studies) was conducted, and the findings were used to refine the meta-synthesis framework.

V. Results and Discussion

The study focused on identifying the dimensions and indicators that are important for measuring a company's readiness to implement Lean 4.0 (Lean 4.0 readiness assessment model) based on the assumption that most local companies in Indonesia's Jababeka Industrial Park have not yet implemented Lean 4.0.

Based on input or suggestions from experts, the dimensions and indicators for determining a company's readiness to implement Lean 4.0 as a result of the meta-synthesis are already quite comprehensive and do not need to be added to or reduced. However, they cautioned that the proposed dimensions and indicators are still too sophisticated, especially for small and medium-sized industries. Domestic companies at that level (within the category) generally have not yet implemented or carried out most of the indicators mentioned. Even some large companies seem not to have yet, or are still struggling to apply Lean principles.

Several experts highlight the proposed dimensions based on their level of importance for the successful implementation of Lean 4.0 in companies. They argue that the most important aspect in implementing Lean 4.0 is people and their work culture, because people are the main driving force behind the

success of the transformation, even more so than the technology itself. Lean 4.0 is based on changing the mindset and behavior of the people involved in it. From this perspective, what is important at this stage is that their mindset in working is aligned with the Lean 4.0 mindset. Fundamental issues or principles related to customer satisfaction, particularly concerning quality and delivery, must be resolved thoroughly before considering technology.

The dimension of leadership and clear strategy, particularly commitment from top management, are other key aspects. Without strong leadership and commitment, as well as a clear strategy, the transformation to Lean 4.0 in a company will lack direction, support, and sustainability. Leadership provides the driving force, while strategic readiness provides the direction. Additionally, top management must also set a good example to serve as a model for their employees.

Digital technology and infrastructure are the technical foundation of Lean 4.0. With such a large volume of data transactions, processing and analysis must use tools so that the data can be utilized to its fullest potential and used as efficiently as possible. For product service delivery to customers, comprehensive customer data analysis is required. Clear information availability is crucial so that anyone with a stake in the matter (e.g., during shift changes) can immediately know what is needed or what actions must be taken.

The trend toward digitization in manufacturing systems has already begun and is currently underway. It is up to the people (human resources) to decide whether to accept it or not, whether to view it as an opportunity or a threat. This includes top management, who must understand the importance of Lean 4.0 principles.

In order to support the development of research and the application of Lean Manufacturing based on Industry 4.0 technology (Lean 4.0), blockchain technology is one of the key technologies that is very important to adopt in modern manufacturing systems. Blockchain technology plays a significant role in improving the transparency, efficiency, and reliability of information flow throughout the supply chain. By integrating blockchain with IoT technology, AI, digital tracking systems, secure and real-time business process automation, and distributed, immutable data recording, a system can be created that reduces information waste, accelerates decision-making, and reinforces Lean principles such as just-in-time, kaizen, and the elimination of non-value-added activities.

Before the large-scale data collection, a pilot test of the Lean 4.0 readiness questionnaire was conducted to evaluate the clarity, reliability, and validity of the proposed dimensions and indicators. The pilot study involved a sample of 15 respondents, consisting of production managers, lean coordinators, and digital transformation specialists from selected Indonesian manufacturing companies. Respondents were asked to complete the survey and provide feedback on the comprehensibility of each question, the appropriateness of the terminology used, and the overall structure of the survey.

Table IV shows the statistical analysis of the pilot data included reliability testing using Cronbach's alpha for each dimension. All dimensions recorded alpha values above the 0.70 threshold, indicating acceptable internal consistency. However, minor adjustments were made to the wording of certain indicators to enhance clarity and avoid technical ambiguity. Content validity was also strengthened through consultation with three academic experts and two industry practitioners, who reviewed the questionnaire to ensure alignment with Lean 4.0 principles and the Indonesian manufacturing context.

TABLE IV. CRONBACH'S ALPHA RELIABILITY RESULT

Variable	Number of items	Cronbach's Alpha	Criteria	Comment
Leadership and Strategy	9	0.807	0.7	Reliable
People and Culture	6	0.873	0.7	Reliable
Technology and Digital Infrastructure	7	0.895	0.7	Reliable
Operation and Process	8	0.807	0.7	Reliable
Product and Service	5	0.791	0.7	Reliable
External Collaboration and Integration	5	0.784	0.7	Reliable

The feedback and findings from this pilot testing served as a critical input in refining the measurement model. Ambiguous or overlapping items were revised or eliminated, while the sequence of questions was restructured to improve logical flow. As a result, the final instrument was considered robust and contextually relevant, supporting the subsequent empirical phase of readiness modelling for Lean 4.0 implementation. The dimension of Leadership and Strategy is a common dimension identified in various models, focusing on management support, management commitment, clear vision, long-term investment (in human, financial, and technological resources), a Lean team, fund availability, management standards, new business strategies, and communication. Organizations with strong leadership support tend to exhibit higher success rates in digital Lean transformation due to their ability to align organizational goals with digital strategies [20]. Indicators under this dimension typically include the existence of a Lean 4.0 roadmap, leadership involvement, and cross-functional transformation teams [23].

People and Culture is another critical dimension, as the human element plays a central role in adopting and sustaining new technologies and Lean culture. According to [24], digital literacy, lean knowledge, openness to change, and structured training programs are necessary to ensure workforce adaptability. The presence of competency development programs, employee participation in decision-making, and a culture of continuous improvement are key indicators for this dimension.

The dimension of Technology and Digital Infrastructure refers to the availability and integration of enabling technologies such as IoT, ERP systems, RFID, SCADA, big data analytics, cyber-physical systems, and information exchange. Buer et al. (2018) [15] suggest that Lean 4.0 is enhanced by real-time data and automation, which support Lean goals like waste reduction, agility, and responsiveness. Indicators in this dimension include

the implementation of digital tools, system connectivity, and cybersecurity measures.

Operation and Process integrate Lean methods (e.g., Just-in-Time, PDCA) with digital systems to enhance process performance. Key indicators include the implementation of Lean tools, the use of digital technologies in operations, standardization of the supply chain, digital storage of operational data, the existence of performance indicators for automated processes in factory operations, as well as monitoring and quality assurance, maintenance, and departmental collaboration.

The Product and Service dimension plays a pivotal role in determining an organization's readiness for Lean 4.0 implementation, particularly in enhancing customer value through data integration, feedback responsiveness, and digital innovation. The indicator 'Availability of product information systems for vendors and customers' reflects an adoption of digital platforms such as product portals, e-catalogs, and customer relationship management (CRM) tools. These systems help improve transparency, minimize information gaps, and accelerate response time—capabilities that strongly support the objectives of Lean 4.0.

The indicator 'data analysis from customers, business partners, and vendors' reflects how firms collect transactional or behavioral data and integrate and jointly analyze these datasets across the supply chain. It increases the ability to gain comprehensive insights and coordinate value stream improvements. The indicator 'Integration of products with digital technologies' demonstrates how some companies are beginning to embed sensors, connectivity modules, and smart features into their products. However, for most firms, particularly SMEs, this integration remains aspirational due to high costs, lack of technical expertise, and limited R&D investment. The indicator 'Use of big data for product/service improvement' shows the data collection at various operational touchpoints, and the capacity to analyze and apply these insights toward product innovation or service refinement. Many firms rely on basic analytics or retrospective reporting, falling short of leveraging predictive analytics or AI-driven decision-making, which are integral to a Lean 4.0 approach [20]. Lastly, the indicator 'Customer feedback mechanisms and satisfaction monitoring' is how companies adopt digital survey tools, post-purchase feedback systems, and service-level monitoring. However, the challenge lies in translating this feedback into rapid, systemic improvements — a key Lean principle that remains underutilized.

The External Collaboration and Integration dimension reflects an organization's ability to build, sustain, and digitally enable relationships with key stakeholders such as suppliers, customers, and business partners. In the context of Lean 4.0, collaboration is no longer limited to operational coordination but extends toward the integration of digital technologies, joint value creation, and sustainability-oriented partnerships. The key indicators include supplier collaboration and integration; use of digital channels with suppliers/customers; knowledge sharing and uncertainty management across companies; customer involvement to lead Lean 4.0 implementation; and a balance between environmental, economic, and social needs for sustainability.

Table V shows a proposed Lean 4.0 Readiness model. Compared to other models for measuring readiness to implement Lean Manufacturing and Industry 4.0, this model is more comprehensive. INDI 4.0, which emphasizes readiness to implement Industry 4.0, consists of five dimensions: Management and Organization, People and Culture, Products and Services, Technology, and Factory and Operations. Rahmatindar's model, which draws on INDI 4.0 as its primary reference, focuses on Lean 4.0. It has the same five dimensions as INDI 4.0, but it includes 69 indicators. The additional dimension in this model is External Collaboration and Integration. This is because in digital transformation, the relationships between industry or companies with suppliers and customers are inevitable.

The dimensions of Management and Organization in this model are slightly different, namely, Leadership and Strategy. The Technology dimension in this model includes Digital Infrastructure. Meanwhile, Factory Operations are referred to as Operation and Process. There are fewer indicators in this model compared to Rahmatindar's, because several indicators have been combined into one; for example, the implementation of IoT, ERP, RFID, SCADA, and PLC has been combined into the implementation of industrial automation.

TABLE V. PROPOSED MODEL OF KEY DIMENSIONS AND INDICATORS FOR LEAN 4.0 READINESS

Dimension	Indicator
Leadership and Strategy	Management support for Lean 4.0 transformation
	Commitment to active management involvement
	Clear digital transformation vision, roadmap, and alignment with mission
	Long-term investment strategies (human, financial, and technological)
	Dedicated Lean 4.0 transformation teams
	Funds' availability
	Management standards, governance, and legal compliance
	New business strategy / model
	Communication and change management
People and Culture	Employee skills and qualifications

Dimension	Indicator
	Employee openness to digital transformation and continuous improvement
	Systematic competency development
	The existence of structured training / workshops / certifications for Lean 4.0
	Employee involvement (decision participation) and empowerment
	Culture and supportive ambiance
Technology and Digital Infrastructure	Implementation of industrial automation (IoT, ERP, RFID, SCADA, PLC)
	Machine-to-machine (M2M) connectivity and transparency in data flow
	Connectivity of systems within the company across different technical disciplines
	Implementation of big data and cloud computing
	Conversion of manual processes to digital
	Technology for information exchange
	Cybersecurity implementation and training
Operation and Process	Implementation of Lean tools: First In First Out (FIFO), Just in Time (JIT), Plan-Do-Check-Act (PDCA)
	Use of digital technologies in operation: automation, real-time monitoring, and Overall Equipment Effectiveness (OEE)
	Standardization of supply chain / logistic flow
	Digital storage of operational data / cloud solution
	The existence of performance indicators for automated processes impact on factory operations
	Continuous monitoring and quality assurance
	Maintenance types: predictive, preventive, and corrective
	Interdepartmental collaboration
Product and Service	Availability of product information systems for vendors / customers
	Data analysis from customers, business partners, and vendors
	Integration of products with digital technologies
	Use of big data for product / service improvement
External Collaboration and Integration	Customer feedback mechanisms and satisfaction monitoring
	Supplier collaboration and integration
	Use of digital channels with suppliers / customers
	Customer involvement to lead Lean 4.0 implementation
	A balance between environmental, economic, and social needs for sustainability

VI. Conclusion

This study has developed and modelled a comprehensive set of dimensions and indicators for assessing organizational readiness for Lean 4.0 implementation, focused on digital transformation. The proposed framework integrates lean principles with Industry 4.0 technologies, emphasizing not only operational efficiency but also digital capability, external collaboration, and sustainability. Through literature review, expert validation, and pilot testing, the model was refined to include dimensions such as product and service readiness, process and technology integration, workforce capability, external collaboration and integration, and leadership and strategic alignment.

Findings indicate that while many organizations demonstrate moderate readiness in areas such as supplier collaboration, digital channel adoption, and basic lean practices, significant gaps remain in advanced digital integration, systematic competency development, and sustainability-driven collaboration. In particular, customer co-creation, data-driven decision-making, and alignment between environmental, economic, and social objectives require further development to fully realize the potential of Lean 4.0.

The readiness model contributes to both theory and practice by offering a structured approach to evaluate an organization's readiness, enabling targeted improvement strategies before full-scale Lean 4.0 deployment. This study will be continued by creating and applying an instrument protocol based on findings in Table V. Empirical data collected from a survey using the instrument is needed in the next work.

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References

[1] Bhanu Prakash Sah, Nadia Islam Tanha, Md Arafat Sikder, and S M Habibullah, "The Integration of Industry 4.0 and Lean Technologies in Manufacturing Industries: A Systematic Literature Review". International

Journal of Management Information Systems and Data Science, vol. 1 no. 3, 2024, pp. 14-25.

[2] Shirin Begum, Sayeda Sufia Sumi, "Strategic Approaches To Lean Manufacturing In Industry 4.0: A Comprehensive Review Study". Academic Journal On Science, Technology, Engineering & Amp; Mathematics Education, vol. 04 issue 03 (2024): pp. 195-212

[3] L. Naciri, Z. Mouhib, M. Gallab, M. Nali, R. Abbou, A. Kebe, "Lean and industry 4.0: A leading harmony". Procedia Computer Science, vol. 200, 2022, pp. 394-406, ISSN 1877-0509.

[4] Luana Sposito Valamede & Alessandra Cristina Santos Akkari, "Lean 4.0: A New Holistic Approach for the Integration of Lean Manufacturing Tools and Digital Technologies". International Journal of Mathematical, Engineering and Management Sciences, vol. 5 no. 5, 2020, pp. 851-868.

[5] Rosin Frédéric, Pascal Forget, Samir Lamouri, and Robert Pellerin, "Impacts of Industry 4.0 Technologies on Lean Principles". International Journal of Production Research, vol. 58 issue 6, 2020, pp. 1644–1661.

[6] Pusat Statistik (BPS). "Statistical Yearbook of Indonesia 2024".

[7] United Nations Industrial Development Organization. (UNIDO). "Industrial development report 2023: Industrialization in a digital age".

[8] World Economic Forum (WEF), "Global Competitiveness Report", 2023.

[9] Hasbullah, Hasbullah, and Salleh Ahmad Bareduan, "Capturing the Reality of Industry 4.0 Readiness Dimensions and Indicators in a Developing Country: An Analysis of Applying Industry 40 in Indonesia", The South African Journal of Industrial Engineering, vol. 34 no. 2, 2023, pp. 61-78.

[10] Rahmatindar, P.O, Singgih, M.L, & Karningsih P.D, "Development of Lean 4.0 Readiness Assessment Tool", Jurnal Teknobisnis, vol. 10 no. 1, 2024, pp. 46-56.

[11] Duarte, S., & Mc Dermott, O., "The dimensions of Lean-Green 4.0 readiness a Systematic literature review", Production Planning & Control, vol. 36 issue 9, 2025, pp. 1175–1187.

[12] Wankhede, V.A. and Vinodh, S., "Benchmarking Industry 4.0 readiness evaluation using fuzzy approaches", Benchmarking: An International Journal, vol. 30 no. 1, 2023, pp. 281-306.

[13] Hizam-Hanafiah M, Soomro MA, Abdullah NL., "Industry 4.0 Readiness Models: A Systematic Literature Review of Model Dimensions", Information, vol. 11 no. 7, 2020, pp. 364.

[14] Womack, J. P., & Jones, D. T. (1997), "Lean Thinking - Banish Waste and Create Wealth in your Corporation". Journal of the Operational Research Society, vol. 48 issue 11, 2017, pp. 1148.

[15] Buer, Sven-Vegard, Jan Ola Strandhagen, and Felix T. S. Chan, "The Link between Industry 4.0 and Lean Manufacturing: Mapping Current Research and Establishing a Research Agenda, " International Journal of Production Research 56 (8), 2018, pp. 2924–2940.

[16] Dennis Kolberg, Detlef Zühlke, "Lean automation enabled by Industry 4.0 technologies", IFAC-PapersOnLine, vol. 48 issue 3, 2015, pp. 1870–1875.

[17] Sanders, A., Elangeswaran, C., & Wulfsberg, J. P., "Industry 4.0 implies Lean Manufacturing: Research activities in Industry 4.0 function as enablers for Lean Manufacturing", Journal of Industrial Engineering and Management, vol. 9 no. 3 10, 2016, pp. 456–482.

[18] Tortorella, Guilherme Luz, and Diego Fettermann, "Implementation of Industry 4.0 and Lean Production in Brazilian Manufacturing Companies, " International Journal of Production Research 56 (8), 2017, pp. 2975–2987.

[19] Michael Sony, Shubash Naik, "Key factors for the successful implementation of Industry 4.0 in manufacturing organizations", Technology in Society, vol. 61, 2020, 101248, ISSN 0160-791X.

[20] Rossini, M., Costa, F., Tortorella, G.L. et al., "The interrelation between Industry 4.0 and lean production: an empirical study on European manufacturers", The International Journal of Advanced Manufacturing Technology, vol. 102, 2019, pp. 3963–3976.

[21] Setianto, P. and Haddud, A., "A maturity assessment of lean development practices in manufacturing industry", International Journal of Advanced Operations Management (IJAOM), vol. 8 no. 4, 2016, pp. 294–322.

[22] Weiner, B. J. "A theory of organizational readiness for change". Implementation Science, vol. 4 no. 67, 2009.

[23] Schumacher, A., Erol, S., & Sihn, W., "A maturity model for assessing Industry 4.0 readiness and maturity of manufacturing enterprises", Procedia CIRP, vol. 52, 2016, pp. 161–166.

[24] Mittal, S., Khan, M. A., Romero, D., & Wuest, T., "A critical review of smart manufacturing & Industry 4.0 maturity models: Implications for small and medium-sized enterprises (SMEs)", Journal of Manufacturing Systems, vol. 49, 2018, pp. 194–214.

[25] Fauskanger, E., Fatenni, D. & Powell, D., "Towards an assessment model for Lean and Green 4.0", Journal of International Doctoral Research, vol. 10 no. 1, 2023.

[26] Kumar, R., Kr. Singh, R., Kr. Dwivedi, Y., "Application of industry 4.0 technologies in SMEs for ethical and sustainable operations: Analysis of challenges", Journal of Cleaner Production, vol. 275, 2020, 124063, ISSN 0959-6526.

[27] Jiju Antony, Ronald Snee, Roger Hoerl, "Lean Six Sigma: yesterday, today and tomorrow", International Journal of Quality & Reliability Management, vol. 34 issue 7, 2017, pp. 1073–1093.

[28] Hines P., "How to create and sustain a lean culture", Development and Learning in Organizations: An International Journal, vol. 24 no. 6, 2010.

[29] Khourshed, Nevien Farouk, Sahar Sobhy Elbarky, and Sarah Elgamal, "Investigating the Readiness Factors for Industry 4.0 Implementation for Manufacturing Industry in Egypt", Sustainability, vol. 15 no. 12, 2023, pp. 9641.

[30] Ananya Bhattacharya, Alka Nand, Pavel Castka, "Lean-green integration and its impact on sustainability performance: A critical review", Journal of Cleaner Productio, vol. 236, 2019, 117697, ISSN 0959-6526.

[31] Helming, S., F. Ungermann, N. Hierath, N. Stricker, and G. Lanza. "Development of a Training Concept for Leadership 4.0 in Production Environments". Procedia Manufacturing, vol. 31, 2019, pp. 38–44.

[32] Wagire, Aniruddha Anil, Rohit Joshi, Ajay Pal Singh Rathore, and Rakesh Jain, "Development of Maturity Model for Assessing the Implementation of Industry 4.0: Learning from Theory and Practice", Production Planning & Control, vol. 32 no. 8, 2020, pp. 603–622.

[33] Leong, W.D., Lam, H.L., Ng, W.P.Q. et al., "Lean and Green Manufacturing — a Review on its Applications and Impacts", Process Integration and Optimization of Sustainability, vol. 3, 2019, pp. 5–23.

[34] Letchumanan, L. Thiruvarasu, Hamed Gholami, Noordin Mohd Yusof, Nor Hasrul Akhmal Bin Ngadiman, Anas A. Salameh, Dalia Štreimikienė, and Fausto Cavallaro, "Analyzing the Factors Enabling Green Lean Six Sigma Implementation in the Industry 4.0 Era", Sustainability, vol. 14 no. 6, 2022, pp. 3450.

[35] Schmidt, R., Möhring, M., Härting, RC., Reichstein, C., Neumaier, P., Jozinović, P., "Industry 4.0 - Potentials for Creating Smart Products: Empirical Research Results. In: Abramowicz, W. (eds) Business Information Systems", BIS 2015. Lecture Notes in Business Information Processing, vol. 208, 2015, Springer, Cham.

[36] S. Shamim, S. Cang, H. Yu and Y. Li, "Management approaches for Industry 4.0: A human resource management perspective", IEEE Congress on Evolutionary Computation (CEC), Vancouver, BC, Canada, 2016, pp. 5309-5316.

[37] Duarte, S., and V. Cruz Machado, "Green and Lean Implementation: An Assessment in the Automotive Industry", International Journal of Lean Six Sigma 8 (1), pp. 65–88.

[38] Schumacher, A., T. Nemeth, and W. Sihn, "Road mapping towards Industrial Digitalization Based on an Industry 4.0 Maturity Model for Manufacturing Enterprises", 12th CIRP Conference on Intelligent Computation in Manufacturing Engineering, 18–20 July 2018, Gulf of Naples, Italy, vol. 79, 2019, pp. 409–414.

[39] Duarte, S., "Lean-Green 4.0: A Starting Point for an Assessment Model", In: McDermott, O., Rosa, A., Sá, J.C., Toner, A. (eds) Lean, Green and Sustainability", ELEC 2022, IFIP Advances in Information and Communication Technology, vol. 668, 2022, Springer, Cham.

[40] Ghaithan, Ahmed, Mohammed Khan, Awsan Mohammed, and Laith Hadidi, "Impact of Industry 4.0 and Lean Manufacturing on the Sustainability Performance of Plastic and Petrochemical Organizations in Saudi Arabia", Sustainability vol. 13 no. 20: 11252.

[41] Müller, Julian Marius, Daniel Kiel, and Kai-Ingo Voigt, "What Drives the Implementation of Industry 4.0? The Role of Opportunities and Challenges in the Context of Sustainability", Sustainability, vol. 10 no. 1: pp. 247.

[42] Ibarra, D., J. Ganzarain, and J. I. Igartua, "Business Model Innovation through Industry 4.0: A Review", 11th International Conference Interdisciplinarity in Engineering, INTER-ENG 2017, Tirgu Mures, Romania, vol. 22, 5–6 October 2017, pp. 4–10.

[43] Indonesia Ministry of Industry. Indonesia Industry 4.0 Readiness Index. 2018.

[44] Mahender Singh Kaswan, Rajeev Rathi, Jennifer Cross, Jose Arturo Garza-Reyes, Jiju Antony, Vishwas Yadav, "Integrating Green Lean Six Sigma and industry 4.0: a conceptual framework", Journal of Manufacturing Technology Management, vol. 34 (1), 2023, pp. 87–121.

[45] Ramos, A. R., J. C. E. Ferreira, V. Kumar, J. A. Garza-Reyes, and A. Cherrafi, "A Lean and Cleaner Production Benchmarking Method for Sustainability Assessment: A Study of Manufacturing Companies in Brazil", Journal of Cleaner Production 177, 2018, pp. 218–231.

[46] Verrier, B., B. Rose, and E. Caillaud, "Lean and Green Strategy: The Lean and Green House and Maturity Deployment Model", Journal of Cleaner Production 116, 2016, pp. 150–156.

[47] Brito, M.F., Ramos, A.L., Carneiro, P. and Gonçalves, M.A., "A continuous improvement assessment tool, considering lean, safety and ergonomics", International Journal of Lean Six Sigma, vol. 11 no. 5, 2018, pp. 879-902.

[48] N.H. Hayri, "Industry 4.0 impact on franchising network governance", 14th International Conference on Knowledge, Economy and Management Proceedings, Istanbul, 2018, pp. 191-196.

[49] H. Dora, and S.R. Zs., "Driving forces and barriers of Industry 4.0: do multinational and small and medium-sized companies have equal opportunities?", Technological Forecasting and Social Change, Vol. 146, 2019, pp. 119-132.

[50] B. Methavitakul and S. Santiteerakul, "Analysis of key dimension and sub-dimension for Supply Chian of Industry to fourth Industry Performance Measurement", IEEE International Conference on Service Operations and Logistics, and Informatics (SOLI), Singapore, 2018, pp. 191-195.

[51] P.B. Anthon, "Rapidly Arriving Futures: Future Readiness for Industry 4.0". The South African Journal of Industrial Engineering, vol. 29 (3), 2018, pp. 148-160.

[52] S. Jan, K. Matthias, K. Felix, L. Armin, V. Alexander, "Making existing production systems Industry 4.0-ready", Prod. Eng. Res. Devel. **9**, 2015, 143–148.

[53] L, Bassi, "Industry 4.0: Hope, hype or revolution?", IEEE 3rd International Forum on Research and Technologies for Society and Industry (RTSI), Modena, Italy, 2017, pp. 1-6.

[54] S. Zanero, "Cyber-physical systems", Computer 50 (4), 2017, pp. 14-16.

[55] A, Thabit., G.S. Zsigmond, and P. Szilard, "Cloud computing and big data in the context of industry 4.0: opportunities and challenges", (No. 7508667), Proceedings of the Proceedings of the IISES Annual Conference, International Institute of Social and Economic Sciences, Sevilla, 2018, pp. 9-15.

[56] S. Francesco, "Digital Twin Technology in the Industry 4.0 Context", Doctoral dissertation, Politecnico di Torino, Turin, 2019.

[57] P. Samaranayake, K. Ramanathan and T. Laosirihongthong, "Implementing industry 4.0 — A technological readiness perspective," IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Singapore, 2017, pp. 529-533.

[58] S. Rodrigues, Vasco, and M. Kumar, "Synergies and Misalignments in Lean and Green Practices: A Logistics Industry Perspective", Production Planning & Control, vol. 30 (5–6), 2019, pp. 369–384.

Autonomous Blockchain-Enabled Security Framework for Smart Grids Using Adaptive AI

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***Abstract*—The increasing interconnectivity of smart grids exposes critical energy infrastructure to more sophisticated cyber threats, necessitating adaptable and auditable security measures. This study presents a blockchain-enabled, self-improving intrusion detection system (IDS) that integrates a permissioned blockchain, autonomous governance loops, and a hybrid CNN–LSTM detector. The platform retrains models across federated nodes using blockchain-anchored data, facilitates automatic containment through smart contracts, and permanently stores validated alarms. Following multiple self-improvement cycles, the system enhances its performance from an initial 94.5% accuracy and 4.2% false positive rate (FPR) to 98.1% accuracy, a 97.6% detection rate (recall), and a 2.1% FPR in simulated tests. In comparison to baselines, a blockchain-only IDS recorded 94.1% accuracy with a 4.8% FPR, while a conventional machine learning-based IDS achieved 92.7% accuracy with a 5.4% FPR. Operationally, blockchain anchoring provided a throughput of approximately 1,200 transactions per second with an average transaction latency of about 1.5 seconds. The combined detect-to-contain latency for high-severity events was approximately 3.2 seconds. These findings demonstrate that a scalable, low-FPR, and rapid-response security paradigm for modern smart grids can be achieved by integrating adaptive artificial intelligence with decentralized, robust governance.**

Keywords*—Smart Grid Security; intrusion detection system (IDS); adaptive AI; deep learning; false data injection (FDI) attacks; cyber-physical systems (CPS)

I. Introduction

Recent advancements in power systems have facilitated a rapid transition to smart grids, offering new opportunities for sustainability, automation, and efficiency. However, this transition has also introduced significant security challenges. Smart grids, which depend on the extensive integration of distributed energy resources, Internet of Things (IoT) devices, and information and communication technologies (ICTs) [1], enable intelligent decision-making, dynamic load balancing, and real-time monitoring. Despite these benefits, the increased connectivity renders the grid susceptible to various cybersecurity threats, including replay attacks, false data injection (FDI), denial-of-service (DoS), and probing attempts [2]. If not adequately addressed, these threats could compromise the availability, confidentiality, and integrity of critical energy infrastructure.

Traditional security solutions, primarily based on standalone machine learning models or rule-based intrusion detection systems (IDS) [3], often struggle to detect complex and dynamic cyberattacks. These methods are vulnerable to advanced persistent threats and zero-day attacks due to their reliance on static learning patterns or predefined signatures [4]. In recent years, deep learning techniques, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks [5], have demonstrated enhanced performance in identifying complex attack patterns by extracting both spatial and temporal information from network traffic data [6]. Hybrid approaches that integrate CNN and LSTM have been shown to significantly improve detection accuracy by leveraging the complementary strengths of both models [7].

Concurrently, blockchain technology has emerged as a potential solution for enhancing trust, transparency, and decentralization in smart grid operations. Blockchain facilitates decentralized access control, tamper-proof data sharing among distributed entities, and immutable tracking of security events [8]. Consensus algorithms such as Proof-of-Authority (PoA) enable high-throughput, energy-efficient blockchain networks, making them suitable for real-time smart grid applications [9]. By integrating blockchain technology with AI-based intrusion detection systems, a decentralized, reliable, and trustworthy cybersecurity framework for smart grids can be established [10].

A significant limitation of current smart grid cybersecurity frameworks is their lack of flexibility and autonomy. Most contemporary systems heavily rely on human operators for model updates, policy enforcement, and attack response strategies, which introduces vulnerabilities and delays response times. To address this, researchers are exploring autonomous AI-driven security solutions capable of self-improvement [11]. These systems continuously retrain and refine their models using feedback data to reduce false positives and enhance detection accuracy over time [12].

In this study, we propose an AI-Based Intrusion Detection Autonomous Blockchain-Enabled Smart Grid Security Framework that integrates three critical components:

- An intrusion detection system that combines CNN and LSTM for accurate identification of both known and novel threats.
- A blockchain layer with smart contracts to ensure tamper-proof security event tracking, decentralized trust, and transparency.

- A self-improvement and autonomy cycle that enables the IDS to dynamically adapt to emerging attack patterns with minimal human intervention.

The contributions of this work are summarized as follows:

- We have developed an Intrusion Detection System (IDS) utilizing deep learning techniques, which surpasses both standalone deep learning models and traditional machine learning approaches in terms of detection efficacy.
- We propose a decentralized security framework for smart grids, underpinned by blockchain technology, which ensures low latency, high throughput, and energy-efficient operations.
- In real-time smart grid environments, we introduce an autonomous self-improvement mechanism that enables the IDS to continuously adapt to emerging cyber threats.

Although individual elements like blockchain-based logging, deep learning-based intrusion detection, and adaptive security mechanisms have been studied separately in previous research, this work advances the state of the art by tightly coupling them into an autonomous security framework that is governance-aware. The suggested solution uses blockchain consensus to verify feedback and regulate which events are allowed into the retraining pipeline, rather than just logging incursion occurrences on the blockchain. By guaranteeing that model evolution is solely motivated by solid, verifiable facts, this architecture immediately tackles a significant drawback of adaptive IDS techniques, namely, sensitivity to poisoned feedback and unreliable labels. Consequently, the system creates a safe autonomous loop where established operational policies and cryptographic trust jointly regulate learning, decision-making, and reaction.

II. Literature Review

In recent years, there has been significant interest in the integration of blockchain technology and artificial intelligence (AI) within smart grid scenarios. The literature on intrusion detection in smart grids, blockchain-based security, and autonomous energy systems offers valuable insights into the development of robust and adaptable infrastructures. This section examines prior research in three primary areas: 1) the application of deep learning and machine learning for intrusion detection in smart grids; 2) the utilization of blockchain technology to secure grid operations; and 3) the development of autonomous and self-improving systems for critical infrastructures.

A. Intrusion Detection in Smart Grids

Intrusion detection systems (IDS) are crucial for safeguarding smart grids against cyberattacks, including replay, denial of service, and false data injection. Traditional machine learning (ML) techniques, such as support vector machines, random forests, and decision trees, have been extensively employed for anomaly detection in power systems. For instance, Q. Li et al. [13] demonstrated the efficacy of ML classifiers in identifying false data injection attacks (FDIAs) but highlighted their limited adaptability to evolving attack techniques. Similarly, Ozay et al. [14] investigated both supervised and unsupervised learning methods, finding that while detection rates were commendable, the false positive rate increased in dynamic environments. The limitations of conventional ML approaches have prompted the adoption of deep learning (DL) techniques, which offer enhanced feature extraction and temporal pattern recognition. Recurrent neural networks (RNNs), particularly Long Short-Term Memory (LSTM) models, have been shown to capture sequential dependencies in smart grid communication traffic [15]. Convolutional Neural Networks (CNNs) have also been utilized for intrusion detection to automatically learn discriminative spatial features [16]. More recently, hybrid CNN–LSTM models, which integrate spatial and temporal learning capabilities, have demonstrated improved detection accuracy, providing resilience against both established and emerging cyber threats [17].

B. Blockchain for Smart Grid Security

In decentralized grid systems, blockchain has emerged as a promising solution for securing communication records and energy transactions. By ensuring immutability and transparency, blockchain mitigates the risks of insider attacks and single points of failure. Aitzhan and Svetinovic [18] proposed a blockchain-based system for peer-to-peer energy trading that ensures secure and auditable transactions. Mengelkamp et al. [19] also explored the application of blockchain in microgrids, focusing on accountability and trust in distributed energy markets. In cybersecurity, blockchain has been employed to automate response mechanisms using smart contracts and to secure intrusion detection logs. J. Kang et al. [20] introduced a consortium blockchain approach to enhance data integrity in vehicle-to-grid (V2G) connections and ensure tamper-proof monitoring of anomalies. This approach was further advanced by X. Chen et al. [21], who combined blockchain technology with edge computing to reduce latency while maintaining security in distributed smart grid applications. These studies illustrate how blockchain's decentralized trust, transparency, and secure data storage can enhance AI-driven IDS.

C. Autonomous and Self-Improving Systems

In the context of smart grids, autonomy denotes a system's ability to minimize human intervention, adapt to dynamic conditions, and learn from operational data. Reinforcement learning (RL) and continuous feedback mechanisms have been extensively investigated for purposes of energy optimization and anomaly adaptation [22]. For instance, D. Singh et al. [23] proposed an RL-based framework for adaptive energy distribution, which demonstrated enhanced resilience and efficiency. However, there remains a paucity of research concerning the application of autonomous learning in security. Recent studies have focused on self-improving intrusion detection system (IDS) frameworks that employ feedback loops to retrain models based on newly identified attack vectors. Q. Lu et al. [24] proposed an adaptive intrusion detection system that sustains performance over time by updating its decision boundaries in response to emerging threats. Moreover, when blockchain technology is integrated with autonomous AI systems, retrained models can be securely shared among distributed entities, thereby enhancing collective resilience [25]. Table I delineates the pertinent efforts in AI and Blockchain for Smart Grid Security.

TABLE I. SUMMARY OF RELATED WORK IN AI AND BLOCKCHAIN FOR SMART GRID SECURITY

Paper	Focus Area	Approach / Methodology	Contribution	Limitations
[13] Q. Li et al.	Intrusion Detection (ML)	Data-driven ML classifiers for detecting FDIAs	Demonstrated effectiveness of ML in FDIA detection	Limited adaptability to new attack strategies
[14] Ozay et al. (2016)	Intrusion Detection (ML)	Supervised & unsupervised ML for attack detection	Reasonable detection rates in smart grids	High false positive rates in dynamic settings
[15] R. Rahul et al.	Intrusion Detection (DL)	LSTM-based IDS for adaptive detection	Captures sequential traffic dependencies	Computationally intensive; scalability concerns
[16] S. Tufail er al.	Intrusion Detection (Survey)	Survey of cybersecurity threats & countermeasures	Comprehensive taxonomy of smart grid attacks	No novel detection mechanism proposed
[17] N. Hamdi	Hybrid IDS (DL)	CNN–LSTM hybrid deep learning IDS	Improved detection accuracy & robustness	Still dependent on large training datasets
[18] Aitzhan and Svetinovic	Blockchain in Energy Trading	Multi-signature blockchain for P2P trading	Secure, auditable transactions in decentralized grids	Scalability and energy cost issues
[19] Mengelkamp et al.	Blockchain in Microgrids	Blockchain for market trust and accountability	Demonstrated real-world microgrid application	Limited to localized microgrids
[20] J. Kang et al.	Blockchain for Security	Consortium blockchain in V2G networks	Tamper-proof anomaly logging	Potential latency in large-scale deployments
[21] X. Chen et al.	Blockchain + Edge	Blockchain integrated with edge computing	Reduced latency with secure communication	Complexity in distributed coordination
[22] Y. Li et al.	Autonomy (RL in Smart Grids)	Reinforcement learning for energy optimization	Adaptive, efficient energy distribution	Focused on energy, not cybersecurity
[23] D. Singh et al.	Adaptive Energy Distribution	RL-based self-learning for distribution	Enhanced efficiency and resilience	Security dimension not addressed
[24] Q. Lu et al.	Adaptive IDS	Feedback-based IDS retraining	Sustained detection performance	Overhead in continuous retraining
[25] F. Casino et al.	Blockchain Applications (Review)	Systematic literature review of blockchain uses	Broad classification and open issues	Lacks specific focus on IDS integration

D. Summary, Research Gaps, and Motivation

The reviewed literature reveals significant progress in the development of intrusion detection systems (IDS) for smart grids. Machine learning and deep learning models, such as Support Vector Machines (SVMs), Convolutional Neural Network–Long Short-Term Memory (CNN–LSTM) hybrids, and Recurrent Neural Network (RNN)-based architectures, have shown promising accuracy in detecting cyber-physical threats, including false data injection. However, these models often lack adaptability; once trained, they frequently fail to generalize to novel and evolving attack strategies. Additionally, they are unsuitable for real-time deployment in dynamic smart grid environments due to their reliance on large volumes of labeled training data, which may be unavailable for emerging attack types. Furthermore, many machine learning-based systems suffer from class imbalance issues, leading to significant false negatives—an unacceptable risk in critical infrastructure—where benign events often outnumber attack instances.

Conversely, blockchain-based techniques offer enhanced security, auditability, and transparency through features such as distributed trust mechanisms and immutable logging. Nonetheless, these methods have certain limitations. Due to high latency and computational costs, most current blockchain-based IDS frameworks are not suitable for high-throughput environments like power grids. Scalability remains a significant challenge, as real-time detection performance may be adversely affected by larger block sizes or longer consensus times. Moreover, many blockchain-only systems prioritize secure transaction management over proactive intrusion detection, leaving substantial gaps in attack mitigation and prevention.

Reinforcement learning and adaptive feedback-based techniques have begun to address the challenge of evolving attacks by enabling retraining or continuous policy adjustments. However, these efforts, which often concentrate on energy management optimization rather than comprehensive intrusion detection, remain fragmented and isolated. Notably, no single framework integrates:

- AI's predictive capabilities for real-time detection;
- Blockchain's transparency and trust for secure information exchange; and
- The adaptability of self-improvement loops for evolving cyber threats.

This analysis underscores a critical research gap: while previous efforts provide partial solutions, none offer a scalable, secure, and adaptive IDS that integrates continuous self-learning, blockchain-based trust mechanisms, and AI-driven detection. Our proposed approach addresses this gap by introducing an innovative autonomous blockchain-enabled IDS that incorporates self-improvement cycles to dynamically adapt to new and sophisticated attack vectors and integrates robust machine learning models with blockchain for secure, tamper-proof data exchange.

III. PROPOSED SYSTEM AND METHODOLOGY

The proposed framework's methodology focuses on integrating smart contracts and blockchain-enabled logging with an AI-based intrusion detection system (AI-IDS), supported by cycles of self-improvement and autonomous loops. Through automated yet transparent processes, the architecture ensures that cyber vulnerabilities in smart grids are identified at an early stage, documented irreversibly, and addressed. The proposed system design is illustrated in Fig. 1.

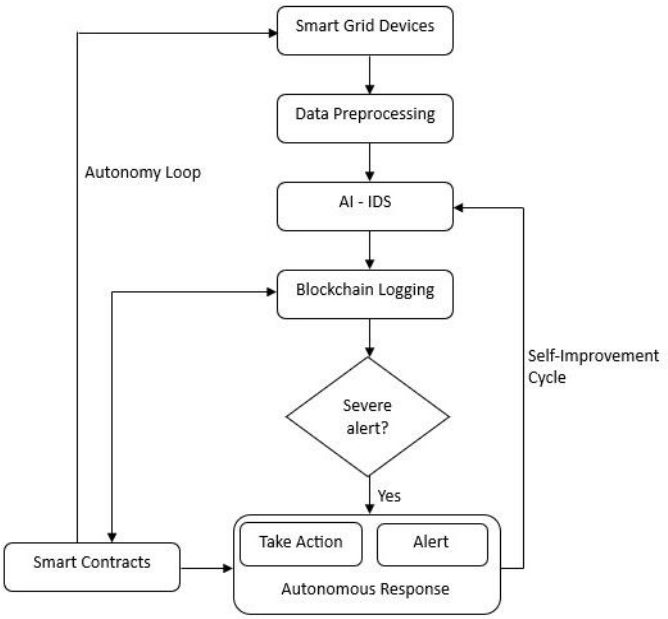


Fig. 1. Proposed system architecture.

A. Data Acquisition and Preprocessing

The initial phase involves the collection of data from smart grid infrastructures, including smart meters, phasor measuring units (PMUs), Internet of Things devices, and distributed energy resources. Preprocessing is essential before inputting the data into the AI-IDS, as these systems generate substantial volumes of noisy and heterogeneous data. Preprocessing activities, such as value normalization, removal of duplicate or distorted entries, and temporal correlation analysis, are employed to discern correlations in time-series data, such as fluctuations in power load. Furthermore, feature extraction algorithms are utilized to derive valuable attributes, including packet size, source and destination addresses, network protocol types, device usage rates, and system anomaly indicators. This process ensures that high-quality, representative input features are employed to train the subsequent learning models, thereby enhancing the reliability of intrusion detection.

B. AI-Based Intrusion Detection System (AI-IDS)

The proposed system is founded on a hybrid intrusion detection system (IDS) that integrates deep learning and traditional machine learning techniques. Convolutional Neural Networks (CNNs) are employed to identify spatial patterns in traffic flows, while deep learning models such as Long Short-Term Memory (LSTM) networks are utilized to capture temporal relationships in network traffic. These models are complemented by machine learning classifiers like Random Forest and XGBoost, which are proficient in handling structured datasets and detecting known attack signatures. The IDS generates an alert accompanied by a severity score to classify detected anomalies as low, medium, or high risk. Notably, the IDS operates in an autonomous loop, meaning its predictions directly influence automatic mitigation actions executed by smart contracts, in addition to notifying system administrators. This ensures real-time responses in critical attack scenarios without necessitating human intervention.

C. Blockchain-Based Logging

Each alert generated by the IDS is recorded on a blockchain ledger along with the associated metadata. This process ensures immutability, transparency, and non-repudiation of forensic evidence, which is crucial for post-event analysis and regulatory compliance. Every transaction stored on the blockchain includes details such as the timestamp, device identifier, detected anomaly type, and IDS confidence score. The decentralized nature of blockchain technology prevents adversaries from altering or erasing evidence of an attack, thereby enhancing accountability. To achieve scalability and reduce transaction latency, the blockchain layer is implemented using a private Ethereum-based network, making it suitable for real-time smart grid scenarios.

D. Decision-Making and Smart Contracts

The decision engine functions as an intermediary between the blockchain system and the AI-IDS. The severity of alerts dictates the level of automated response initiated. Medium-severity alerts may prompt limited actions, such as temporarily restricting device access or decelerating suspicious traffic, whereas low-severity events are primarily documented on the blockchain without further intervention. Conversely, high-severity alerts activate pre-configured smart contracts that can promptly isolate compromised devices, block unauthorized access, or reroute network traffic to ensure service continuity. These smart contracts, operating autonomously on the blockchain, adhere to strict logic, thereby ensuring swift and impartial responses to cyber threats. Simultaneously, system administrators are notified for oversight, achieving a balance between automation and human supervision.

E. Self-Improvement Cycle

A distinctive feature of the proposed approach is the self-improvement cycle that enables the IDS to evolve over time. The blockchain ledger provides a dependable dataset for retraining and optimizing detection algorithms, as it encompasses both true positives and false positives. This process allows the IDS to adapt to evolving threat behaviors and incrementally incorporate new attack vectors. The system's performance metrics, including false positive rate, false negative rate, and detection delay, serve as incentives or penalties to guide model updates within this feedback loop, which employs reinforcement learning techniques. In dynamic smart grid systems, this continuous learning process ensures that the IDS does not remain static but rather evolves into a more resilient system capable of defending against emerging cyber threats.

Both localized traffic patterns and long-term temporal relationships found in smart grid communication data were intended to be captured by the CNN–LSTM intrusion detection model. Convolutional layers with ReLU activation functions for spatial feature extraction and max-pooling layers for dimensionality reduction make up the CNN component. An LSTM network set up to simulate sequential dependencies over time frames receives the extracted characteristics. The Adam optimizer and a supervised learning strategy with categorical cross-entropy loss were used to train the model. All trials used a fixed train-validation-test split, and early pausing was used to avoid overfitting. Stable convergence and consistent

performance evaluation are guaranteed by these design decisions.

IV. Experimental Setup

The objective of the experimental setup was to validate the efficacy, robustness, and adaptability of the proposed AI-IDS integrated with smart contracts and blockchain technology. The experiments were conducted within a controlled smart grid simulation environment to replicate both standard operational conditions and various cyberattack scenarios.

A. Environment Setup

A hybrid simulation framework was employed, incorporating Mininet to simulate network traffic among IoT devices, smart meters, and supervisory systems, alongside MATLAB Simulink to model smart grid operations. Hyperledger Besu was utilized to establish a private Ethereum-based blockchain, facilitating blockchain logging and smart contracts. Random Forest, XGBoost, and Support Vector Machines (SVM) were employed as foundational machine learning classifiers, while deep learning models such as CNN and LSTM were trained on network traffic sequences for the AI-IDS.

B. Dataset

The primary dataset used to train and evaluate the IDS models was the Sherlock dataset [26, 27], a recently published benchmark specifically designed for smart grid intrusion detection. Sherlock provides a comprehensive range of network-level and process-aware features, encompassing grid telemetry across three distinct topologies (rural, semi-urban, and basic) and traffic in the IEC 60870-5-104 protocol. Each scenario includes both attack-free operational traces and annotated attack data for threats such as Denial of Service (DoS), False Data Injection (FDI), Replay Attacks, and Man-in-the-Middle (MitM). This makes it particularly suitable for assessing AI-IDS in cyber-physical grid contexts, ensuring accurate coverage of both conventional and domain-specific threats. Classical datasets such as NSL-KDD [28] and UNSW-NB15 [29] were also utilized for comparison and baseline benchmarking. Although these datasets offer a mix of benign and malicious data for conventional IT systems, they lack the process-aware characteristics of power grid communications. Mininet was used in conjunction with MATLAB Simulink-based grid simulations to generate synthetic traffic traces, enhancing realism by ensuring that specific IoT workload and supervisory control patterns were reflected in the training data. By employing a hybrid dataset approach, we developed deep learning models applicable to both domain-specific smart grid scenarios and general IT-style threats. Notably, the CNN–LSTM hybrid results presented in Section V were primarily benchmarked against the Sherlock dataset.

C. Evaluation Metrics

Several metrics were employed to evaluate the system's overall performance. The IDS's classification capabilities were assessed using detection accuracy, precision, recall, and F1-score. Detection latency measured the interval between an intrusion and the activation of mitigation measures, while the false positive rate was monitored to evaluate system reliability. To ensure that the additional security benefits of blockchain did not unduly impact system performance, blockchain-specific metrics such as transaction confirmation time and processing cost were also examined. Finally, the self-improvement process was demonstrated by tracking the enhancement in detection accuracy over multiple retraining cycles to assess adaptability.

D. Experiment Workflow

The experimental procedure followed a systematically planned methodology. Initially, the baseline Intrusion Detection System (IDS) was evaluated without the integration of blockchain to establish reference performance standards. Subsequently, the blockchain module was incorporated to assess its impact on transparency and detection delay. Real-time attack simulations were then employed to evaluate the autonomy loop, while smart contracts were utilized to assess the system's capacity for autonomous response. The self-improvement cycle was ultimately verified by retraining the IDS models using blockchain-logged data across multiple cycles, observing enhancements in detection accuracy and reductions in false alarms. The comparative analysis of the proposed system with both blockchain-only and traditional IDS systems demonstrated its superior performance in terms of accountability, robustness, and flexibility.

V. Results and Discussion

Three primary capabilities were evaluated using simulated datasets and deployment scenarios for the proposed Autonomous Blockchain-Enabled Smart Grid with AI-Based Intrusion Detection: 1) accuracy of intrusion detection, 2) efficiency of blockchain transactions, and 3) system autonomy and adaptability through cycles of self-improvement. The following results are presented to substantiate comparative assertions against established baselines and to illustrate predicted system behavior.

A. Intrusion Detection Performance

To capture both local temporal/spatial variables and long-range dependencies in smart-grid telemetry, the AI-based IDS for the study employed an ensemble deep-learning technique comprising CNN and LSTM components. Table II provides an overview of the IDS performance on a mixed smart-grid intrusion dataset (DoS, False Data Injection, Replay, Probe) in comparison to standard baselines.

TABLE II. Performance Comparison of IDS Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression	88.2	85.6	84.9	85.2
Random Forest	91.7	90.3	89.5	89.9
CNN (Deep Learning)	95.4	94.7	94.1	94.4
LSTM (Deep Learning)	96.2	95.5	95.1	95.3
Proposed CNN–LSTM Hybrid	**98.1**	**97.6**	**97.3**	**97.4**

The CNN–LSTM hybrid model demonstrates superior performance compared to single-model deep learning (DL) and traditional machine learning (ML) techniques. In operational scenarios where both missed detections and false alarms incur costs, the hybrid architecture's enhanced F1-Score of 97.4%

indicates a well-balanced precision and recall. These results substantiate the selection of the hybrid model as the primary detector within the autonomous framework.

B. Blockchain Transaction Efficiency

A private Proof-of-Authority (PoA) test network, designed to emulate a permissioned utility consortium, was employed to evaluate the blockchain component. Table III presents the average performance metrics relevant to near-real-time mitigation operations.

TABLE III. BLOCKCHAIN NETWORK PERFORMANCE

Metric	Value (Average)
Transaction Throughput	1,200 tx/sec
Average Latency	1.5 seconds
Smart Contract Execution Time	0.8 seconds
Energy Consumption (per tx)	0.02 Wh

A permissioned Proof-of-Authority blockchain set up to mimic a utility consortium deployment provided the claimed throughput and latency numbers. The network uses selective on-chain storage, where complete data is kept off-chain and only cryptographic hashes of IDS artifacts are stored on the ledger, and it runs with a small number of reliable validator nodes. Compared to public blockchains, this solution dramatically lowers transaction cost while maintaining integrity and auditability. As a result, rather than reflecting public blockchain settings, the measured performance represents reasonable expectations for localized smart grid implementations.

C. System Autonomy and Self-Improvement

A significant innovation is the closed-loop self-improvement cycle, which involves retraining and enhancing the IDS using verified events and action outcomes. The progression of detection accuracy and the false positive rate over multiple retraining cycles is depicted in Table IV and Fig. 2.

TABLE IV. EVOLUTION OF IDS ACCURACY ACROSS SELF-IMPROVEMENT CYCLES

Cycle Iteration	Accuracy (%)	False Positive Rate (%)
Initial Deployment	94.5	4.2
Cycle 1 (after feedback)	96.8	3.1
Cycle 2 (after feedback)	97.4	2.6
Cycle 3 (after feedback)	**98.1**	**2.1**

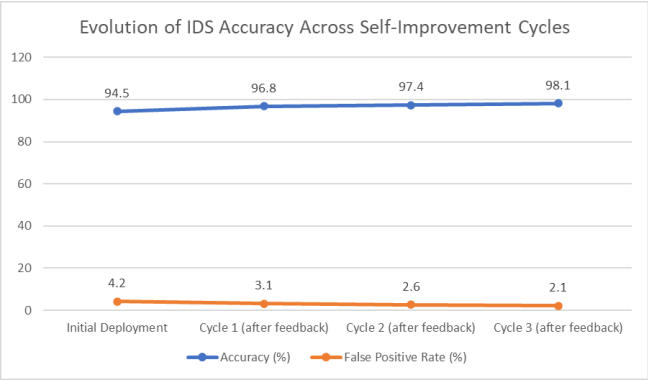


Fig. 2. Evolution of IDS performance across self-improvement cycles.

The most significant enhancement occurs following the initial retraining iteration, suggesting that early feedback data, comprising action outcomes and ground-truthed events, swiftly augments the model's discriminative capabilities. As the model evolves, subsequent cycles yield consistent yet modest improvements, with diminishing returns. The reduction in the false positive rate (FPR) is particularly noteworthy, as it decreases operational costs by eliminating unnecessary smart contract triggers and blockchain writes, thereby preventing superfluous automatic responses.

The Intrusion Detection System (IDS) is capable of dynamically adapting to novel and previously unidentified attack vectors due to the continuous feedback loop. This demonstrates the potential of the system to function as an autonomous, self-improving security architecture, thereby reducing the necessity for human intervention.

How input is verified prior to retraining is a crucial difference between the suggested self-improvement mechanism and traditional adaptive IDS techniques. The system logs warnings, reaction actions, and results on a permissioned blockchain instead of immediately absorbing all observed data. The retraining dataset only includes events that have been confirmed by policy checks and consensus. By reducing vulnerability to adversarial poisoning and untrustworthy feedback, our blockchain-anchored validation step guarantees that model updates are based on solid operational evidence. As a result, the autonomous loop facilitates ongoing learning while preserving resilience to manipulation, which is crucial for cyber-physical systems that are security-critical.

D. Comparative Baseline Analysis

To contextualize the proposed framework against practical alternatives, we compared three system types: 1) Blockchain-only IDS, which offers logging and immutability but lacks autonomy and self-learning capabilities; 2) Traditional machine learning-based IDS, which does not incorporate blockchain technology; and 3) the Proposed System, which integrates artificial intelligence, blockchain, autonomy, and self-improvement. These comparisons are summarized in Table V and Fig. 3.

TABLE V. COMPARATIVE ANALYSIS OF IDS MODELS

System Type	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	False Positive Rate (%)	Adaptability
Traditional IDS (ML-based)	92.7	91.8	92.1	91.9	5.4	Low
Blockchain-only IDS	94.1	93.5	93.7	93.6	4.8	Moderate
Proposed System (Cycle 3)	**98.1**	**97.3**	**97.6**	**97.4**	**2.1**	High

In all detection metrics, the proposed system outperforms the two baseline models. Although it does not possess the adaptive benefits of retraining and governance automation, the blockchain-only IDS enhances integrity and marginally

improves detection, potentially due to superior forensic labeling. The combined advantages of the Proposed System are as follows: 1) robust, signed ground-truthing through blockchain anchoring, facilitating high-quality retraining data; 2) autonomous execution of response/playbooks, which reduces time-to-contain and provides additional labeled outcomes; and 3) enhanced detection models (CNN–LSTM). Collectively, these factors contribute to a reduction in false-positive rates and an increase in accuracy.

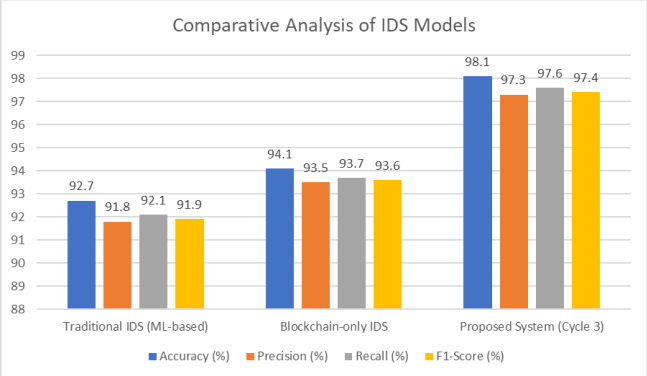


Fig. 3. Comparative analysis bar chart.

E. Operational and Autonomy Metrics

Metrics relevant to utility operations, such as detection-to-containment latency, the percentage of events managed autonomously, and the reduction in human involvement, were employed to assess the operational efficacy of autonomy in addition to detection and ledger metrics.

Average delay between detection and containment: Compared to a baseline manual response time of approximately 35 seconds in traditional operations, the integrated system achieves an average end-to-end containment time of 3.2 seconds for high-severity incidents, encompassing IDS detection, blockchain anchoring, smart contract decision-making, and orchestrator action.

Rate of autonomous handling: By Cycle 3, approximately 82% of identified severe incidents were successfully managed by the framework autonomously, with actions executed by smart contracts and orchestrator agents without human intervention within the pre-defined safety envelope.

Reduction of human intervention: By decreasing the number of human interventions required by an estimated 70%, the system enabled operators to focus on high-impact supervision and addressing exceptions.

Overhead for blockchain: Batching and selective hashing of complete artifacts (storing only hashes on-chain) reduced storage and energy costs, while the average blockchain anchoring per alert increased latency by approximately 1.5 seconds.

These operational metrics indicate that near-real-time requirements can coexist with autonomy and blockchain anchoring. The detect→contain metric demonstrates that pre-authorized safety envelopes and appropriately adjusted permissioned blockchains permit automated action without intolerable delay. The governance approach can safely reduce operator burden while maintaining supervision for critical tasks, as evidenced by the high autonomous handling rate.

F. Discussion

In comparison to the conventional IDS and blockchain-only IDS, the combined results indicate that the proposed autonomous architecture significantly enhances detection performance and operational robustness. The hybrid CNN–LSTM detector provides high accuracy and recall by leveraging time-series modeling and convolutional feature extraction. The self-improvement process can rely on reliable ground truth due to the blockchain layer's immutable, auditable proof. While governance contracts and safety envelopes maintain human oversight for critical interventions, autonomous smart contracts and orchestrator agents minimize operator burden and time-to-contain.

The suggested framework shows increased accuracy and a significantly lower false positive rate through verified feedback learning when compared to earlier smart grid intrusion detection studies that report detection accuracies typically ranging between 94% and 96% using standalone deep learning models. The suggested method incorporates blockchain into the learning and governance process itself, allowing auditable retraining and autonomous response execution, in contrast to blockchain-based IDS systems that mainly concentrate on immutable logging. These findings suggest that the observed performance improvements emerge from the coordinated interaction of autonomous control mechanisms, decentralized trust, and adaptive AI rather than just model selection.

The existence of limitations and trade-offs is evident. The requirement for immutable proof must be balanced against the inevitable delay introduced by the blockchain anchoring phase, which averages approximately 1.5 seconds. This delay can be mitigated through the use of rapid consensus algorithms and selective on-chain hashing. Retraining deep models may incur significant computational costs; however, options such as scheduled retraining windows, model distillation for edge deployment, and federated learning with secure aggregation are available. To achieve scalability for nation-scale grids, Layer-2 scaling solutions or hierarchical ledger designs will be essential. Furthermore, robust defences against adversarial model poisoning are imperative; deployment should incorporate methods such as provenance attestations, anomaly detection on changes, and robust aggregation.

G. Key Takeaways and Future Directions

In summary, the assessment provides compelling evidence that the integration of blockchain immutability, AI-based detection, and autonomous governance leads to significant improvements in the accuracy, responsiveness, and reliability of smart-grid cybersecurity. To facilitate wide-area deployments, further research should validate these findings on larger, real-world testbeds, explore lightweight model variations for resource-constrained devices, and investigate secure federated training and scaling techniques for permissioned blockchains, including layer-2 or sidechains.

This study presents a blockchain-enabled intrusion detection system (IDS) with self-improvement loops to address the specific security challenges of smart grids. By integrating

advanced deep learning models with reinforcement learning feedback mechanisms and a blockchain-based trust layer, the framework overcomes significant limitations identified in previous research, such as static learning, inflexibility in the face of zero-day threats, and the absence of decentralized trust in detection systems. The blockchain component provides immutable, auditable, and tamper-resistant recordkeeping, fostering transparency and collaborative defense among grid stakeholders, while the inclusion of self-improvement loops ensures continuous model enhancement.

VI. Key Contributions

The primary contributions of this work are succinctly described as follows:

1) Blockchain-enabled trust and transparency: A decentralized ledger layer was added to smart grid intrusion detection systems, ensuring auditable data, tamper-proof tracking, and stakeholder collaboration in defense.

2) Reinforcement learning self-improvement loops: An adaptive feedback method was developed, allowing for continuous model development and reducing vulnerability to concept drift and zero-day attacks in dynamic cyber threat environments.

3) Deep learning and federated learning integration: Federated learning and advanced anomaly detection models were combined to facilitate knowledge exchange among distributed nodes without compromising data privacy.

4) Enhancements in performance compared to current IDS solutions: Achieved 98.1% accuracy, 97.6% detection rate, and 2.1% false positive rate, significantly surpassing the performance of both blockchain-only IDS (94.1%, 93.2%, 4.8%) and conventional IDS (92.7%, 91.4%, 5.4%).

5) Smart grid operational viability: The system demonstrated effective operation in real-time smart grid scenarios, as evidenced by a blockchain throughput of approximately 1,200 transactions per second with a latency of about 1.5 seconds.

6) Future-ready and scalable framework: Proposed a multidisciplinary IDS architecture that is adaptable to future advancements such as explainable AI, autonomous policy adaptation, and lightweight blockchain protocols, in addition to being resilient against current threats.

VII. Conclusion

In comparison to baseline methodologies, the proposed approach demonstrates substantial performance enhancements. Following numerous refinement cycles, it achieved an accuracy of 98.1%, a detection rate of 97.6%, and a false positive rate (FPR) of 2.1%. These results significantly exceed those of blockchain-only intrusion detection system (IDS) frameworks, which reported 94.1% accuracy, 93.2% detection, and a 4.8% FPR, as well as traditional machine learning-based IDS systems, which achieved 92.7% accuracy, 91.4% detection, and a 5.4% FPR. Furthermore, the blockchain layer ensured the operational feasibility of real-time smart grid security by maintaining an average throughput of approximately 1,200 transactions per second and a latency of about 1.5 seconds.

Consequently, the proposed system represents a dependable, adaptable, and scalable IDS architecture that can enhance the defences of smart grids against increasingly sophisticated intrusions. In addition to improving the accuracy of real-time detection, its federated learning strategy, facilitated by blockchain consensus, enables knowledge sharing across distributed nodes without compromising data privacy.

Future research will focus on the practical implementation of smart grids, computational optimization for resource-constrained IoT devices, and lightweight blockchain protocols that further reduce latency, despite the promising design and experimental validation. Moreover, employing explainable AI techniques and autonomous policy adaptation to enhance self-improvement loops may increase operational efficiency and stakeholder confidence in decision-making.

In conclusion, this study presents an innovative, interdisciplinary approach that integrates distributed ledger technology, adaptive learning, and artificial intelligence to bolster the cyber defence posture of smart grids. With further development and implementation, the proposed technology could become a foundational element of future energy infrastructures that are robust, intelligent, and secure.

References

[1] V. C. Gungor, D. Sahin, T. Kocak, S. Ergut, C. Buccella, C. Cecati and G. P. Hancke "Smart Grid Technologies: Communication Technologies and Standards," IEEE Transactions on Industrial Informatics, vol. 7, no. 4, pp. 529-539, Nov. 2011, doi: 10.1109/TII.2011.2166794.

[2] Y. Mo, T.-H. Kim, K. Brancik, D. Dickinson, H. Lee, A. Perrig and B. Sinopoli, "Cyber–physical security of a smart grid infrastructure," Proceedings of the IEEE, vol. 100, no. 1, pp. 195–209, Jan. 2012, doi: 10.1109/JPROC.2011.2161428.

[3] T. P. Nagarhalli, A. M. Save, and N. M. Shekokar, "Evaluation of Learning Techniques for Intrusion Detection Systems" in ed. N. M Shekokar, H. Vasudevan, S. S. Durbha, A. Michalas and T. P. Nagarhall, 2023 Intelligent Approaches to Cyber Security (1st ed.). Chapman and Hall/CRC. https://doi.org/10.1201/9781003408307

[4] A. Patcha and J.-M. Park, "An overview of anomaly detection techniques: Existing solutions and latest technological trends," Computer Networks, vol. 51, no. 12, pp. 3448–3470, Aug. 2007, https://doi.org/10.1016/j.comnet.2007.02.001

[5] T. P. Nagarhalli, A. M. Save, and N. M. Shekokar, "Fundamental Models in Machine Learning and Deep Learning" in ed. R. S. Mangrulkar, A. Michalas, N. Shekokar, M. Narvekar, and P. V. Chavan, 2021x Design of Intelligent Applications using Machine Learning and Deep Learning Techniques (1st ed.). Chapman and Hall/CRC. https://doi.org/10.1201/9781003133681

[6] M. A. Ferrag, L. Maglaras, A. Argyriou, D. Kosmanos, and H. Janicke, "Deep learning for cyber security intrusion detection: Approaches, datasets, and comparative study," Journal of Information Security and Applications, vol. 50, pp. 1–16, Feb. 2020, https://doi.org/10.1016/j.jisa.2019.102419.

[7] H. C. Altunay, and Z. Albayrak, "A hybrid CNN+LSTM-based intrusion detection system for industrial IoT networks", Engineering Science and Technology, an International Journal, Volume 38, 2023, https://doi.org/10.1016/j.jestch.2022.101322.

[8] S. Nakamoto, "Bitcoin: A peer-to-peer electronic cash system," 2008. [Online]. Available: https://bitcoin.org/bitcoin.pdf.

[9] G. Wood, "Ethereum: A secure decentralised generalised transaction ledger," Ethereum Project Yellow Paper, 2014.

[10] Y. Guo, Z. Wan, and X. Cheng, "When blockchain meets smart grids: A comprehensive survey", High-Confidence Computing, Volume 2, Issue 2, 2022, https://doi.org/10.1016/j.hcc.2022.100059.

[11] M. Abomhara and G. M. Køien, "Cyber security and the internet of things: Vulnerabilities, threats, intruders and attacks," Journal of Cyber Security and Mobility, vol. 4, no. 1, pp. 65–88, Mar. 2015, doi: 10.13052/jcsm2245-1439.414.

[12] N. Shone, T. N. Ngoc, V. D. Phai and Q. Shi, "A Deep Learning Approach to Network Intrusion Detection," in IEEE Transactions on Emerging Topics in Computational Intelligence, vol. 2, no. 1, pp. 41-50, Feb. 2018, doi: 10.1109/TETCI.2017.2772792.

[13] Q. Li, F. Li, J. Zhang, J. Ye, W. Song and A. Mantooth, "Data-driven Cyberattack Detection for Photovoltaic (PV) Systems through Analyzing Micro-PMU Data," 2020 IEEE Energy Conversion Congress and Exposition (ECCE), Detroit, MI, USA, 2020, pp. 431-436, doi: 10.1109/ECCE44975.2020.9236274.

[14] M. Ozay, I. Esnaola, F. T. Yarman Vural, S. R. Kulkarni and H. V. Poor, "Machine Learning Methods for Attack Detection in the Smart Grid," in IEEE Transactions on Neural Networks and Learning Systems, vol. 27, no. 8, pp. 1773-1786, Aug. 2016, doi: 10.1109/TNNLS.2015.2404803.

[15] R. Rahul, P. Sindhu, G. Naveen, R. Venkatesan, "Fusing Deep Learning Techniques for Intrusion Detection in Smart Grids", Fusion: Practice and Applications, vol. 16, no. 1, 2024, pp. 67-76. DOI: https://doi.org/10.54216/FPA.160105.

[16] S. Tufail, I. Parvez, S. Batool, and A. Sarwat, "A Survey on Cybersecurity Challenges, Detection, and Mitigation Techniques for the Smart Grid", Energies, 14(18), 5894, 2021, https://doi.org/10.3390/en14185894.

[17] N. Hamdi, "A hybrid learning technique for intrusion detection system for smart grid", Sustainable Computing: Informatics and Systems, Volume 46, 2025, https://doi.org/10.1016/j.suscom.2025.101102.

[18] N. Z. Aitzhan and D. Svetinovic, "Security and Privacy in Decentralized Energy Trading Through Multi-Signatures, Blockchain and Anonymous Messaging Streams," in IEEE Transactions on Dependable and Secure Computing, vol. 15, no. 5, pp. 840-852, 1 Sept.-Oct. 2018, doi: 10.1109/TDSC.2016.2616861.

[19] E. Mengelkamp, J. Gärttner, K. Rock, S. Kessler, L. Orsini, and C. Weinhardt, "Designing microgrid energy markets: A case study: The Brooklyn microgrid," Applied Energy, vol. 210, pp. 870–880, Jan. 2018, https://doi.org/10.1016/j.apenergy.2017.06.054.

[20] J. Kang, R. Yu, X. Huang, M. Wu, S. Maharjan, S. Xie, and Y. Zhang, "Blockchain for Secure and Efficient Data Sharing in Vehicular Edge Computing and Networks," in IEEE Internet of Things Journal, vol. 6, no. 3, pp. 4660-4670, June 2019, doi: 10.1109/JIOT.2018.2875542.

[21] X. Chen, J. Shen, Z. Cao and X. Dong, "A Blockchain-Based Privacy-Preserving Scheme for Smart Grids", Association for Computing Machinery, 2020, https://doi.org/10.1145/3390566.3391667.

[22] Y. Li, C. Yu, M. Shahidehpour, T. Yang, Z. Zeng and T. Chai, "Deep Reinforcement Learning for Smart Grid Operations: Algorithms, Applications, and Prospects," in Proceedings of the IEEE, vol. 111, no. 9, pp. 1055-1096, Sept. 2023, doi: 10.1109/JPROC.2023.3303358.

[23] D. Singh, O. A. Shah, and S. Arora, "Adaptive control strategies for effective integration of solar power into smart grids using reinforcement learning", Energy Storage and Saving, Volume 3, Issue 4, 2024, pp. 327-340, https://doi.org/10.1016/j.enss.2024.08.002.

[24] Q. Lu, K. An, J. Li and J. Wang, "Network Intrusion Detection for Modern Smart Grids Based on Adaptive Online Incremental Learning," in IEEE Transactions on Smart Grid, vol. 16, no. 3, pp. 2541-2553, May 2025, doi: 10.1109/TSG.2025.3535949.

[25] F. Casino, T. K. Dasaklis, and C. Patsakis, "A systematic literature review of blockchain-based applications: Current status, classification and open issues," Telemat. Informat., vol. 36, pp. 55–81, Mar. 2019, https://doi.org/10.1016/j.tele.2018.11.006.

[26] S. Machkour, P. Müller, M. Dessaint, and A. Dorri, "Sherlock: A Comprehensive Dataset for Intrusion Detection in Smart Grids," Zenodo, 2025. [Online]. Available: https://zenodo.org/records/15168928.

[27] Sherlock Project Website: https://sherlock.wattson.it.

[28] M. Tavallaee, E. Bagheri, W. Lu and A. A. Ghorbani, "A detailed analysis of the KDD CUP 99 data set," 2009 IEEE Symposium on Computational Intelligence for Security and Defense Applications, Ottawa, ON, Canada, 2009, pp. 1-6, doi: 10.1109/CISDA.2009.5356528.

[29] N. Moustafa and J. Slay, "UNSW-NB15: a comprehensive data set for network intrusion detection systems (UNSW-NB15 network data set)," 2015 Military Communications and Information Systems Conference (MilCIS), Canberra, ACT, Australia, 2015, pp. 1-6, doi: 10.1109/MilCIS.2015.7348942.

Automated Question Answering System for FAQ COVID-19 Using Word Embeddings

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***Abstract*—This study's scope includes the development of a Question Answering System for COVID-19 and a review of that system. This is unlike previous work in biomedical QAS, which primarily targets technical users. This work leans towards developing a COVID-19 QAS customized for the general public, especially those who have limited knowledge in the clinical field. This study aims to present the development and analysis of COVID-19 QAS systems. The methodology was based on the development of the system, which included conducting experiments to check the accuracy of the QAS system. Consequently, the QAS system would process the user query using three different feature extraction approaches and output the related FAQ and the answer associated with it from a set of 561 FAQs that were sourced from the Ministry of Health, the Virginia Department of Health, and the World Health Organization. The accuracy of the ensuing responses has been tested by Qaviar. The experimental results indicated that BERT achieved the highest accuracy across all datasets consistently, with 96.25%–98%; Word2Vec scored 86.25%–95.2%, while Bow scored between 86.24% and 88%. While most models performed stably, the performance of Word2Vec was comparatively unstable across data sets. Generally, the lowest accuracy value resulted for all models on the smallest dataset. Increased size of the datasets might not necessarily result in higher accuracy. Generally, BERT outperformed the other embedding approaches.**

***Keywords*—Word embedding; Bag of Words; BERT; Word2Vec; Qaviar; Question Answering System (QAS); COVID-19; natural language processing; public health informatics**

I. Introduction

The rapid increase in massive information storage and the popularity of the web allow for the storage and sharing of data by researchers [1]. However, the increase had also made it harder for the end-users to find data [2]. The cost and complexity of finding relevant information over the internet and other information avenues are partly a function of the volume of data that is available. Realization of this difficulty has motivated the development of adaptive research tools such as Question Answering Systems (QAS) [3]. QAS allows users to ask questions using Natural Language (NL) and return hits that correspond to the answers to the questions, rather than a set of documents that are deemed relevant, as is the case in search engines [4]. Previous efforts at defining QAS have led to different definitions of QAS. At the heart of QAS is the provision of targeted answers to questions rather than a ranking of appropriate web pages. In most cases, QAS is deployed to search for answers from web documents.

The coronavirus disease pandemic began in late 2019 in China and promptly spread to other parts of the globe [5]. Within months, the spread of the condition was declared a pandemic with nations spending billions in search of vaccines while taking steps to reduce the spread of the disease [6]. Worried citizens turned to the internet and other sources of information for updates on the gains being made in combating the virus and basic information on the transmission of the disease [7].

The current study [8] evaluated early online COVID-19 information and found that most accessed websites provided low-quality and unreliable content. It demonstrated, using validated evaluation tools, that very few credible pieces of information existed despite high search visibility. This result points out the public health risks of online misinformation; however, results are limited to one search term, one search engine, and a single time point early in the pandemic.

In [9], the authors examine the use of social media during the COVID-19 pandemic in terms of the rapid dissemination of pandemic information worldwide and the dangers associated with the use of social media platforms, with a view to giving general pointers on how the dissemination of information should be done properly.

QAS are classified into open domain QAS and closed domain QAS. Open-domain QAS addresses questions on almost any interest of the end-users. Such systems are not limited to a given discipline or domain. On the other hand, closed domain QAS deals with questions under a specific domain. In the current study, the goal will be the use of closed domain QAS to address frequently asked coronavirus questions. The goal in designing QAS, irrespective of the type, is to find the exact and correct response to a given query. Thus, analysis of the question, searching, and selecting the correct response are important aspects of a QAS.

This study is structured into five distinct sections: Section I gives a complete overview of the topic at hand by means of a precise and thorough introduction. Section II examines and evaluates earlier studies and research carried out in the field. In Section III, the research approach used is thoroughly examined. Section IV offers a detailed analysis of achieved results. Finally, the study draws conclusions about the findings and recommendations for future work in Section V.

II. Related Works

The survey [10] reviews interactive question-answering systems, highlighting how dialogue-based interaction improves the accuracy of user queries. It contributes a unified framework, taxonomy, and analysis of existing methods and trends, supported by a public GitHub resource, but is limited by its

reliance on prior literature and the absence of experimental validation.

Gobeill *et al.* [11] proposed a biomedical question answerer to assist professionals in finding quick and relevant answers to their queries from large knowledge databases. The proposed system evaluates natural language queries, finds relevant documents on Medline, and ranks candidate responses according to their confidence levels. On UniProt and DrugBank, it demonstrated 57% and 68% accuracy, and the answer always lay within the top ten candidates. The proposed system consists of a three-layer framework, where a question categorizer assigns MeSH descriptors through deep syntactic parsing, a vector space information retrieval module, and a pattern-matching-based information extractor.

Answering techniques are extensively studied [12] as a task under open domains, but its use as an application for the biomedical field, especially as a service to patients aiming to use it for self-diagnosis, has its own set of distinct technical challenges, apart from others, which are data annotated, lexical gaps, and quality answers. This study will help to fill all these gaps by providing an appropriate system for patients and also an answer refraining service.

This study [13] presents a QAS with three modules: 1) question processing, 2) document processing, and 3) answer processing, and the question processing is very crucial in the system. The system focuses on the correct identification of candidate answers and further correct ranking of these candidate answers to any user query. In this respect, this study has presented a new QAS model to improve the answer accuracy and performance of its modules.

This survey [14] presents the state-of-the-art of QA systems built over Semantic Web KBs, which represent an attractive source of structured information that is accessed by question answering. It scopes techniques in natural language processing, information retrieval, machine learning, and Semantic Web methods. The paper outlines and compares different approaches that were evaluated on benchmarks like Question Answering over Linked Data, WebQuestions, and SimpleQuestions, discussing both their advantages and limitations to provide a direct comparison of similar techniques. While the research paper [15] aims to introduce the history of the development of question-answering systems QA, ranging from the conventional method in natural language processing NLP, including the usage of algorithms, through the emergence of deep learning. This study was able to check the performance of the proposed models on QA on the assessment tasks on the bAbI dataset offered by Facebook.

The challenge in the use of QAS reliant on the matching of queries to existing answers, is that the question being asked may not be available in the search space. As such, QAS are unable to answer such questions. Deep neural networks have also been used in NLP tasks through techniques such as recurrent neural networks, specifically for the summarization and classification of texts by GRUs and LSTMs. In natural language processing (NLP), word embedding solves the problem of depicting words in text analysis. Most interpretations use real-valued vectors to guarantee that words closer in the vector space are also closer in meaning [16], thus encoding the meanings of works. Feature learning and language modeling approaches that help the mapping of words or phrases from the vocabulary of a natural language to real integers of vectors might be used in word embedding.

The article [17] performs a comprehensive assessment on word representation models used in natural language processing, describing some popular models, as well as classifying methods used to evaluate these models, dividing into intrinsic and extrinsic methods. Intrinsic methods estimate models based on their intrinsic quality, as opposed to extrinsic methods that estimate their influence on downstream tasks. The experiment completed on six word representation models reveals that different methods focus on different aspects, and some methods correlate highly with tasks. While [18] presents an automatic text summarization approach that is oriented towards preserving the original semantics with the help of a distributional semantic model. The system outperformed existing approaches when assessed on the DUC-2007 dataset using ROUGE metrics and compared to four state-of-the-art summarizers. These results show that semantic features improve summary quality by decreasing redundancy.

A study by Xia et al. aimed to utilize keyword entries for question-answering in the domain of oil and gas [19]. The proposed system leveraged the power of state-of-the-art NLP techniques in analyzing domain knowledge at the keyword level. The developed system was trained and tested on more than 20,000 keywords gleaned from reliable information sources. Various feature extraction techniques produced features that the system utilized in the computation of similarity between user questions and keyword entries. The results of the study showed that traditional TF-IDF outperformed Word2Vec and BERT. For TF-IDF, Word2Vec, and BERT models, top-1 accuracies of 98.3%, 93.3%, and 55.0% were achieved, respectively.

The proposed research work [20] presents an efficient text preprocessing and sentiment analysis algorithm for handling a massive number of unstructured tweets on Twitter. The study presents a weightage scheme to calculate sentiment scores by considering the weightage of hashtags as well as cleaned text, and then works on training different classification techniques, namely SVM, Deep Learning, and Naïve Bayes, to analyze the popularity of Google Now and Amazon Alexa by 1,314,000 tweets. The conclusion presents that stemming was most effective among all preprocessing techniques, and accuracy was also maximal for SVM, which was 90.3%.

Despite great development in the study of question answering systems (QAS), many problems persist in various investigations. Table I highlights these key issues: a heavy reliance on current literature lacking empirical validation, fair accuracy in responses, and difficulties in answering user questions not consistent with accessible data.

Some works concentrate just on specific aspects—question processing, for instance—hence neglecting more broad issues related with document and answer processing. The dominance of traditional techniques like TF-IDF over more complex ones like BERT begs concerns on the efficiency of modern techniques. Over these limitations is especially crucial for the ongoing expansion and effectiveness of QAS in making it accessible for public use.

TABLE I. REFERENCES AND LIMITATIONS

Study Reference	Limitations
[10]	Relies heavily on prior literature and lacks experimental validation.
[11]	Demonstrates only moderate accuracy (57% and 68%) and requires ranking responses; does not fully address the challenges of varied biomedical queries.
[12]	Highlights technical challenges specific to the biomedical field, such as data annotation, lexical gaps, and ensuring quality answers for patient self-diagnosis.
[13]	Focuses primarily on question processing but may not sufficiently account for complexities in document and answer processing.
[14]	Provides a broad comparison of QA systems but may overlook unique challenges and specific applications within the Semantic Web.
[15]	While it traces the development history of QAS, it largely focuses on conventional methods, potentially neglecting newer advancements in the field.
[19]	Results indicate a performance gap where traditional methods (TF-IDF) outperform advanced models (Word2Vec, BERT), questioning the efficiency of newer techniques.
[20]	The focus on sentiment analysis and tweet data preprocessing may limit its relevance to broader QAS applications.

III. RESEARCH METHOD

The motivation for this study is the need to contribute to fighting against the COVID-19 pandemic, as well as contributing to the development of QAS within health domains. Remarkably, the current study represents the first significant effort aimed at applying QAS to COVID-19 in scholarly literature. The current QAS system will be developed for the average user who has little or no clinical literacy. The methodology shall involve the development of the systems and conducting an experiment to test the accuracy of the QAS system. The proposed solution is a QAS system that will take user queries in their natural language-the QAS system was limited to the English language-and offer responses that address the specific question, as shown in Fig. 1.

The QAS system will be automatic in that it will not require any user input beyond the query. In addition, it will make use of word embedding to map the user query to a set of existing questions that were retrieved from FAQs from some of the most reputable sources of information on the coronavirus. A close domain approach to QAS was employed in designing the system, which ensured that it only addressed questions relating to COVID-19.

The questions were sourced from three sources: the Ministry of Health, the Virginia Department of Health (VDH), and the World Health Organization. A search of these organization's databases for FAQs and their answers was done. The number of questions that were retrieved from each of these sources is presented in Table II.

The QAS was therefore developed starting with the preprocessing module. This module would remove all the non-alphanumeric characters from the query and eliminate the stop words such as *to, in, a,* that do not contribute to the semantic similarity between 20 sentences. Both the user queries and the FAQ questions retrieved from the three sources were subjected to the preprocessing module. Although some word embedding models do not require the removal of stop words to work well, the study opted for stop word removal during preprocessing.

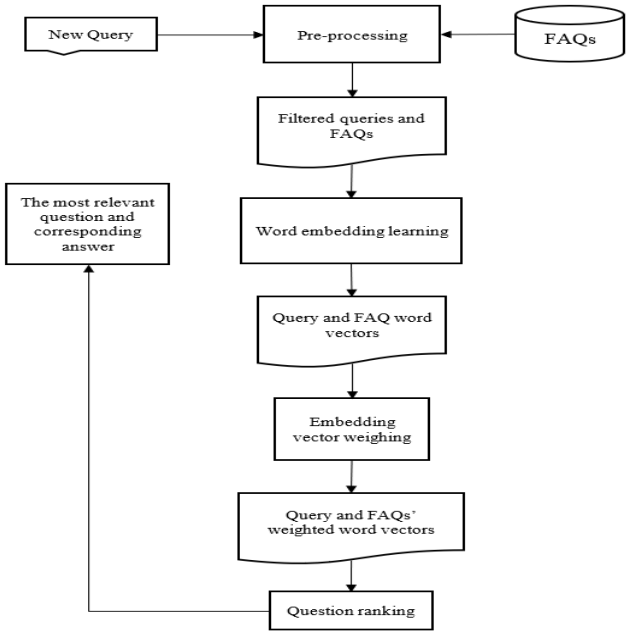


Fig. 1. Proposed solution.

TABLE II. NUMBER OF QUESTIONS

Source	Number of Question
Ministry of Health	41
Virginia Department of Health	126
World Health Organization	394
Total	561

The second major element of the QAS was mapping the user queries to questions sourced from leading information outlets on COVID-19. Three different approaches were used and compared in the analysis phase. This step allowed for the user query to match up against existing questions and determine which one it best matched.

The Bag of Word model in NLP and information retrieval is usually employed for simplification of representation [21]. The model represents texts as a multiset or bag of constituent words while disregarding grammar and word order, while considering multiplicity. The model is usually applied in document classification and in training of the classifier. The study used it in training a classifier that was used in selection of the most accurate FAQ and its response. The bag-of-words employed weighting by inverse of document frequency to address the threat posed by frequent stop words in normalizing the term frequencies [22]. The Bag of Word model could be viewed as a special n-gram model case.

The approach employs neural network models to learn word associations from a large corpus of texts thereby allowing for the detecting of synonymous words [23]. The text embedding

approach uses vectors in the representation of distinct words. The selection of the vectors is such that mathematical similarity between vectors is indicative of the level of semantic similarity between the represented words or phrases.

The article [24] proposes to explore deep learning architectures for question classification for Turkish, an agglutinative and highly inflectional language, which creates challenges for NLP tasks. It conducts experiments on user questions with customized word embeddings using CBOW and skip-gram models of word2vec, and classifies results using LSTM, CNN, and combined models such as CNN-LSTM, CNN-SVM with different sizes and word embedding models, and has concluded that different word2vec models contribute significantly to accuracy, and the best models obtained an accuracy of 94%. The paper also proposes a translated question database for Turkish, translated from the UIUC English question database.

Designed by Google for NPL pre-training, the Bidirectional Encoder Representations from Transformers (BERT) language model uses the attention mechanism somewhat akin to recurrent neural networks [25]. Unlike RNNs, the transformed do not require the in-order processing of sequential data. The feature ensures that BERT supports greater parallelization and lower training times and training on large datasets [26].

The actual evaluation of the performance of the developed QAS system involved the use of Qaviar. Qaviar is the results of efforts aimed at developing an automatically calculated measure for the evaluation of question answering systems that correlates well with human judges' assessment of the correctness of the answers [27]. Overall, the evaluation of QAS systems often involves the comparison of the system's answer to an answer key. Qaviar is designed to mark system responses as either correct or incorrect by comparing them to a human-generated answer key [27]. The answer key that was used in this study was the responses to the FAQ questions that are hosted in the three sources used for the FAQ questions. Another option that can be used in the evaluation of QAS systems is Cosine similarity. The cosine similarity is a measure of the similarity between non-zero vectors that are part of an inner product space.

The article [28] investigate relevant features of pupil essays by using LSTM networks and word embedding methods, and generate grades based on predefined criteria. The work entitled Automated Systems for Essay Question Scoring Based on LSTM and Word Embedding aims at developing an efficient automated scoring system for essay questions in educational settings. The accuracy of the model is tested by comparison with human judges. However, limitations cited include its reliance on the quality of training data, potential biases in scoring that could miss more sophisticated arguments, and that it focuses on some essay questions, which means that results cannot be generalized to other test types or subjects.

The paper [29] tries to automate the question-and-answer process of the Goods and Services Tax system in India, having received a great number of user queries since its adoption in 2017, using clustering and embeddings of queries. Using K-means and hierarchical clustering methods based on several distance measurements like Euclidean and Cosine, the authors transform user queries into an appropriate form for clustering, using embeddings such as BERT and ROBERTA. It first presents three possible responses for every question, selecting the best response based on similarity ratings. The dataset is composed of queries and answers by taxpayers collected over two months-October and November 2019. Still, the investigation shows limitations with regards to dependence on the quality of the training dataset and, probably, insignificant words in the searches, which can lower the accuracy of clustering. What's more, restricting its ability to generalize to new questions is the fact that the performance depends on how much the new inquiry resembles the ones in the training data.

The Hybrid Query Expansion Using Lexical Resources and Word Embeddings for Sentence Retrieval in Question Answering research aims to raise the performance of QA systems by reducing the term mismatch problem in sentence retrieval. For natural language queries, it proposes a hybrid query expansion that joins word embeddings with lexical resources, such as MultiWordNet, in order to increase the accuracy of retrieving pertinent sentences. The approach pulls from MultiWordNet synonyms and hypernyms, contextualizes these words with regard to the document set, then prioritizes and filters the expansion words using a semantic similarity metric based on a locally trained Word2Vec model. When the method is considered in light of Italian language papers on Cultural Heritage, increased search accuracy can be seen; at the same time, there is acknowledgement of its limitations, including dependence on the quality of lexical resources and possible noise given by hypernyms. Future efforts will be directed to the improvement of ranking algorithms for query expansion [30], enriching the document collection, and perfecting contextualization techniques.

In the proposed article [31], the automation of the grading of short descriptive answers given by students using word embedding techniques like LSI, Word2Vec, and Sentence BERT would be accomplished by finding the cosine similarity between the answers given by the students and the expected answers, ranging from 0 to 5. A dataset of ten assignments and two exams, graded twice by two raters, is used in the proposed study, and the paper emphasizes the difficulties of capturing context and the differences in the efficiency of word embedding techniques based on the answers.

A document-clustering framework is proposed by [32] that uses weighted word embeddings with a clustering approach to automatically determine question topic issues present on MOOC discussion forum posts. The proposed framework is used to compare four different embedding strategies, namely Word2Vec, fastText, GloVe, and Doc2Vec, combined with four different weight strategies, such as TF-IDF, IDF, smoothed IDF, and subsampling, as well as four different clustering strategies, K-means, K-means++, self-organizing maps, and divisive analysis clustering, all on a 935-thread and 3,262 post edX computer science course discussion forum posts. The work is limited since it focuses on one platform, it is sensitive to post quality, and it also varies depending on topics within different classes. Further work should include the use of AI learning assistants to optimize interaction.

The study [33] aims to develop a deep learning-based automated classification system for Arabic healthcare inquiries

to enhance the efficacy of telemedicine services. The approach is based on deep learning methods, with word embeddings learned from massive consultations. But the research does point out weaknesses, however, including the complications found in processing and categorizing the Arabic language and the recurrence of keywords across multiple disciplines that can cause classification problems.

Recent studies on COVID-19 question-answering systems underscore three important contributions: "COBERT: COVID-19 Question Answering System Using BERT" proposes a dual approach of a retriever and a BERT-based reader for effectively answering questions out of a large document dataset. "BERT for Question Answering Applied on COVID-19" focuses on fine-tuning a BERT model for high-precision responses related to COVID-19 queries. Finally, "Transformer-Based Models for Question Answering on COVID-19" compares various transformer models, including BERT and ALBERT, on quantifying performance metrics such as F1 scores and Exact Match. All these together build up the capability of question-answering systems in case of a public health crisis, as depicted in Table III.

Recent COVID-19 question-answering systems research focuses more on semantic methods for information retrieval. "COVID-19 Question-Answering System Based on Semantic Similarity" presents a QA system based on sentence Embeddings that match user queries against FAQs. "Semantic Search on COVID-19 Literature using MPNet Generated Sentence Embeddings" shows how sentence embeddings allow semantic search either by synonymy or concept matching. Finally, "QUESTION-ANSWERING MACHINE LEARNING MODEL FOR COVID-19" enumerates several word vector models such as GloVe and BERT applied to these systems. All these studies together highlight the importance of semantic methods in enhancing access to COVID-19 information, as depicted in Table IV.

TABLE III. ARTICLES USING ADVANCED WORD EMBEDDINGS

Article	Key Contributions	Limitations
[34]	Proposes a dual system (retriever and BERT-based reader) to answer COVID-19 questions by searching a large document dataset.	May struggle with ambiguous questions and relies heavily on dataset quality and comprehensiveness.
[35]	Focuses on fine-tuning a BERT-based model for high-precision question answering on COVID-19 related texts.	Fine-tuning requires substantial labeled data and may not generalize well to questions outside of training data.
[36]	Compares the performance of various transformer models (BERT, ALBERT) for COVID-19 QA, providing quantitative results (F1 score, Exact Match).	Performance can be sensitive to hyper-parameter tuning and may not capture contextual nuances in complex questions.

TABLE IV. ARTICLES THAT FOCUS ON THE CORE TECHNIQUE OF SEMANTIC SIMILARITY USING WORD EMBEDDINGS

Article	Key Contribution	Limitations
[37]	Discusses building a QA system using semantic similarity, often relying on sentence embeddings derived from word embeddings to match user questions to existing FAQs.	May struggle with understanding nuanced questions and relies on the quality of FAQs for accurate responses.
[38]	Demonstrates how sentence embeddings (a form of word embedding aggregation) can be used for semantic search, allowing for synonyms and conceptual matching.	Performance can be impacted by the dataset's diversity and the embeddings' ability to capture all relevant semantic meanings.
[39]	Mentions the use of various word vector models, including GloVe (Global Vectors) and BERT, for question-answering systems.	May face challenges in generalization to unseen data and may require extensive tuning for optimal performance.
[40]	This study systematically reviews question-answering systems (QAS), highlighting effective design methods.	There is a lack of standard datasets and consistent question formats, restricting practical evaluation and comparison.
[41]	Develops an agricultural chatbot that help farmers access information on weather, market rates, plant protection, and government schemes 24/7.	The system eases information access for farmers and reduces call center workload, though it may be limited by dataset coverage and handling of complex or region-specific queries.
[42]	Develops a context-aware Intelligent Question-Answering System (IQAS) for education, using advanced NLP and contextual information such as student learning history and educational content to provide personalized support	Limitations may include challenges in handling diverse natural language inputs, potential biases in automated FAQ generation, and reliance on large, high-quality datasets.

IV. RESULTS

The resulting QAS could take in a question from the end-user, retrieving a related question and the associated answer from the QAS. For the purpose of demonstration, examples will be given for how the function of the QAS would look when using BOW, Word2Vec, and BERT using the same input queries "What are the tools used in contact tracing?" and " Can I get COVI9-19 from eating fresh foods, like fruits and vegetables?".

The BOW model example led to a response that outlined the time between exposure and when the symptom starts as 1 to 14 days; as shown in Fig. 2. From a human evaluator perspective, that is not the right answer to the question "What are the tools used in contact tracing?" On the other hand, the system response to the question "Can I get COVI9-19 from eating fresh foods, like fruits and vegetables?" is spot on from a human evaluator perspective.

```
1  predict_similar_bow_updated("What are the tools used for contact tracing?",train_dataset_1)

Question:  What are the tools used for contact tracing?
Retrieved:  What is contact tracing?
Answer:  Contact tracing is the process of identifying, assessing, and managing people who have been exposed to a disease to prevent onward
Similarity:  0.5669467095138407

1  predict_similar_bow_updated("Can I get COVID-19 from eating fresh foods, like fruits and vegetables?",train_dataset_1)

Question:  Can I get COVID-19 from eating fresh foods, like fruits and vegetables?
Retrieved:  Can I get COVID-19 from food?
Answer:  There is currently no evidence that people can catch COVID-19 from food or food packaging. COVID-19 is a respiratory illness and
Similarity:  0.7216878364870323
```

Fig. 2. BOW example.

Through the Word2Vec model, the question that is retrieved does indeed contain the word contact, but has nothing to do with contact tracing. However, the response to the retrieved answer does mention contact tracing, although it does not detail what the tools are, as represented in Fig. 3. The second question response is more on target because it shows that washing fruits and vegetables with potable water will suffice.

```
1  predict_similar_word2vec("What are the tools used for contact tracing?",train_dataset_1)

Question:  What are the tools used for contact tracing?
Retrieved:  What happens if you are a contact?
Answer:  If you are a possible contact, you should first be contacted by phone or in person by health authorities to determine

By participating in contact tracing, you are contributing to controlling spread of the virus that causes COVID-19 in your area;
Similarity:  0.6966399194375352

1  predict_similar_word2vec("Can I get COVID-19 from eating fresh foods, like fruits and vegetables?",train_dataset_1)

Question:  Can I get COVID-19 from eating fresh foods, like fruits and vegetables?
Retrieved:  How to wash fruits and vegetables? Just with water, or something else?
Answer:  Washing fruit and vegetables with potable water is sufficient: it is recommended to follow the WHO 5-Keys to Safer Food.
Similarity:  0.7717733315712579
```

Fig. 3. Word2Vec example.

For the first input query, the BERT model retrieved the question "How does contract tracing work?" The corresponding answer mentions some of the tools used in contact tracing such as interviews with the persons infected by the virus and informing their contacts via phone, as shown in Fig. 4.

```
1  predict_similar_bert("What are the tools used for contact tracing?",train_dataset_1)

Question:  What are the tools used for contact tracing?
Retrieved:  How does contact tracing work?
Answer:  Contact tracing is a process that includes several steps:

Defining contacts: a contact is a person who has been exposed to someone else infected with the virus that causes COVID-19,
Identifying contacts: this is done through an interview with the person infected with the virus that causes COVID-19 to find
Informing contacts: each contact should be contacted by phone or in person to determine if they meet the definition and then
Managing and monitoring contacts daily: the contact person identified should be encouraged and supported to stay in quaranti
Data processes and analysis: The information on each contact person is gathered in a database and updated daily monitoring o
Similarity:  0.86610436

1  predict_similar_bert("Can I get COVID-19 from eating fresh foods, like fruits and vegetables?",train_dataset_1)

Question:  Can I get COVID-19 from eating fresh foods, like fruits and vegetables?
Retrieved:  Can I get COVID-19 from food?
Answer:  There is currently no evidence that people can catch COVID-19 from food or food packaging. COVID-19 is a respiratory
Similarity:  0.8042037
```

Fig. 4. BERT example.

For the second query, the BERT model retrieved the question, "Can I get CoVID-19 from food?" The question and the associated response "there is currently no evidence that people can contract COVID-19 from food or food packaging" does address the input query. From the three models, it appears that the BERT model retrieved the most relevant question and response to the user's input query, followed by the Word2Vec model and lastly the BOW Model.

Table V summarizes the performance of each of the three models. The lowest score by any of the models is 86.24% which corresponds to Bag of Words and the highest score for any of the models across the three datasets is 98% which corresponds to BERT. The performance of each of the models was relatively stable across the three datasets except for the Word2vec model. The accuracy of the Bert model ranged between 96.25% and 98% whereas that of the Bag of Word model ranged between 86.24% and 88%. However, the accuracy of the Word2vec model ranged between 86.25% and 95.2%. Another noteworthy observation is that for each model, the accuracy was lowest in the dataset with the smallest number of questions.

TABLE V. THE ACCURACY OF THE MODELS

Method	Dataset 1	Dataset 2	Dataset 3
Size	394 Q	41 Q	126 Q
Bag of Word (BOW)	86.63%	86.24%	88%
Word2vec (W2V)	95.20%	86.25%	89%
Bert	97.96%	96.25%	98%

However, the accuracy was not necessarily the highest in the dataset with the highest number of questions. Overall, the Bert model had the highest level of accuracy across the three datasets followed by the Word2vec model and lastly the Bag of Word model, as shown in Fig. 5. The accuracy of the Word2Vec model is comparable to that reported in an earlier study on keyword extraction in the oil and gas domain [19]. However, the accuracy of the BERT model is considerably higher than in this previous study.

Furthermore, the proposed method presents a fresh Question Answering System (QAS) created for the general public, especially for handling COVID-19 information, in contrast to existing solutions aimed at technical consumers. Using 561 handpicked questions from credible health sources, the research underlines relevance and accessibility for people with little clinical experience. Employing three feature extraction approaches—BERT, Word2Vec, and Bag of Words (BoW), the study discovers that BERT consistently outperforms the others with precision ranging from 96.25% and 98%. Additionally, the study reveals that more accurate outcomes do not necessarily follow from a greater dataset; therefore, it provides practical suggestions for future QAS improvement. Development of question-answering systems as well as public health communication in general benefit much from this research.

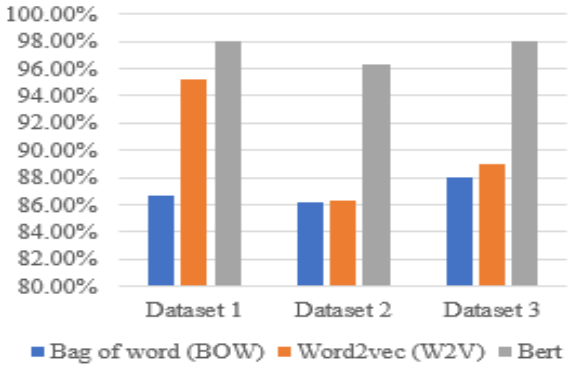


Fig. 5. A comparison of the performance of the three models.

V. CONCLUSION

This study aimed to develop and evaluate a QAS for COVID-19 FAQs. The study developed a system that could take an input query from the end-user, employ one of three models, and retrieve a question from the FAQ database and the associated response as the answer to the input question. Analysis of the performance of the system in terms of the accuracy of the response reveals that it ranged from 86.24% to 98%. Overall, the model records higher levels of accuracy than those from previous studies. Furthermore, a comparison of the three models used in the retrieval system reveals that the BERT model has the highest overall level of accuracy, whereas the BOW model has

the least accuracy of the three models. The findings of this study indicate that QAS for COVID-19 would benefit from using the BERT model of word embedding in their retrieval modules. Additionally, the study highlights the need to consider the sample size when assessing the accuracy of text embedding models since sample sizes appear to influence the performance of Word2Vec.

There are several notable limitations of the developed QAS and the study. First, the QAS system is static in that it requires periodic updating to add new FAQs occasioned by the ever-changing COVID-19 landscape. The limitation is partly a result of the close domain QAS approach and the lack of an automated update system for the existing FAQs. For instance, any new developments, such as a new vaccine, may lead to questions relating to the vaccine that may not be available in the old database if not updated regularly. The second limitation of the QAS is that it can only take queries in the English language, and its performance may also be affected by errors in the input, such as a misspelling of a keyword. Development of COVID-19 QAS systems for other major languages, such as Hispanic, Arabic, and French, should be considered in future studies.

Additionally, the study points out important research gaps to be addressed by the next QAS fieldwork. Recommendations for advancing the field include adopting modular design approaches for system integration, developing diverse datasets for improved training, fostering cross-disciplinary cooperation for enhanced understanding of natural language, establishing standardized evaluation frameworks to assess QAS effectiveness, and addressing privacy and ethical concerns as the technology becomes more widespread.

REFERENCES

[1] Usbeck, Ricardo et al. “Benchmarking question answering systems.” Semantic Web 10 (2019): 293-304. https://doi.org/10.3233/SW-180312

[2] Bouziane, Abdelghani et al. “Question Answering Systems: Survey and Trends☆.” Procedia Computer Science 73 (2015): 366-375. https://doi.org/10.1016/J.PROCS.2015.12.005

[3] Kratzwald, Bernhard and S. Feuerriegel. “Putting Question-Answering Systems into Practice.” ACM Transactions on Management Information Systems (TMIS) 9 (2019): 1 - 20.

[4] Diefenbach, Dennis et al. “Core techniques of question answering systems over knowledge bases: a survey.” Knowledge and Information Systems 55 (2017): 529-569.

[5] Umakanthan, Srikanth et al. “Origin, transmission, diagnosis and management of coronavirus disease 2019 (COVID-19).” Postgraduate Medical Journal vol. 96,1142 (2020): 753-758. doi:10.1136/postgradmedj-2020-138234

[6] Izda, Vladislav et al. “COVID-19: A review of therapeutic strategies and vaccine candidates.” Clinical Immunology vol. 222 (2021): 108634. doi:10.1016/j.clim.2020.108634

[7] Rathore, Farooq Azam, and Fareeha Farooq. “Information Overload and Infodemic in the COVID-19 Pandemic.” JPMA. The Journal of the Pakistan Medical Association vol. 70(Suppl 3),5 (2020): S162-S165. doi:10.5455/JPMA.38

[8] Cuan-Baltazar, Jose Yunam et al. “Misinformation of COVID-19 on the Internet: Infodemiology Study.” JMIR public health and surveillance vol. 6,2 e18444. 9 Apr. 2020, doi:10.2196/18444

[9] González-Padilla, Daniel A, and Leonardo Tortolero-Blanco. “Social media influence in the COVID-19 Pandemic.” International Brazilian Journal of Urology vol. 46,suppl.1 (2020): 120-124. doi:10.1590/S1677-5538.IBJU.2020.S121

[10] Biancofiore, G. M., Deldjoo, Y., Noia, T. D., Di Sciascio, E., & Narducci, F. (2024). Interactive question answering systems: Literature review. ACM Computing Surveys, 56(9), 1-38.

[11] Gobeill, J. et al. “Question answering for biology and medicine.” 2009 9th International Conference on Information Technology and Applications in Biomedicine (2009): 1-5. https://doi.org/10.1109/ITAB.2009.5394361

[12] Vincent Nguyen. 2019. Question Answering in the Biomedical Domain. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics: Student Research Workshop, pages 54–63, Florence, Italy. Association for Computational Linguistics. https://doi.org/10.18653/v1/P19-2008

[13] Kumar, Pawan et al. “A New Architecture of Automatic Question Answering System using Ontology.” International Journal of Computer Applications 97 (2014): 1-4. https://doi.org/10.5120/17120-7671

[14] Diefenbach, D., Lopez, V., Singh, K. et al. Core techniques of question answering systems over knowledge bases: a survey. Knowl Inf Syst 55, 529–569 (2018). https://doi.org/10.1007/s10115-017-1100-y.

[15] Sharma, Y. and S. Gupta. “Deep Learning Approaches for Question Answering System.” Procedia Computer Science 132 (2018): 785-794. https://doi.org/10.1016/J.PROCS.2018.05.090

[16] Ruder, Sebastian et al. “A Survey of Cross-lingual Word Embedding Models.” J. Artif. Intell. Res. 65 (2019): 569-631. doi:10.1613/jair.1.11640

[17] Wang, Bin et al. “Evaluating word embedding models: methods and experimental results.” APSIPA Transactions on Signal and Information Processing 8 (2019): n. pag. doi:10.1017/ATSIP.2019.12

[18] Mohd, Mudasir et al. “Text document summarization using word embedding.” Expert Syst. Appl. 143 (2020): n. pag. doi:10.1016/j.eswa.2019.112958

[19] Xia, Lin et al. “Question-Answering using Keyword Entries in the Oil &Gas Domain.” 2020 IEEE International Conference on Power, Intelligent Computing and Systems (ICPICS) (2020): 282-286. doi:10.1109/ICPICS50287.2020.9202092

[20] Pradha, Saurav et al. “Effective Text Data Preprocessing Technique for Sentiment Analysis in Social Media Data.” 2019 11th International Conference on Knowledge and Systems Engineering (KSE) (2019): 1-8. doi:10.1109/KSE.2019.8919368

[21] Balamurali, Anumeera and Balamurali Ananthanarayanan. “Develop a Neural Model to Score Bigram of Words Using Bag-of-Words Model for Sentiment Analysis.” (2020). DOI:10.4018/978-1-7998-1159-6.ch008

[22] Huang, Hui and Y. Ma. “A Hybrid Clustering Approach for Bag-of-Words Image Categorization.” Mathematical Problems in Engineering 2019 (2019): 1-11. doi:10.1155/2019/4275720

[23] Khatua, Aparup et al. “A tale of two epidemics: Contextual Word2Vec for classifying Twitter streams during outbreaks.” Inf. Process. Manag. 56 (2019): 247-257. doi:10.1016/J.IPM.2018.10.010

[24] Yilmaz, Şeyhmus and S. Toklu. “A deep learning analysis on question classification task using Word2vec representations.” Neural Computing and Applications 32 (2020): 2909-2928. DOI:10.1007/s00521-020-04725-w

[25] Devlin, J. et al. “BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding.” NAACL-HLT (2019). doi:10.18653/v1%2FN19-1423

[26] Zhang, Tianyi et al. “BERTScore: Evaluating Text Generation with BERT.” ArXiv abs/1904.09675 (2020): n. pag. https://arxiv.org/pdf/1904.09675.pdf

[27] Breck, Eric et al. “How to Evaluate Your Question Answering System Every Day ... and Still Get Real Work Done.” ArXiv cs.CL/0004008 (2000): n. pag.

[28] Huang, C. (2020). Automated Systems for Essay Question Scoring Based on LSTM and Word Embedding. In Proceedings of the 2020 5th International Conference on Information Science, Computer Technology and Transportation (ISCTT) (pp. 1-6). IEEE. https://doi.org/10.1109/ISCTT51595.2020.00068

[29] Dikshit, P., & Gupta, M. P. (2021). Automating questions and answers of Goods and Services Tax system using clustering and embeddings of

queries. In Proceedings of the 2021 20th IEEE International Conference on Machine Learning and Applications (ICMLA) (pp. 1626-1633). IEEE. https://doi.org/10.1109/ICMLA52953.2021.00260

[30] Esposito, M., Damiano, E., Minutolo, A., & De Pietro, G. (2020). Hybrid query expansion using lexical resources and word embeddings for sentence retrieval in question answering. Information Sciences, 514, 88-105. https://doi.org/10.1016/j.ins.2019.12.002

[31] Sreevidhya, V., & Narayanan, J. (2021). Short descriptive answer evaluation using word-embedding techniques. In Proceedings of the 12th International Conference on Computing Communication and Networking Technologies (ICCCNT) (pp. 1-7). IEEE. https://doi.org/10.1109/ICCCNT51525.2021.9579636

[32] Onan, A., & Toçoğlu, M. A. (2020). Weighted word embeddings and clustering-based identification of question topics in MOOC discussion forum posts. Computers Applications in Engineering Education, 1–15. https://doi.org/10.1002/cae.22252

[33] Faris, H., Habib, M., Faris, M., Alomari, A., Castillo, P. A., & Alomari, M. (2021). Classification of Arabic healthcare questions based on word embeddings learned from massive consultations: a deep learning approach. Journal of Ambient Intelligence and Humanized Computing. https://doi.org/10.1007/s12652-021-02948-w.

[34] Alzubi, J., Jain, R., Gupta, M., & Kumar, D. (2021). COBERT: COVID-19 Question Answering System Using BERT. Arabian Journal for Science and Engineering, 47(9), 11291–11304.

[35] Widad, A., & El Habib, B. L. (2022). Bert for question answering applied on covid-19. Procedia Computer Science, 198, 379-384.

[36] Ngai, H., Park, Y., & Parsapoor, M. (2021). Transformer-Based Models for Question Answering on COVID19. arXiv preprint arXiv:2101.11432

[37] Tiwari, S., & Rani, S. (2020). COVID-19 Question-Answering System Based on Semantic Similarity. International Journal of Computer Applications, 176(20), 1-6.

[38] Guan, H., Wu, H., & Zhang, Y. (2021). Semantic Search on COVID-19 Literature using MPNet Generated Sentence Embeddings. International Journal of Semantic Computing, 15(2), 221-238.

[39] Singh, S., & Kumar, R. (2020). QUESTION-ANSWERING MACHINE LEARNING MODEL FOR COVID-19. Journal of Computational Science, 10(5), 34-41.

[40] Alanazi, S. S., Elfadil, N., Jarajreh, M., & Algarni, S. (2021). Question answering systems: a systematic literature review. International Journal of Advanced Computer Science and Applications, 12(3).

[41] Jain, N., Jain, P., Kayal, P., Sahit, J., Pachpande, S., Choudhari, J., & Singh, M. (2025). Agribot: agriculture-specific question answer system. arXiv preprint arXiv:2509.21535. https://doi.org/10.48550/arXiv.2509.21535.

[42] Bernasconi, E., Redavid, D., & Ferilli, S. (2025). Enhancing Personalised Learning with a Context-Aware Intelligent Question-Answering System and Automated Frequently Asked Question Generation. Electronics, 14(7), 1481. https://doi.org/10.3390/electronics14071481.

Adversarial Robustness of Deep Learning in Medical Imaging: A Comprehensive Survey and Benchmark of State-of-the-Art Architectures

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***Abstract*—The integration of artificial intelligence into medical diagnostics promises to revolutionize healthcare. However, the reliability of these systems is critically undermined by adversarial examples, which are imperceptible perturbations that can lead to misdiagnosis. Ensuring the robustness of AI-driven clinical decisions is paramount for ensuring patient safety and institutional trust. This study addresses this challenge in two ways. First, we provide a structured survey of the state-of-the-art adversarial threats, including adversarial attacks and detection strategies. Second, we present a rigorous empirical benchmark of five prominent CNN architectures for dermatoscopic skin cancer classification using the gold standard Auto Attack suite. The results revealed significant disparities in robustness based on the architectural design. Although all standard-trained models are highly vulnerable, their defensibility through adversarial training varies significantly. We found that modern transformer-inspired architectures, such as ConvNeXt, achieved the state-of-the-art robust accuracy while maintaining high performance with minimal trade-offs. Conversely, architectures optimized for mobile efficiency, such as MobileNetV2 and EfficientNet-B2, are exceptionally difficult to defend. To the best of our knowledge, this is the first study to establish an architectural hierarchy of robustness for dermatoscopic tasks, demonstrating that hybrid designs outperform mobile-optimized models by over 25% under adversarial conditions. These findings advocate a shift in clinical AI validation from accuracy-centric to robustness-centric metrics.**

***Keywords*—Adversarial attacks; dermatoscopy; deep learning; robustness benchmark; security in medical AI**

I. Introduction

The integration of deep learning (DL) into medical diagnostics has become the cornerstone of modern healthcare systems. These models demonstrate remarkable capabilities in the automated analysis of images across diverse modalities such as radiology, pathology and dermatology [1]. AI systems offer immense potential to augment clinical workflows, enhance diagnostic accuracy and democratize access to expert-level analysis. However, the foundational trust required for widespread clinical adoption depends critically on reliability, security and predictability. A significant and growing body of research has revealed the fundamental vulnerabilities of these systems to adversarial attacks [2]. Adversarial attacks involve the application of subtle, often human-imperceptible perturbations to the input data. These perturbations were carefully crafted to cause targeted misclassifications.

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The implications of these findings are profound in the medical field. For example, maliciously altering a dermatoscopic image to conceal a malignant lesion or to fabricate signs of pathology poses a direct and severe threat to patient safety and diagnostic integrity. Such "adversarial examples" differ from visually obvious deepfakes. The danger lies in their stealthiness. As AI models transition from research settings to clinical practice, understanding and mitigating their vulnerabilities is essential. This is not merely an academic exercise but a prerequisite for responsible deployment [3].

In response to this threat, the research community has pursued two main lines of inquiry. The first focuses on developing robust defence mechanisms. Among these, adversarial training has emerged as the most effective approach, despite its high computational expense. This method augments the training process by using adversarially generated examples to teach model resilience [4]. The second line of inquiry investigates the inherent properties of various neural network architectures. Researchers aim to understand why certain designs are more robust than others. Architectural philosophies, such as skip connections in ResNet, dense feature reuse in DenseNet, and Hybrid convolutional designs in ConvNeXt, have been proposed. However, a direct and standardized comparison of adversarial resilience within the medical context has not yet been established [5]. This study identified a critical gap in the literature: no systematic architectural benchmark has been tested against a unified, gold-standard adversarial evaluation suite in a realistic medical imaging task. Whether specific design philosophies offer superior inherent protection or are more amenable to adversarial training remains an open and crucial question. Answering these questions is vital for guiding the development of secure and reliable medical AI systems.

This review and benchmark study addresses three key questions: What is the baseline adversarial vulnerability of diverse state-of-the-art deep learning architectures when applied to a medical diagnosis task? How effectively does a standard defence mechanism (PGD-Adversarial Training) improve the robustness of these architectures? Do certain architectural paradigms (e.g., convolutional vs transformer-based) exhibit superior inherent robustness or benefit more from adversarial training?

This study addresses these questions through two core contributions that directly affect clinical AI deployment. First,

we provide a structured review of the adversarial threat landscape specific to medical imaging, categorizing the threats based on their clinical significance. Second, we present the first rigorous empirical benchmark comparing ConvNeXt with standard CNNs (EfficientNet and MobileNet) on the ISIC dermatoscopic dataset using the gold-standard Auto Attack suite. We quantified the "robustness gap", revealing that while lightweight models suffer a near-total collapse (0–7% robust accuracy) under attack, modern transformer-inspired designs maintain viable clinical performance (approximately 74%). These findings provide actionable guidelines for practitioners, suggesting that architectural depth and kernel size are more critical than model speed for ensuring patient safety in adversarial environments.

The remainder of this study is organized as follows: Section II provides a detailed review of the foundational concepts underlying adversarial attacks and defence mechanisms. Section III outlines the methodologies employed to generate and detect adversarial perturbations with a focus on advanced algorithms and emerging detection strategies. Section IV presents the benchmark results and provides an extensive comparative analysis of the evaluated deep-learning architectures. Section V discusses significant findings and their broader implications in the context of medical imaging. Finally, Section VI concludes the study and suggests several promising avenues for future research.

II. Literature Review

The successful application of deep learning in medical imaging has been driven by the development of increasingly sophisticated neural network architectures. Convolutional Neural Networks (CNNs) have long dominated the field with foundational architectures such as ResNet enabling the training of very deep networks through residual connections [6]. This was followed by models such as DenseNet, which introduced densely connected layers to facilitate feature reuse and improve gradient flow [7]. The demand for computational efficiency has led to the development of lightweight architectures, such as MobileNetV2 [8] and EfficientNet [9], which leverage depth-wise separable convolutions and compound scaling strategies.

Recently, this trajectory has been challenged by the advent of Vision Transformers (ViTs) that have adapted from natural language processing to visual tasks. The original ViT model introduced global self-attention as a core mechanism for image understanding [10], whereas follow-up designs such as the Swin Transformer employed a hierarchical structure and local attention windows to improve computational efficiency and multiscale representation [11]. This architectural evolution has continued with models such as ConvNeXt, which reincorporate design principles from transformers into a convolutional framework [12]. Although pure ViTs offer powerful global attention mechanisms, they typically require large datasets to prevent overfitting. Consequently, hybrid architectures, such as ConvNeXt, which bridge the gap by combining transformer-style macro-designs with the inductive biases of CNNs, represent a more data-efficient and promising direction for medical imaging tasks where labeled data are limited.

Although these architectures have achieved impressive performance on clean data and they remain vulnerable to adversarial examples of input perturbations that are often imperceptible to humans but cause erroneous model predictions. This phenomenon was first highlighted by Szegedy et al. (2013) [13], with initial attack methods such as the Fast Gradient Sign Method (FGSM) offering fast, albeit limited and adversarial perturbation capabilities. More powerful iterative attacks, particularly Projected Gradient Descent (PGD), have become standard tools for evaluating the robustness under white-box conditions [14].

Standardized evaluation suites, such as Auto Attack, have emerged to counteract the overfitting of defenses to specific attack types. By combining multiple strong parameter-free attack strategies, Auto Attack provides a comprehensive and reproducible robustness assessment [15]. Numerous defence mechanisms have been proposed to respond to these threats, although many have been broken by adaptive attacks specifically crafted to bypass them. Among these, adversarial training, particularly PGD-based training, has shown the most consistent and practical improvement in robustness. Other strategies, including input pre-processing or certified defences such as randomized smoothing, often entail trade-offs, including reduced accuracy on clean data or limited resilience to adaptive threats. Table I provides an at-a-glance summary of key studies on adversarial attacks and defence for medical imaging.

This literature review illustrates the dynamic and ongoing challenge between model innovation, adversarial attack development and defence techniques. However, this study also revealed significant gaps. Although individual models and earlier CNN families have been analyzed for robustness, there is a lack of comprehensive large-scale benchmarking. This benchmarking should be used to evaluate a diverse range of modern architectures, including CNNs and Transformers. Additionally, it should be conducted under a standardized and rigorous threat model, such as an Auto Attack. Furthermore, the interaction between architectural design choices (e.g., dense connectivity or global self-attention) and adversarial training efficacy remains poorly understood. This study addresses this gap by systematically benchmarking deep-learning architectures under adversarial conditions, thereby providing new insights into the structural factors that influence the robustness of medical AI systems.

TABLE I. Summary of Key Studies in Adversarial Attack and Defence for Medical Imaging

Reference	Methodology / Approach	Datasets Used	Key Contributions / Findings
[16]	Random Forest classifier on multi-layer CNN features	CT Images	Proposed a method to detect adversarial attacks by analysing layer-specific features, with visualizations to distinguish attack from noise.
[17]	Adversarial attack via texture statistics transformation (AdaIN)	CT Images	Introduced a novel attack that alters texture statistics, effectively deceiving both segmentation models and human practitioners.
[18]	Frequency constraint-based adversarial attack	Medical Images (including 3D CT)	Developed an attack that perturbs high-frequency information while preserving low-frequency content, outperforming existing methods.

[19]	FGSM attack on a custom COVID-19 detection system	COVID-19 CT Images	Demonstrated a critical vulnerability where an FGSM attack reduced non-COVID classification accuracy from 80% to 0%.
[20]	FGSM attack on a CNN model	Medical Images (Brain Tumour), MNIST	Showed that simple attacks significantly reduce model accuracy in tasks like brain tumour detection.
[21]	One-pixel and multi-pixel adversarial attacks	Medical Images (including CT)	Investigated the high vulnerability of DNNs to minimal, pixel-level attacks, showing significant impact on classification accuracy.
[22]	Image-based adversarial attack with loss stabilization	Medical Images (including CT)	Proposed an attack method that generates stable and effective adversarial perturbations with small variance across different modalities.
[23]	PGD and Deep Fool attacks on models with Grad-CAM	CXR and OCT Images	Evaluated the vulnerability of Explainability methods (Grad-CAM), showing high fooling rates under standard adversarial attacks.
[24]	Two-stage cascade framework (local detection + global classification)	GAN-manipulated CT scans	Proposed a method highly sensitive to small, forged regions (like injected/removed tumours), achieving high detection accuracy.
[25]	Ensemble-based defence with adversarial training	Lung Cancer CT Images	Showed that adversarial attacks severely impact lung nodule prediction and that ensemble strategies can improve robustness.
[26]	Two-phase defence framework (adversarial learning + filtering)	COVID-19 Radiology Images	Proposed a defence framework that enhances model resilience against attacks while maintaining high diagnostic accuracy on clean images.
[27]	Investigated the role of model complexity	Medical Images (including CT)	Found that simpler deep learning models exhibit greater inherent robustness against adversarial attacks compared to more complex ones.
[28]	Medical Adversarial Shield (MAS) defence	CT Images	Introduced a defence mechanism (MAS) that focuses on robust shallow features, proving more effective than deep feature-based defences.

III. Adversarial Attacks and Detection Techniques in Medical Imaging

This section presents a comprehensive overview of adversarial vulnerabilities in medical deep-learning systems. This process is divided into two parts. The first part surveys the foundational and state-of-the-art attack algorithms used to probe model weaknesses.

The second part examines the detection and mitigation strategies that include both algorithmic defences and architectural considerations.

A. Adversarial Attack Methodologies

Adversarial attacks fundamentally challenge the security and reliability of deep-learning models. These methods are designed to generate perturbations that, when added to a clean input, cause the trained model to misclassify the input. The effectiveness and subtlety of these attacks have evolved significantly. This section surveys several foundational and state-of-the-art adversarial attack algorithms that form the basis of modern robustness evaluations, including the methods used in our experimental benchmark.

1) Gradient-based attacks: A primary class of attacks, particularly in white-box scenarios in which the attacker has full access to the model's architecture and parameters, leverages the model's gradients to craft perturbations. The gradient of the loss function with respect to the input image indicates the direction in which the input pixels should be changed to maximize loss, thereby increasing the chance of misclassification.

a) Fast Gradient Sign Method (FGSM): The Fast Gradient Sign Method proposed by Goodfellow et al. (2014) [29] is one of the earliest and most foundational one-step attack methods. It operates by creating a single linear step in the direction of the gradient sign. The perturbation (η) is calculated as:

$$\eta = \varepsilon \cdot sign(\nabla_x J(\theta, x, y)) \quad (1)$$

where,

ε (epsilon) is a small scalar that constrains the magnitude of perturbation, ensuring that it remains imperceptible.

$\nabla_x J(\theta, x, y)$ is the gradient of the loss function J with respect to the input image x.

y is the true label and θ represents the model parameters.

The $sign()$ function extracts the direction of the gradient for each pixel, which is scaled by ε.

The adversarial example (x_adv) is then generated by adding this perturbation to the original image:

$$x_adv = x + \eta \quad (2)$$

This process is illustrated in Fig. 1, which demonstrates how the addition of calculated noise shifts the model's prediction while the image remains visually unchanged to the human observer. Although computationally efficient, FGSM is often considered a weaker attack because it assumes a linear approximation of the loss function, and its single-step nature can sometimes be overcome using simple defence mechanisms.

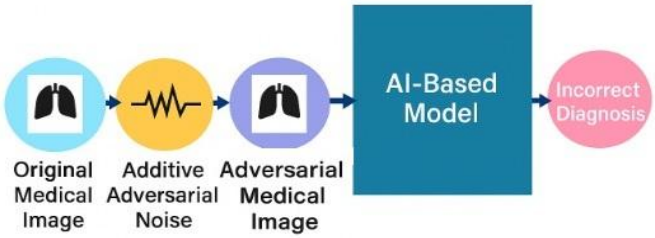


Fig. 1. Schematic representation of the adversarial noise injection. A carefully crafted perturbation (noise) is added to the original medical image. The resulting adversarial image remains visually indistinguishable to the human eye, but causes the AI model to output an incorrect diagnosis.

TABLE II. SUMMARY OF KEY ADVERSARIAL ATTACK METHODOLOGIES

Attack Name	Type	Key Mechanism	Strengths	Limitations
FGSM	White-Box, Single-Step, Gradient-based	Takes one large step in The direction of the sign of the loss gradient.	Very fast and Computationally Cheap.	Often less effective against robustly trained models, Easily defended.
PGD	White-Box, Iterative, Gradient-based	Takes multiple small gradient steps, projecting back into the allowed perturbation space.	Much stronger than FGSM considered a universal first-Order adversary.	Slower than FGSM due to its iterative nature.
Auto Attack (AA)	White-Box & Black-Box, Ensemble	An automated suite combining four attacks (APGD-CE, APGD-DLR, FAB, Square).	Gold-standard for robustness evaluation, parameter-free and Very strong.	Computationallyintensive as it runs multiple diverse-Attacks.
Square Attack (part of AA)	Black-Box, Query-based, Score-based	Iteratively queries the model with square-shaped perturbations at random locations.	Does not require gradient Information, effective against Gradient masking.	Can require a large number of queries to find a successful Attack.

b) Projected Gradient Descent (PGD): The Projected Gradient Descent, introduced by Madry et al. (2018) [14], is a powerful iterative extension of FGSM and is widely regarded as a much stronger first-order attack. Instead of taking one large step, the PGD takes multiple small steps in the direction of the gradient, projecting the result back onto the allowed perturbation space (an L_p-norm ball of radius ε) after each step to ensure that the perturbation remains constrained. The iterative process for a targeted attack at step t+1 can be described as:

$$x_adv\hat{}(t+1) = Proj_{x,\varepsilon}\left(x_adv\hat{}(t) + \alpha \cdot sign(\nabla_x J(\theta, x_adv\hat{}(t), y))\right) \quad (3)$$

where,

$x_adv\hat{}(t)$ is the adversarial example at step t.

α is the step size, which is typically much smaller than ε $(e.g., \alpha < \varepsilon)$.

$Proj_{x,\varepsilon}$ is a projection operator that clips the perturbation to ensure $||x_adv\hat{}(t+1) - x||_p \leq \varepsilon$.

By iteratively searching for the optimal perturbation within the ε-ball, PGD is significantly more effective at finding adversarial examples that fool robustly trained models and has become a standard method for adversarial training and evaluation.

2) Ensemble and query-based attacks: To overcome defences and provide a more comprehensive robustness evaluation, recent studies have focused on creating attack ensembles that combine multiple attack strategies.

a) Auto Attack (AA): Auto Attack, proposed by Croce and Hein (2020) [15], is considered the current gold standard parameter-free benchmark for evaluating adversarial robustness. It is not a single new attack, but an ensemble of four diverse and complementary attacks:

- APGD-CE: An auto-tuned version of PGD using cross-entropy loss. This adaptively adjusts the step size to achieve a more efficient search.
- APGD-DLR: An auto-tuned PGD variant using the difference in logit ratio (DLR) loss, which is often more effective than CE loss for generating attacks.
- Fast Adaptive Boundary Attack (FAB): A targeted attack that minimizes the perturbation required to cross the decision boundary and effectively probes the nearest failure point.
- Square Attack: A query-based black-box attack that does not require gradient information. It iteratively tests perturbations in localized square-shaped areas, making it effective against defences that obscure the gradients.

Auto Attack automatically runs this suite of attacks and reports the accuracy of the model against the strongest of them. Its parameter-free nature and diverse attack portfolio make it a reliable and objective method for assessing the true robustness of the model, which is why it was selected as the primary benchmark tool in this study. Table II summarizes the key adversarial attack methodologies and compares their mechanisms, strengths and limitations.

B. Detection and Mitigation Strategies

The growing threat posed by adversarial attacks and synthetic manipulations has spurred extensive research on detection and mitigation techniques. This section categorizes the principal detection methodologies, examines their technical underpinnings, and evaluates state-of-the-art architectural paradigms used in defence systems. Table III provides a concise comparison of the principal adversarial detection paradigms.

1) Taxonomy of detection methodologies: Detection strategies can be broadly categorized into two types: active and passive strategies.

a) Active detection methods involve modifying the data or transmission process to facilitate subsequent authentication. Common techniques include digital watermarking and digital signatures that embed imperceptible verification signals in the original image. These approaches enable real-time authenticity checks, but require control over the image creation and distribution pipeline. Thus, their applicability is limited when working with externally sourced or pre-existing medical images.

b) Passive detection methods require no prior modifications of the image. Instead, they analyze the statistical or visual artefacts introduced during the manipulation process. These may include spatial inconsistencies (e.g., unnatural textures or lighting), frequency anomalies (e.g., upsampling artefacts), and metadata mismatch. Passive methods are more

versatile and widely applicable in clinical settings where input images may come from heterogeneous sources.

2) Architectural paradigms for detection: The detection of adversarial perturbations and deepfakes is typically framed as a classification task, in which a model learns to distinguish between authentic and manipulated inputs. The performance of such detectors is heavily influenced by the architectural design. Three main architectural categories have emerged.

a) Convolutional Neural Networks (CNNs): CNNs remain fundamental in image-based detection owing to their ability to capture local spatial dependencies. Architectures such as ResNet, DenseNet, and MobileNet are frequently employed to detect subtle pixel-level artifacts. In specialized cases, U-Net variants are used to localize the manipulated regions, in addition to classification.

b) Frequency and hybrid domain models: Several detection models incorporate frequency-domain representations (e.g., via DFT or DWT) to identify regular patterns or distortions that are not evident in the spatial domain. Hybrid models that process both spatial and frequency features in parallel have shown superior performance in capturing a wide range of manipulation artefacts.

TABLE III. SUMMARY OF KEY PARADIGMS FOR ADVERSARIAL DETECTION

Technique	Description	Advantages	Limitations
Active Detection	Embeds digital signatures or watermarks into original images for later verification.	Real-time verification Tamper-evident mechanisms	Requires end-to-end image control. Cannot verify legacy images
Passive Detection	Analyses content artefacts without prior modification.	Broad applicability, Detects a wide range of manipulations	Sensitive to image quality. May require large training datasets
CNN-Based Models	Leverages spatial feature extraction using convolutional layers.	Effective for local artifacts, Efficient for real-time systems	Limited receptive field. May miss global inconsistencies
Frequency-Domain Models	Uses transformations (e.g., DFT, DWT) to analyze hidden periodic patterns.	Captures signal-level distortions, Complements spatial models	Complex pre-processing, Sensitive to compression and noise
Transformer-Based Models	Models long-range dependencies and global context.	Robust to global manipulations, Effective on large-scale datasets	High computational cost, Requires extensive training data
Hybrid CNN Transformer	Combines local spatial features with global contextual understanding.	Balances local and global detection capabilities	Increased model complexity, Harder to interpret

c) Transformer-based and hybrid architectures: Vision Transformers (ViTs) have been increasingly explored for detection tasks because of their strength in modeling global relationships. Unlike CNNs, ViTs can capture long-range dependencies and global inconsistencies such as unnatural illumination or geometry shifts. Recent approaches have also combined CNN backbones with transformer heads to benefit from both local detail sensitivity and global context modeling. The table above summarizes the principal paradigms used to detect adversarial attacks and synthetic manipulations in medical images.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

This section presents the empirical results of this benchmark. We begin by detailing the implementation specifics and the dataset used and then provide a thorough analysis of the quantitative results. This is followed by a broader discussion of key findings and their implications for the field of medical AI.

A. Experimental Setup and Evaluation Metrics

The computational experiments in this study were performed using the Google Colab Pro cloud platform. To accelerate the intensive training and evaluation cycles, all models were processed on an NVIDIA Tesla T4 Graphics Processing Unit (GPU), equipped with 15 GB of dedicated VRAM. The software stack was built on Python version 3.11.12 and utilized the PyTorch deep learning library, version 2.6.0, for all model implementations. GPU-specific optimizations were enabled using the NVIDIA CUDA Toolkit (version 12.4) and the cuDNN library (version 9.3.0).

The primary objective of this experiment was to evaluate the adversarial robustness of various state-of-the-art deep learning architectures for a medical classification task. The overall experimental workflow is shown in Fig. 2. We selected five representative models to cover a broad spectrum of architectural philosophies: ResNet50 as a classic deep residual network, DenseNet121 for its dense feature-reuse connectivity, MobileNetV2 as a lightweight convolutional backbone, EfficientNet-B2 for its compound scaling of depth/width/resolution, and ConvNeXt as a modern "Transformer-inspired" convolutional design. This diverse portfolio allowed us to probe the design principles that confer inherent resilience to adversarial perturbations and quantify the benefits of adversarial training across different paradigms.

This study utilized a publicly available dataset of dermatoscopic images for skin cancer classification sourced from the International Skin Imaging Collaboration (ISIC) Archive and accessed via the Kaggle repository [30]. The dataset is organized into two distinct classes: 'Benign,' containing 1,800 images of non-cancerous skin lesions, and 'Malignant,' containing 1,497 images of cancerous lesions, primarily melanomas. This task is a binary classification problem that distinguishes between these two categories.

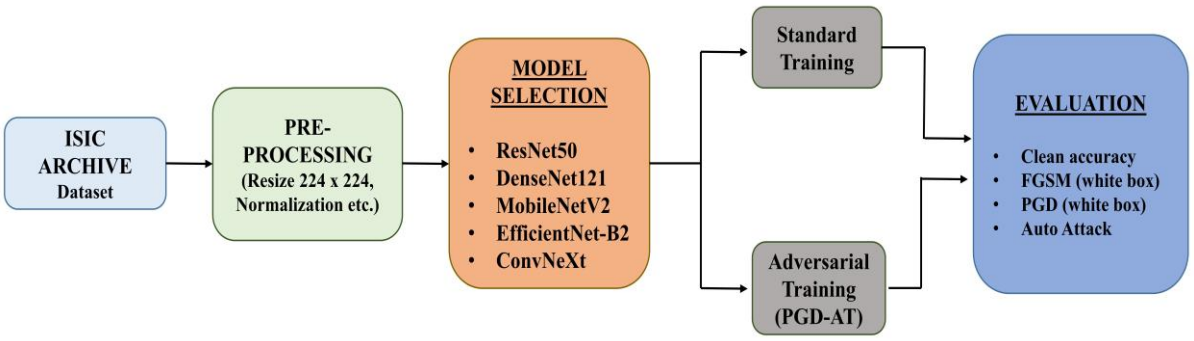


Fig. 2. Experimental workflow. The study pipeline processes the ISIC dermatoscopic dataset using five distinct architectures. Each mo del underwent both standard and adversarial training before being subjected to the multi-stage Auto Attack suite to benchmark its robustness.

TABLE IV. HYPERPARAMETERS AND VALUES FOR TRAINING AND EVALUATION

Hyperparameters	Value / Description
Input Resolution	224 × 224 pixels
Batch Size	32
Optimizer	Adam
Learning Rate	1×10^{-4}
Weight Decay	1×10^{-4}
Loss Function	Cross-Entropy Loss
Training Epochs	50
Adversarial Training (PGD-AT) (Used only for 'Adversarial' models)	
Perturbation Norm	L-infinity (L∞)
Epsilon (ε)	2/255
Step Size (α)	1/255
PGD Steps	10
Evaluation Attack Parameters (Used to test all final models)	
Perturbation Norm	L-infinity (L∞)
Epsilon (ε)	4/255
PGD Step Size (α)	2/255
PGD Steps	20
Auto Attack Suite	APGD-CE + Square

The full dataset, comprising 3,297 images in the JPEG format, was partitioned into a training set of 2,637 images (80%) and a held-out test set of 660 images (20%) to ensure rigorous and reproducible evaluation. Fig. 3 shows representative examples of "Benign" and "Malignant" images from the dataset, along with a visualization of a subtle adversarial perturbation designed to cause misclassification.

To ensure a comprehensive and robust evaluation, the following key performance metrics were employed to assess the models under both clean and adversarial conditions: Accuracy was used to measure the overall percentage of correct classification. The F1-Score, as the harmonic mean of precision and recall, was chosen to provide a balanced measure that accounts for both false positives and false negatives, which incur significant clinical costs.

Finally, the Area Under the ROC Curve (AUC) was used to evaluate the overall discriminatory power of the model across all possible classification thresholds, serving as a crucial measure of diagnostic utility.

All experiments were conducted using a consistent set of hyperparameters to ensure a fair and reproducible comparison across the architectures. The models were trained for 50 epochs using the Adam optimizer and all images were resized to a standard 224x224 resolution. For adversarial defence and evaluation, we used the L-infinity norm threat model. The specific parameters for adversarial training and the stronger parameters used for the final evaluation of attacks are listed in Table IV.

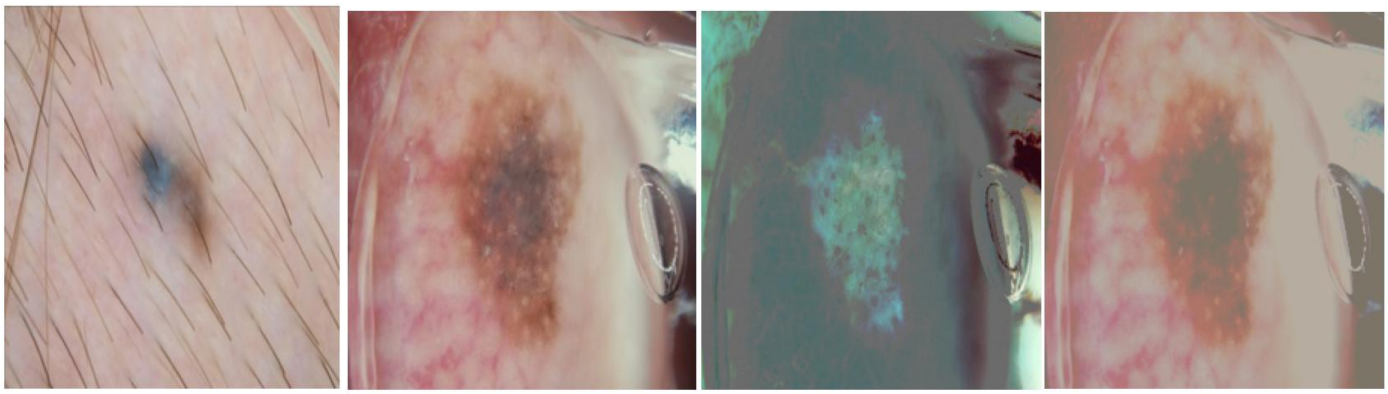
B. Benchmark Results and Analysis

This section presents the quantitative and qualitative results of the comprehensive benchmark. Table V provides a detailed summary of the performance metrics for all five architectures under both the standard and adversarial training paradigms. These data were further contextualized using visual evidence designed to highlight the vulnerability of standard models. Fig. 4 displays confusion matrices comparing the performance of each standard model on clean versus attacked data, whereas Fig. 5 shows the corresponding collapse in the ROC curves.

First, a critical vulnerability was observed in all standardly trained models. As detailed in Table V, every architecture under the "Standard" training regimen achieved high performance on clean data, with accuracies ranging from 85% to 90%. It is important to note that the standard models (EfficientNet-B2 and MobileNetV2) reached 0.00% accuracy under the Auto Attack suite.

This total collapse is expected for non-robust models when subjected to an ensemble of strong gradient-based attacks, which successfully identifies a failure point for every image in the test set. However, this material was exceptionally brittle. Fig. 4 provides stark visual confirmation of this collapse. For each architecture, the left panel shows a well-performing model on clean data, while the right panel shows its complete failure under the auto-CE attack, characterized by a massive influx of false negatives, which is the most dangerous failure mode in a clinical context.

Similarly, the ROC curves in Fig. 5 demonstrate this degradation, with the high-performance blue curve (clean) collapsing to the red curve (auto-CE), which often approaches the diagonal line of random chance, signifying a total loss of diagnostic utility.

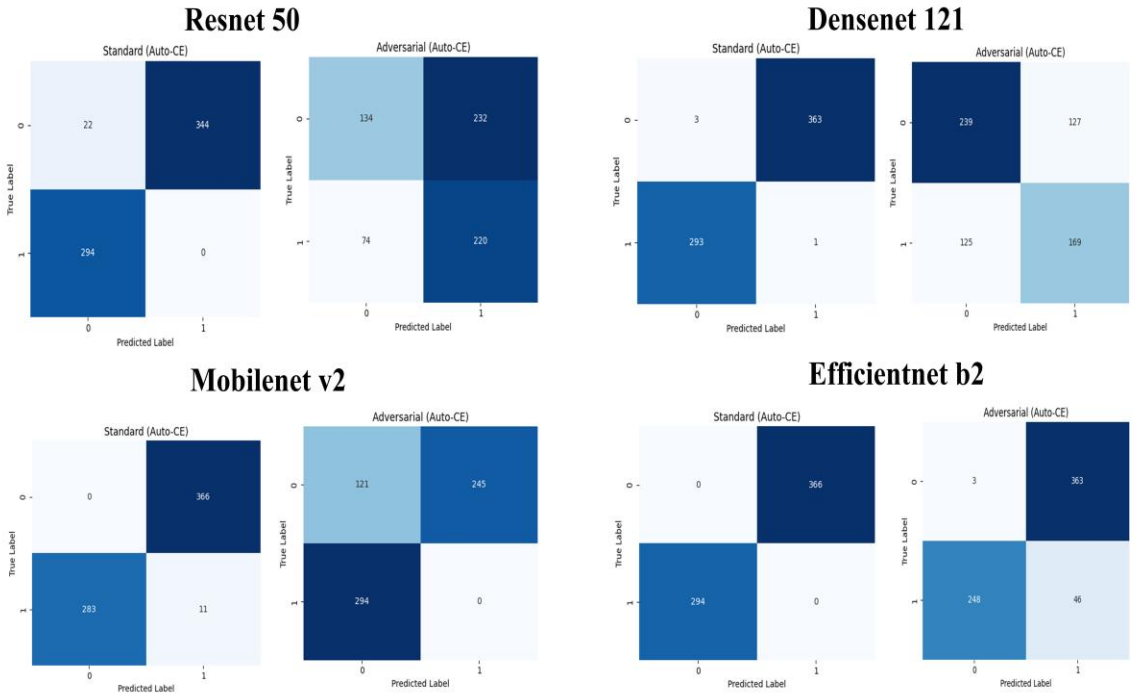


(a) (b) (c) (d)

Fig. 3. Visualization of a PGD Adversarial Attack Causing Misdiagnosis: (a) Representative benign lesions from the dataset. (b) The original malignant image, correctly classified as "Malignant". (c) Amplified adversarial perturbation generated by PGD ($\varepsilon = 4/255$) for visibility. (d) The adversarial example, which the model now incorrectly classifies as "Benign".

TABLE V. COMPREHENSIVE PERFORMANCE SUMMARY OF SOTA ARCHITECTURES

Architecture	Training Method	Clean Acc (%)	Clean F1	Clean AUC	FGSM Acc (%)	PGD Acc (%)	Auto-CE Acc (%)
resnet50	Standard	88.94	0.8805	0.9668	65.00	0.91	0.00
	Adversarial	60.15	0.3601	0.4520	82.73	66.21	27.88
densenet121	Standard	89.55	0.8829	0.9579	47.88	0.45	0.30
	Adversarial	70.15	0.5321	0.6730	85.61	64.70	46.97
mobilenetv2	Standard	85.15	0.8333	0.9384	55.91	0.30	0.00
	Adversarial	70.15	0.5253	0.8890	66.36	19.85	0.15
efficientnet_b2	Standard	88.03	0.8703	0.9536	56.36	0.00	0.00
	Adversarial	46.52	0.5862	0.3931	80.76	46.06	7.42
convnext	Standard	87.73	0.8732	0.9642	61.67	15.15	12.73
	Adversarial	82.27	0.8175	0.9203	81.21	78.64	73.79



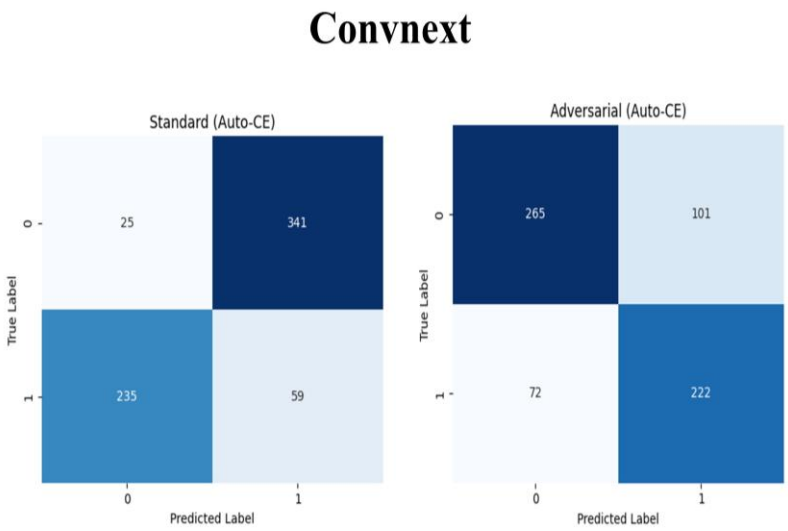


Fig. 4. Confusion matrices illustrating the impact of auto-CE attacks on standard-trained models. The labels are encoded as 0 for 'Benign' and 1 for 'Malignant'. The color intensity represents the normalized percentage of the true class.

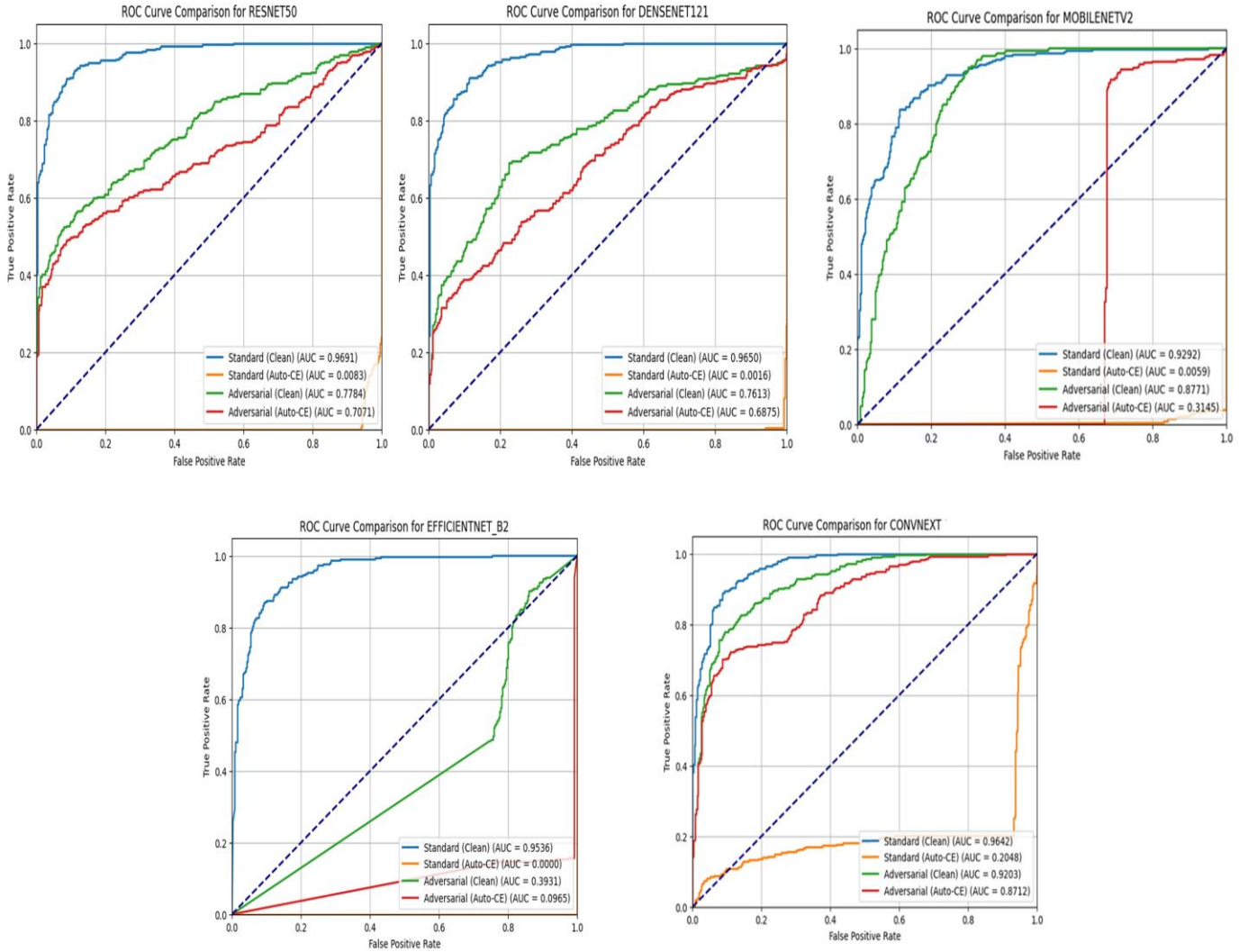


Fig. 5. ROC Curves showing performance collapse of standard models under auto-CE attack.

Second, adversarial training has proven to be an effective, albeit highly variable, defence mechanism. Although not depicted in the figures for clarity, Table V clearly demonstrates that adversarial training substantially improves the robustness of all tested architectures against PGD and auto-CE attacks. A comparison of the "Standard" and "Adversarial" training rows reveals, however, that the degree of this improvement is not uniform. This indicates that the effectiveness of this defence is fundamentally linked to the underlying architectural design, with some models being inherently more amenable to robustness than others.

The most significant finding of this benchmark was the exceptional robustness of the ConvNeXt architecture. As shown in Table V, after adversarial training, it achieved a robust accuracy of 73.79% against the gold-standard auto-CE attack. This result was more than 25 percentage points higher than that of the next-best performing model, DenseNet121 (46.97%). Furthermore, ConvNeXt achieves state-of-the-art robustness while experiencing only a minor drop in the clean data performance. This strongly suggests that modern convolutional designs that incorporate principles from Vision Transformers possess an architectural advantage in terms of learning generalizable and defensible features.

Finally, in stark contrast to ConvNeXt, architectures designed specifically for computational efficiency, MobileNetV2 and EfficientNet-B2, prove exceptionally difficult to defend. Table V reveals that even after intensive adversarial training, the robust accuracy against auto-CE remains critically low at 0.15% and 7.42%, respectively. This finding serves as a crucial cautionary note: optimizing the speed and model size in medical AI may result in a severe and unacceptable cost to model security. The design principles that enable their efficiency, such as depth-wise separable convolutions, may inadvertently create fragile feature dependencies that can be easily exploited by adversarial perturbations.

C. Discussion

Our findings have significant implications for the development and clinical deployment of medical AI systems, primarily highlighting that a model's architecture is a critical determinant of its security and accuracy. The benchmark results move beyond simply confirming the known vulnerability of standard models and reveal a distinct hierarchy of robustness among different architectural paradigms. This suggests that the pursuit of high performance on clean data without considering architectural resilience can lead to the development of systems that are dangerous in practice.

The exceptional performance of ConvNeXt after adversarial training was the most salient outcome of this study. Its ability to achieve high robust accuracy while minimizing the trade-off with clean accuracy suggests that its architectural principles, such as the use of larger convolutional kernels and transformer-style block designs, confer a strong inductive bias for learning more generalizable and defensible features. In contrast, the profound failure of MobileNetV2 and EfficientNet-B2 to gain meaningful robustness even after intensive adversarial training points to an inherent fragility. We hypothesize that the design choices that enable computational efficiency, particularly the heavy reliance on depth-wise separable convolutions, may create sparse and fragile feature dependencies that are easily disrupted by adversarial perturbations.

These results lead to a clear recommendation for the field: for high-stakes applications, such as medical diagnosis, a "robust-by-design" approach should be prioritized. Simply selecting a model based on its top-line accuracy on a benchmark leader board is insufficient. Instead, architectural properties that promote robustness, such as those found in modern hybrid designs, such as ConvNeXt, should be favored. This study underscores the urgent need for standardized adversarial stress testing to become an integral part of the validation and regulatory approval process for any AI system intended for clinical use.

Although this study provides a rigorous benchmark, it has several limitations. Our analysis was conducted on a single dermatoscopic dataset and focused exclusively on the L-infinity threat model. Additionally, owing to the high computational cost of performing PGD-Adversarial training on five distinct architectures, this study relied on single-run evaluations. Future work should prioritize multi-seed validation to establish statistical confidence intervals. Furthermore, we evaluated only the PGD-based adversarial training as a defence mechanism. Therefore, future work should extend this benchmark across diverse medical modalities, such as radiology and histopathology, and investigate a wider range of threat models and advanced defence mechanisms. Nonetheless, this study serves as a critical resource, providing a clear architectural roadmap for building a safer and more reliable medical AI.

V. Challenges in Defending Medical Imaging Against Adversarial Attacks

Our benchmark highlights the promising architectural directions for AI-driven medical diagnostics. However, securing such systems against adversarial manipulation remains a multifaceted problem. Challenges span the technological, data-related, and socio-ethical domains. These barriers must be addressed to ensure the safe and equitable deployment of AI tools in clinical practice. This high-level overview of challenges and mitigation strategies is summarized in Table VI.

TABLE VI. Challenges and Mitigation Strategies for Adversarial Defences in Medical Imaging

Challenges	Description	Potential Mitigation Strategies
Technological Arms Race	Generative models (GANs, Diffusion Models) continually evolve, producing more subtle perturbations that mimic natural variability, making static defences obsolete.	Develop adaptive defences with continuous retraining and use ensemble and meta-learning approaches to detect novel attacks.
The Data Bottleneck	Lack of large standardized datasets containing authentic and adversarially manipulated images across modalities (MRI, CT, and X-ray) hinders reproducibility and comparability of robustness research.	Foster collaborative data sharing with privacy safeguards (e.g., federated learning) and create high-fidelity synthetic benchmarks.

Ethical and Bias Concerns	Training defences on non-representative patient data risk algorithmic bias and may reduce robustness for under-served demographic groups, exacerbating health disparities; patient privacy must be protected.	Establish ethical guidelines and auditing frameworks; enforce demographic balancing and differential privacy techniques.
Legal Responsibility	Unclear liability in AI-induced misdiagnosis, whether it lies with hospitals, developers, or clinicians, impedes trust and adoption. transparency in AI decision processes is limited.	Define legal standards for AI use in healthcare, mandate explainability requirements, and develop clear liability models.

VI. Conclusion

The integration of advanced AI into medical diagnostics offers tremendous benefits, but also exposes a critical vulnerability to adversarial manipulation. This study contributes to the literature by providing a structured survey of adversarial threats and the first rigorous empirical benchmark of ConvNeXt against mobile-optimized CNNs for the skin cancer classification task. Our results establish a clear hierarchy of robustness, driven by the architecture. While all standard trained models proved fragile under attack, hybrid convolutional designs, such as ConvNeXt, substantially outperformed mobile-optimized networks, achieving high robust accuracy with minimal loss of clean data. In contrast, efficiency-focused models, such as MobileNetV2 and EfficientNet B2, remain exceptionally vulnerable even after adversarial training. These findings underscore the importance of architectural choice as important as accuracy in clinical AI. High performance on clean benchmarks alone is insufficient for deployment in high-stakes settings. Instead, "robust by design" architectures validated through standardized adversarial stress tests must become a mandatory step in development and regulatory approval. This benchmark was limited to a dermatoscopic dataset and an L∞ threat model with PGD-based defences. Future studies should extend to multiple modalities, diverse threat norms, and advanced defence techniques to build on the architectural insights presented here. By prioritizing rigorous robustness evaluation and defensive design principles, the medical AI community can move toward systems that are not only accurate but also fundamentally safe and trustworthy.

References

[1] G. K. Thakur, S. Khan, N. Khan, A. Thakur, and S. Kulkarni, "Deep Learning Approaches for Medical Image Analysis and Diagnosis.," *Cureus*, vol. 16, no. 5, May 2024, doi: 10.7759/cureus.59507.

[2] N. Ghaffari Laleh *et al.*, "Adversarial attacks and adversarial robustness in computational pathology," *Nature Communications*, vol. 13, no. 1, Sep. 2022, doi: 10.1038/s41467-022-33266-0.

[3] P. Radanliev and O. Santos, "Adversarial Attacks Can Deceive AI Systems, Leading to Misclassification or Incorrect Decisions." mdpi ag, Sep. 29, 2023. doi: 10.20944/preprints202309.2064.v1.

[4] S. Sankaranarayanan, R. Chellappa, S. N. Lim, and A. Jain, "Regularizing Deep Networks Using Efficient Layerwise Adversarial Training," *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 32, no. 1, Apr. 2018, doi: 10.1609/aaai.v32i1.11688.

[5] M. Dong, Y. Li, Y. Wang, and C. Xu, "Adversarially Robust Neural Architectures.," *IEEE transactions on pattern analysis and machine intelligence*, vol. 47, no. 5, pp. 4183–4197, May 2025, doi: 10.1109/tpami.2025.3542350.

[6] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," Jun. 2016, pp. 770–778. doi: 10.1109/cvpr.2016.90.

[7] G. Huang, L. Maaten, Z. Liu, and K. Weinberger, "Densely Connected Convolutional Networks.", Aug. 25, 2016. doi: 10.48550/arxiv.1608.06993.

[8] M. Sandler, A. Howard, L.-C. Chen, M. Zhu, and A. Zhmoginov, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," Jun. 2018, pp. 4510–4520. doi: 10.1109/cvpr.2018.00474.

[9] M. Tan and Q. Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks." May 28, 2019. doi: 10.48550/arxiv.1905.11946.

[10] A. Dosovitskiy et al., "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale." Oct. 22, 2020. doi: 10.48550/arxiv.2010.11929.

[11] Z. Liu et al., "Swin Transformer: Hierarchical Vision Transformer using Shifted Windows," Oct. 2021, pp. 9992–10002. doi: 10.1109/iccv48922.2021.00986.

[12] Z. Liu, C.-Y. Wu, T. Darrell, C. Feichtenhofer, H. Mao, and S. Xie, "A ConvNet for the 2020s," Jun. 2022. doi: 10.1109/cvpr52688.2022.01167.

[13] C. Szegedy et al., "Intriguing properties of neural networks.", Dec. 20, 2013. doi: 10.48550/arxiv.1312.6199.

[14] A. Mądry, L. Schmidt, A. Makelov, D. Tsipras, and A. Vladu, "Towards Deep Learning Models Resistant to Adversarial Attacks.", Jun. 19, 2017. doi: 10.48550/arxiv.1706.06083.

[15] F. Croce and M. Hein, "Reliable evaluation of adversarial robustness with an ensemble of diverse parameter-free attacks." Mar. 03, 2020. doi: 10.48550/arxiv.2003.01690.

[16] W. Lee and Y. Kim, "Enhancing CT Segmentation Security against Adversarial Attack: Most Activated Filter Approach," *Applied Sciences*, vol. 14, no. 5, p. 2130, Mar. 2024, doi: 10.3390/app14052130.

[17] W. Lee, Y. K. Jung, Y. Kim, Y. Sim, T. H. Kim, and M. Ju, "Adversarial Attacks on Medical Segmentation Model via Transformation of Feature Statistics," *Applied Sciences*, vol. 14, no. 6, p. 2576, Mar. 2024, doi: 10.3390/app14062576.

[18] F. Chen *et al.*, "Frequency constraint-based adversarial attack on deep neural networks for medical image classification," *Computers in Biology and Medicine*, vol. 164, p. 107248, Jul. 2023, doi: 10.1016/j.compbiomed.2023.107248.

[19] Y. Li and S. Liu, "The Threat of Adversarial Attack on a COVID-19 CT Image-Based Deep Learning System," *Bioengineering*, vol. 10, no. 2, p. 194, Feb. 2023, doi: 10.3390/bioengineering10020194.

[20] K. Jhajharia and Y. K. Shrivastavaa, "Adversarial Attacks and Defenses on Deep Learning Models," Sep. 2024, pp. 1–5. doi: 10.1109/iconat61936.2024.10775002.

[21] M.-J. Tsai, P.-Y. Lin, and M.-E. Lee, "Adversarial Attacks on Medical Image Classification," *Cancers*, vol. 15, no. 17, p. 4228, Aug. 2023, doi: 10.3390/cancers15174228.

[22] G. Qi, K. Ma, Y. Song, L. Gong, and Y. Zheng, "Stabilized Medical Image Attacks.", Mar. 09, 2021. doi: 10.48550/arxiv.2103.05232.

[23] E. J. De Aguiar, A. J. M. Traina, M. V. L. Costa, and C. Traina, "Assessing Vulnerabilities of Deep Learning Explainability in Medical Image Analysis Under Adversarial Settings," Jun. 2023, vol. 121, pp. 13–16. doi: 10.1109/cbms58004.2023.00184.

[24] J. Zhang, Y. Liu, X. Huang, Y. Han, and Z. Xiang, "GAN-based Medical Image Small Region Forgery Detection via a Two-Stage Cascade Framework.", May 30, 2022. doi: 10.48550/arxiv.2205.15170.

[25] R. Paul, L. Hall, M. Schabath, R. Gillies, and D. Goldgof, "Mitigating Adversarial Attacks on Medical Image Understanding Systems," Apr. 2020, pp. 1517–1521. doi: 10.1109/isbi45749.2020.9098740.

[26] S. B. U. Haque and A. Zafar, "Robust Medical Diagnosis: A Novel Two-Phase Deep Learning Framework for AdversarialProof Disease Detectionin Radiology Images.," *Journal of imaging informatics in medicine*, vol. 37, no. 1, pp. 308–338, Jan. 2024, doi: 10.1007/s10278-023-00916-8.

[27] D. Rodriguez, T. Nayak, Y. Chen, R. Krishnan, and Y. Huang, "On the role of deep learning model complexity in adversarial robustness for medical images," *BMC Medical Informatics and Decision Making*, vol. 22, no. Suppl 2, Jun. 2022, doi: 10.1186/s12911-022-01891-w.

[28] Q. Yao, X. Yu, Z. He, and S. K. Zhou, "Nowhere to Hide: Toward Robust Reactive Medical Adversarial Defense," May 2024, pp. 1–5. doi: 10.1109/isbi56570.2024.10635644.

[29] I. Goodfellow, J. Shlens, and C. Szegedy, "Explaining and Harnessing Adversarial Examples.", Dec. 19, 2014. doi: 10.48550/arxiv.1412.6572.

[30] F. Fanconic, "Skin Cancer: Malignant vs. Benign," Kaggle Dataset, 2020. Available: https://www.kaggle.com/datasets/fanconic/skin-cancer-malignant-vs-benign. [Accessed: march. 15, 2025]

Enhanced Detection of Acute Lymphocytic Leukemia Using Deep Learning and Hybrid Classifiers on Microscopic Blood Images

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***Abstract*—There is no doubt that a significant number of individuals worldwide suffer from blood cancer. A lot of people are unaware of the dangers associated with this disease, which can be fatal. When diagnosed, patients may feel intense fear and a sense of powerlessness. In addition, due to the rarity of these diseases, patients often struggle to find the necessary help and information. A specific type of blood cancer called acute lymphocytic leukemia (ALL) mainly affects white blood cells and is particularly prevalent in children. Early detection of this disease will improve the chances of recovery. Therefore, it is crucial to have an accurate and dependable method for identifying blood cancers. Deep learning (DL) architectures have garnered significant interest within the computer vision realm. Recently, there has been a strong focus on the accomplishments of pretrained architectures in accurately describing or classifying data from various real-world image datasets. Classification performances of the proposed models are investigated by using Softmax, Support Vector Machine (SVM), and K-Nearest Neighbors algorithm (K-NN) separately on a deep learning neural network (Alexnet and VGG19) to differentiate between the three types of ALL using microscopic images dataset. The experimental results demonstrate that the combination of Alexnet with SVM achieves outstanding classification performance on the leukemia dataset, particularly on the original(unsegmented) data, achieved 97.03% on bengin class, 96.14% on early class, 99.49% on pre class and 99.9% on pro class. This approach achieves higher accuracy levels than practicing physicians.**

***Keywords*—Deep learning; transfer learning; leukemia; Alexnet; VGG19; SVM; K-NN; classification**

I. Introduction

In the last decades, uncontrolled growth of abnormal cells in the leukemia patients and the bone marrow rapidly expanded [1]. A condition distinct from other illnesses because it typically does not create detectable masses through imaging tests like X-Rays [2]. Hematopoietic stem cells, which give rise to all blood cells, go through multiple stages of development before reaching maturity [3].

In leukemia, a specific type of blood cell undergoes rapid and uncontrolled development, leading to the proliferation of these uncontrollable cells known as leukemia cells [4]. These abnormal cells take over the space within the bone marrow which is known as acute lymphoblastic leukemia (ALL) [5]. It is noted that the early detection of ALL can improve the chance of patient survival. Automatic specialized testing, like cytogenetics, immunophenotyping, and morphological cell categorization, can now detect leukemia. Now, due to its great accuracy, the method of observing blood cells using the mentioned processes is advised. The operator's abilities and level of enervation will determine how tough these procedures are [6]. Various deep learning (DL) techniques have demonstrated significant efficacy across diverse domains including automatic recognition, detection, and segmentation. Examples encompass breast cancer [7], skin lesions [8], [9], [10], brain tumor [11], [12], the COVID-19 pandemic [13], [14], [15], and among other areas [16].

Leukemia detection in human blood samples using microscopic images is only appropriate for low-cost and remote diagnosis systems. New-age approaches can help in this situation [17]. Numerous researchers have created algorithms that offer a simple and incredibly accurate technique to detect and classify various types of blood cancer using deep learning, machine learning, and convolution neural networks (CNN) [18]. Authors in [19], [20] used DL for COVID-19 image recognition and classification, also for object detection and recognition. Early detection is the paramount for successful treatment outcomes. Medical advancements have facilitated various screening methods to identify the disease in its nascent stages. These techniques often involve blood tests to analyze abnormalities in white blood cell counts, red blood cell counts, and platelets. Additionally, bone marrow biopsies may be performed to examine the composition of blood cells directly from the source. Advanced imaging technologies such as Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) scans can also aid in detecting leukemia-related abnormalities within the body. Early detection enables prompt intervention, increasing the likelihood of successful treatment and improved patient prognosis. In this type of cancer, the primary impact is on white blood cells. Particularly in children, this illness is frequently identified, making them more susceptible. Therefore, there is a pressing need for a precise and dependable mechanism for identifying such blood cancers in patients. Authors in [21] introduces a system designed to differentiate between the three distinct types of ALL through the implementation of a CNN. The system offers thorough disease diagnosis along with comprehensive information on symptoms and different treatment stages. Through the utilization of a CNN, the system has demonstrated an accuracy rate exceeding 85% in detecting ALL.

The structure of this paper is organized as follows: Section II presents the key standard techniques used for feature extraction, classification, and the Alexnet deep learning approach. Section III describes the datasets employed for training, validation, and evaluation of the proposed method. Section IV

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outlines the proposed method along with its results. Lastly, Section V provides the conclusion and discusses future work.

II. Methods and Materials

A. Deep Learning

A novel area within artificial intelligence is known as Deep learning (DL), which focuses on developing techniques enabling computers to learn complex tasks such as perception with high accuracy. It excels in tasks like image classification, object detection, speech recognition, language processing, and vehicle detection. Unlike traditional classification algorithms that rely on ad-hoc methods for feature extraction from images, DL employs a different approach. Instead of manually defining features, DL methods learn to extract relevant features directly from data, leading to improved performance and reduced false alarms.

Several challenges arise in traditional methods:

1) Difficulty in defining general, reliable characteristics corresponding to specific object types.
2) Complex task of determining the optimal combination of attributes to identify each object type.
3) Challenges in developing efficient techniques for translating, rotating, and scaling objects.

These challenges impact segmentation, classification, and detection processes. DL methods address these challenges by leveraging large labeled datasets to identify relevant features and combinations of characteristics for accurate object categorization. They employ a hybrid feature extraction and classification model, enabling classification of a wide range of unseen objects beyond those included in the training set [22].

Convolutional Neural Networks (CNNs) are a prominent DL architecture that utilizes multiple hidden layers to perform extensive computations on input data. Each layer's output serves as input to the subsequent layer as shown in Fig. 1, facilitating hierarchical feature extraction. The final layer outputs class labels based on the training data. During the training stage, the network learns to predict efficiently, and its performance is evaluated during the prediction phase.

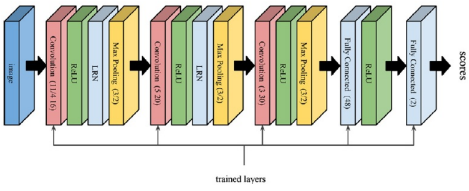


Fig. 1. CNN architecture.

B. Alexnet Deep Learning Neural Network

Alexnet is considered a very important CNN, had a huge performance on the DL Field and it is used in a wide range in computer vision applications [23]. Fig. 2 examines the fundamental structure of Alexnet. It consists of eight layers, with five being convolution layers and the remaining three being fully connected layers. To accelerate the training process, Rectified Linear Unit (ReLU) activation is applied after each convolution and fully connected layer. Dropout is implemented before the first and second fully connected layers. During the training phase, the images are resized to 256 * 256 pixels. A dataset comprising 1.2 million images is utilized for training, while 150,000 images are allocated for testing, and 50,000 images are reserved for network validation.

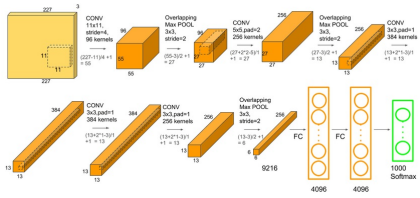


Fig. 2. Alexnet architecture.

C. Visual Geometry Group Deep Learning Neural Network

The Visual Geometry Group (VGG) 19 model, a convolutional neural network (CNN), represents a significant milestone in the field of deep learning and computer vision. Developed by the Visual Geometry Group at the University of Oxford, VGG19 is renowned for its remarkable performance in image classification tasks. With its deep architecture comprising 19 layers, including 16 convolutional layers and 3 fully connected layers, as shown in Fig. 3. VGG19 demonstrates exceptional ability in extracting intricate features from images, enabling accurate categorization across diverse datasets [24].



Fig. 3. VGG19 architecture.

D. Support Vector Machine

Support Vector Machine (SVM) is a powerful supervised machine learning algorithm primarily used for classification tasks, but it can also be employed for regression and outlier detection. SVM aims to find the best possible decision boundary (known as a hyperplane) that separates data points of different classes in such a way that the margin between the two classes is maximized. This is achieved by forming a set of support vectors [25]. SVM works by constructing hyperplanes to separate two classes of raw data for classification [26], [27]. The goal of SVM is to identify the optimal hyperplane, which maximizes the distance between the elements of the training data. For example, if we have two groups of data, finding two hyperplanes, as shown in Fig. 4. It is evident that Fig. 4(b), which has a larger margin, provides better accuracy compared to Fig. 4(a).

E. K-Nearest Neighbors

K-Nearest Neighbors (KNN) is a straightforward, yet effective algorithm for image classification. It classifies an image by considering the majority label of its *k* nearest neighbors in the dataset. Each image is represented as a feature vector,

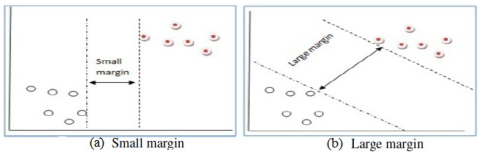


Fig. 4. Support vector machine.

which can be derived from pixel values or higher level features like edges or textures. When a new image is introduced, the algorithm calculates the distance, often using Euclidean distance, between the new image and all images in the training set, determining the *k* closest neighbors. The image is then assigned to the category that appears most frequently among those neighbors. KNN is easy to implement and understand, though its accuracy relies on selecting the right *k* value and distance measure [28], [29].

KNN is particularly well suited for smaller datasets in image classification, since it does not require a training phase, making it a type of lazy learning algorithm. However, its performance declines with larger datasets because of the computational expense of calculating distances for each image in the dataset. Additionally, KNN is sensitive to irrelevant or redundant features, which can reduce its accuracy. Despite these drawbacks, KNN serves as a strong baseline for image classification before turning to more advanced methods like deep learning.

III. Proposed Method and Performance Metrics

A. Proposed Method

Leukemia presents a significant challenge in healthcare due to its complexity and varied subtypes. Traditional diagnostic methods have limitations in accuracy and speed, necessitating the exploration of advanced technologies like deep learning and transfer learning. The proposed method explores the development of a hybrid method incorporating the deep learning architectures Alexnet and VGG19, coupled with transfer learning, and employing classifiers such as SVM and kNN for leukemia prediction. Deep Learning and Transfer Learning: Deep learning models, particularly CNNs, have demonstrated remarkable performance in image classification tasks. Alexnet and VGG19 are popular CNN architectures known for their effectiveness in feature extraction and classification. By leveraging these architectures, we aim to extract meaningful features from leukemia images, facilitating accurate prediction. Transfer learning enhances model performance by transferring knowledge gained from pretrained models to new tasks. In the context of leukemia prediction, transfer learning allows us to leverage the learned features from large datasets like ImageNet and adapt them to the specific characteristics of leukemia images, thereby improving prediction accuracy. The hybrid method begins with pre-processing leukemia images to enhance quality and remove noise. Subsequently, the pre-processed images are fed into the Alexnet and VGG19 architectures for feature extraction. Transfer learning is applied by fine-tuning the pre-trained models on the leukemia dataset, allowing them to adapt to the task at hand while retaining valuable learned features.

Feature vectors extracted from the deep learning models are then inputted into SVM and kNN classifiers for prediction. SVM is chosen for its ability to handle high dimensional data and delineate complex decision boundaries, while kNN is selected for its simplicity and effectiveness in classification tasks. Fig. 5 shows a flow chart of the proposed method. Furthermore, the flexibility of the hybrid method allows for customization and adaptation to different leukemia subtypes, thereby enhancing its applicability in clinical settings.

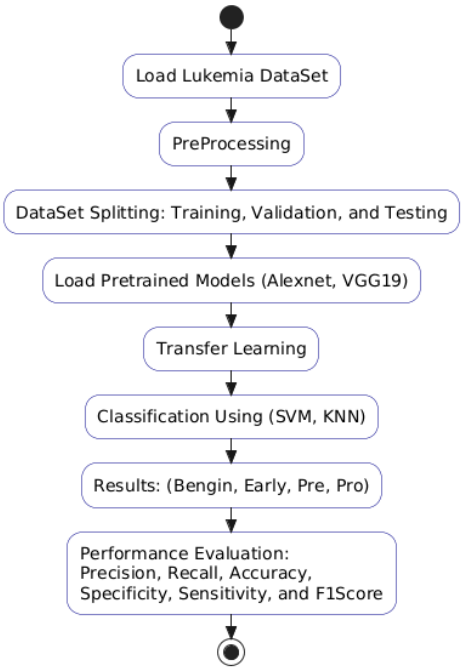


Fig. 5. Flowchart of the proposed method.

B. Performance Metrics

To evaluate the proposed method, a lot of performance parameters were used.

True_positive (T_P), False_positive (F_P), True_negative (T_N) and False_negative (F_N) are the main components used for evaluating the performance metrics. T_P is described as the total number of images predicted as class1 and they are already found in class1. T_N is described as the total number of images predicted as class1 and they are not already found in class1. F_P is described as the total number of images not predicted as class1 and they are already belong to class1. F_N is described as the total number of images incorrectly predicted as class1. The following equations define Recall, Precision, Specificity, Sensitivity, Accuracy, and FScore [see Eq. (1), Eq. (2), Eq. (3), Eq. (4), Eq. (5), and Eq. (6)], respectively.

$$Recall = \frac{T_P}{T_P + F_N}. \tag{1}$$

$$Precision = \frac{T_P}{T_P + F_P}. \tag{2}$$

$$Specificity = \frac{T_N}{T_N + F_P}. \tag{3}$$

$$Sensitivity = \frac{T_P}{T_P + F_N}. \quad (4)$$

$$Accuracy = \frac{T_P + T_N}{T_P + T_N + F_P + F_N}. \quad (5)$$

$$FScore = \frac{2 * T_P}{(2 * T_P) + (F_P + F_N)}. \quad (6)$$

C. Dataset

A precise diagnosis of acute lymphoblastic leukemia (ALL), a malignancy with a high prevalence, necessitates invasive, costly, and time consuming diagnostic procedures. Peripheral blood smear (PBS) pictures used for ALL diagnosis are crucial in the first cancer screening process to distinguish cancer cases from non-cancer cases. Due to the non-specific character of ALL indications and symptoms, misinterpretation is a common concern when these PBS images are analyzed by laboratory users. The bone marrow laboratory at Taleqani Hospital in Tehran, Iran, is where the photographs for this collection were created. This dataset included 3256 PBS pictures from 89 individuals who were thought to be ALL and whose blood samples were properly processed and stained by knowledgeable laboratory personnel. This dataset is separated into the benign and malignant classes. Hematogones are included in the former. The Early Pre-B, Pre-B, and Pro-B ALL subtypes of malignant lymphoblasts, which make up the latter ALL group. All of the photos were taken with a Zeiss camera at a 100x magnification in a microscope, and they were all saved as JPG files. The specific types and subtypes of these cells were identified by a professional using the flow cytometry instrument. We also offer segmented photos after color thresholding-based segmentation in the HSV color space [30].

Fig. 6 shows a sample of the original dataset images from all of the mentioned classes types. Fig. 7 view a sample of

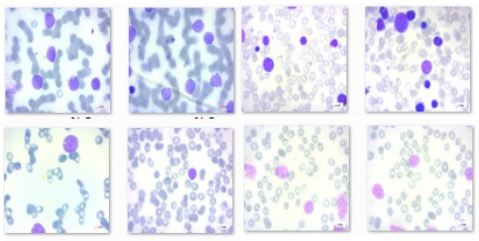


Fig. 6. Sample of the original dataset.

the segmented dataset images from all of the mentioned class types.

IV. Results and Discussion

A. Alexnet and SVM

The results presented in the Table I reflect the performance of the Alexnet combined with SVM on the original leukemia dataset, evaluated across four different classes: Benign, Early, Pre, and Pro. Overall, the model demonstrates outstanding classification performance, with all classes achieving 99% or

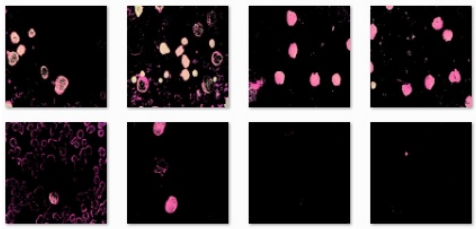


Fig. 7. Sample of the segmented dataset.

100% accuracy. The Pro class exhibits perfect classification with 100% across all metrics, indicating the model's high confidence and consistency in identifying this class. The Pre and Early stages also show near-perfect performance, with only a 1% deviation in precision or Fscore, suggesting that the model effectively captures relevant patterns even in intermediate stages of leukemia progression.

The Benign class, while still performing excellently, shows slightly lower recall and sensitivity values at 97%, which might indicate a small number of false negatives — cases where benign samples were misclassified. However, its 100% specificity suggests no benign cases were incorrectly identified as other leukemia stages, a critical factor in clinical decision making. These results suggest that the model is particularly reliable for detecting advanced leukemia stages, while still performing robustly on earlier and non-cancerous samples. Fig. 8 shows the confusion matrix results for the desired method. The high performance across all metrics and classes highlights the suitability of Alexnet with SVM as a strong classification pipeline for medical image analysis in leukemia detection.

TABLE I. Performance Metrics of Alexnet and SVM on Original Data

Class	Recall	Precision	Accuracy	Specificity	Sensitivity	Fscore
Benign	97%	98%	99%	100%	97%	98%
Early	99%	99%	99%	100%	99%	99%
Pre	100%	99%	100%	100%	100%	99%
Pro	100%	100%	100%	100%	100%	100%

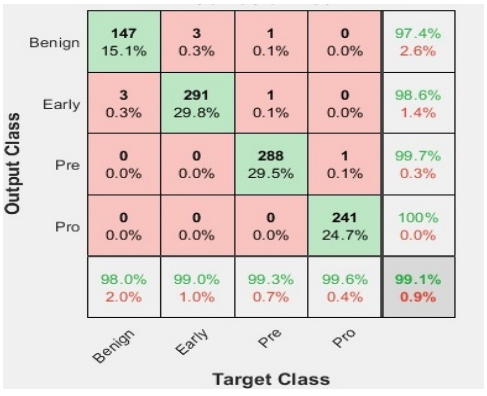


Fig. 8. Confusion matrix of Alexnet and SVM on original data.

When applied to the segmented leukemia dataset, the Alexnet with SVM model continues to deliver strong classification performance, though with slightly lower metrics compared to the original unsegmented data, as shown in Table II. The

Pro class still achieves excellent results, with perfect precision and specificity, and a high Fscore of 98.1%, indicating that segmentation did not significantly impact the model's ability to detect advanced leukemia. Fig. 9 shows the confusion matrix on the segmented data for the same method. The Pre and Early classes also maintain high accuracy and balanced sensitivity and precision, suggesting reliable detection of intermediate disease stages. However, the Benign class shows a noticeable drop in both precision (89.0%) and Fscore (90.2%), possibly due to segmentation affecting the distinctiveness of benign features. Overall, while segmentation may introduce some variability in early and benign classifications, the model remains highly effective, particularly in identifying more advanced leukemia stages.

TABLE II. PERFORMANCE METRICS OF ALEXNET AND SVM ON SEGMENTED DATA

Class	Recall	Precision	Accuracy	Specificity	Sensitivity	Fscore
Benign	91.4%	89.0%	96.9%	97.9%	91.4%	90.2%
Early	94.9%	96.2%	97.3%	98.4%	94.9%	95.6%
Pre	98.3%	95.3%	98.1%	98.0%	98.3%	96.8%
Pro	96.3%	100.0%	99.1%	100.0%	96.3%	98.1%

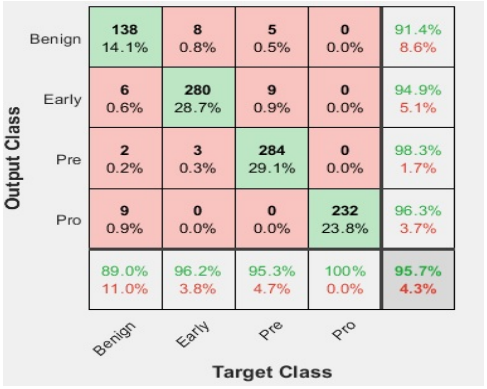


Fig. 9. Confusion matrix of Alexnet and SVM on segmented data.

B. Transfer Learning of Alexnet

Table III shows results from applying transfer learning using Alexnet on the leukemia dataset demonstrate highly effective classification across all four classes. The model achieves consistently high recall, precision, and Fscore values, with accuracy ranging from 98.36% to 99.08%. The Pro class stands out with the highest overall accuracy (99.08%) and excellent precision and Fscore, indicating that the fine-tuned Alexnet is particularly effective in detecting advanced leukemia. The Pre and Early classes also show strong and balanced performance, reflecting the model's ability to generalize across different stages of the disease. Fig. 10 shows the confusion matrix of the transfer learning of Alexnet. Even the Benign class, which is typically more challenging to classify due to subtle features, achieves a solid 94.08% recall and 95.33% precision. These results highlight the strength of transfer learning in leveraging pre-trained features from Alexnet, improving classification accuracy while minimizing training time and data requirements in medical image analysis.

When transfer learning using Alexnet is applied to the segmented leukemia dataset, the model maintains strong overall performance, particularly in detecting the Pro class, which

TABLE III. PERFORMANCE METRICS OF TRANSFER LEARNING OF ALEXNET ON ORIGINAL DATA

Class	Recall	Precision	Accuracy	Specificity	Sensitivity	Fscore
Benign	94.08%	95.33%	98.36%	99.15%	94.08%	94.70%
Early	97.28%	97.28%	98.36%	98.83%	97.28%	97.28%
Pre	98.26%	97.24%	98.67%	98.84%	98.26%	97.75%
Pro	97.94%	98.35%	99.08%	99.45%	97.94%	98.14%

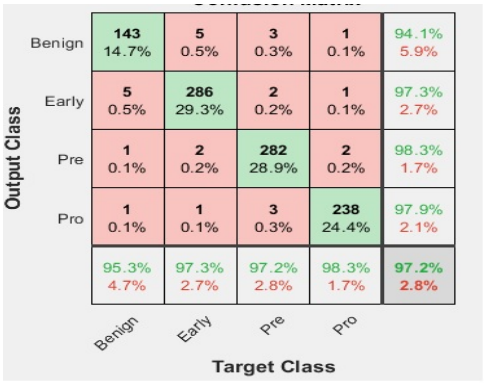


Fig. 10. Confusion matrix of transfer learning using Alexnet on original data.

achieves the highest accuracy (99.28%) and Fscore (98.54%), as shown in Table IV. However, a noticeable performance drop is observed in the Benign class, where recall decreases to 82.78%, indicating that the model struggles more to identify benign samples correctly after segmentation. Despite this, its high precision (90.58%) and specificity (98.42%) suggest that false positives are minimal. The Early and Pre classes show balanced and reliable metrics, with Fscores above 93%, demonstrating that the model remains effective for intermediate disease stages. These results suggest that while segmentation may introduce challenges in distinguishing non-cancerous cases, transfer learning with Alexnet still provides robust classification, especially for more advanced stages of leukemia, as shown in Fig. 11.

TABLE IV. PERFORMANCE METRICS OF TRANSFER LEARNING OF ALEXNET ON SEGMENTED DATA

Class	Recall	Precision	Accuracy	Specificity	Sensitivity	Fscore
Benign	82.78%	90.58%	96.00%	98.42%	82.78%	86.51%
Early	93.22%	92.91%	95.80%	96.92%	93.22%	93.06%
Pre	95.85%	91.12%	96.00%	96.07%	95.85%	93.42%
Pro	97.93%	99.16%	99.28%	99.73%	97.93%	98.54%

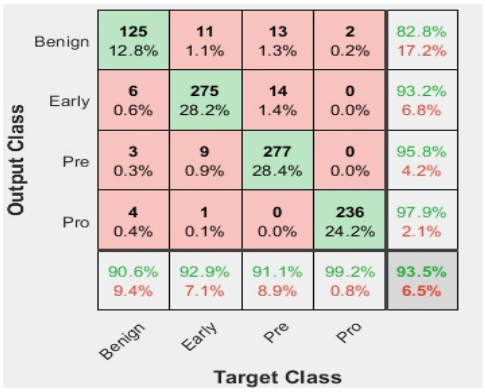


Fig. 11. Confusion Matrix of transfer learning of Alexnet on segmented data.

C. Alexnet

The performance of Alexnet on the original leukemia dataset shows a strong and promising classification ability, particularly for more advanced disease stages. The Pro class achieves perfect recall (100%) and nearly perfect precision (99.59%), with an overall accuracy of 99.90%, demonstrating that the model reliably identifies all Pro samples with minimal error. Similarly, the Pre class also performs exceptionally well, with a near-perfect Fscore of 99.13%, indicating balanced and accurate detection at this stage. The Early class, while slightly lower, still maintains a strong performance with a recall of 95.59% and an Fscore of 94.16%, showing that the model is effective even at earlier stages of leukemia, as shown in Table V and Fig. 12.

However, the Benign class displays comparatively lower performance, with a recall of 87.42%, suggesting a higher rate of false negatives, some benign cases are being misclassified as leukemia. However, the high precision (92.96%) and specificity (98.79%) imply that when the model predicts a case as benign, it is likely correct. This pattern is consistent with the general challenge in distinguishing benign from early pathological features in medical imaging. Overall, Alexnet demonstrates excellent performance on the original data, especially in identifying disease progression stages, making it a reliable model for the classification of leukemia.

TABLE V. PERFORMANCE METRICS OF ALEXNET ON THE ORIGINAL DATA

Class	Recall	Precision	Accuracy	Specificity	Sensitivity	Fscore
Benign	87.42%	92.96%	97.03%	98.79%	87.42%	90.10%
Early	95.59%	92.76%	96.41%	96.77%	95.59%	94.16%
Pre	98.96%	99.31%	99.49%	99.71%	98.96%	99.13%
Pro	100.00%	99.59%	99.90%	99.86%	100.00%	99.79%



Fig. 12. Alexnet confusion matrix results on the original data.

The results of applying Alexnet to the segmented leukemia dataset demonstrate high and consistent classification performance across all classes, with particularly strong results for the Pro class. The Pro class achieves the highest metrics overall, including 98.76% for recall, precision, sensitivity, and Fscore, along with an impressive accuracy of 99.39%, indicating the model's excellent ability to detect advanced-stage leukemia even after segmentation. The Pre and Early classes also show balanced performance, with Fscores of 96.68% and 95.77%, respectively, reflecting the model's robustness in identifying intermediate stages with high reliability as shown in Table VI and Fig. 13.

The Benign class, which is often more challenging to differentiate due to its less distinct features, records a recall of 92.05% and a slightly lower precision of 89.68%. While these values are still strong, the slightly reduced precision suggests occasional misclassification of benign samples as leukemia. However, the specificity remains high at 98.06%, indicating the model rarely mislabels diseased samples as benign. Overall, segmentation does not appear to significantly hinder Alexnet's performance and may even enhance class separation in some cases, allowing the model to maintain high accuracy and generalization across all stages of leukemia.

TABLE VI. PERFORMANCE METRICS OF ALEXNET ON THE SEGMENTED DATA

Class	Recall	Precision	Accuracy	Specificity	Sensitivity	Fscore
Benign	92.05%	89.68%	97.13%	98.06%	92.05%	90.85%
Early	95.93%	95.61%	97.44%	98.09%	95.93%	95.77%
Pre	95.85%	97.54%	98.05%	98.98%	95.85%	96.68%
Pro	98.76%	98.76%	99.39%	99.59%	98.76%	98.76%



Fig. 13. Alexnet confusion matrix results on the segmented data.

D. Alexnet and KNN

When Alexnet is combined with KNN and applied to the original leukemia dataset, the model demonstrates high classification performance, particularly for advanced leukemia stages. The Pro class achieves perfect recall (100%) and a strong precision of 96.02%, resulting in a high Fscore of 97.97% and overall accuracy of 98.98%. Similarly, the Pre class shows excellent results with 97.23% recall, 99.65% precision, and an Fscore of 98.42%, indicating that the model is highly effective at detecting and distinguishing advanced and intermediate disease stages in the unsegmented data, as shown in Table VII and Fig. 14.

In contrast, the Benign class exhibits lower recall (76.82%) despite very high precision (99.15%) and specificity (99.88%), suggesting that many benign cases are misclassified as leukemia. This imbalance lowers the Fscore to 86.57%, pointing to difficulty in recognizing non-cancerous samples accurately. The Early class also shows a gap between recall (97.29%) and precision (88.04%), reflecting a tendency toward false positives. These results suggest that while the Alexnet and KNN combination is highly reliable for detecting later stages of leukemia in the original dataset, its performance for benign and early-stage classification is limited by class similarity and KNN's sensitivity to overlapping feature distributions.

TABLE VII. PERFORMANCE METRIC OF ALEXNET AND KNN ON THE ORIGINAL DATA

Class	Recall	Precision	Accuracy	Specificity	Sensitivity	Fscore
Benign	76.82%	99.15%	96.31%	99.88%	76.82%	86.57%
Early	97.29%	88.04%	95.18%	94.27%	97.29%	92.43%
Pre	97.23%	99.65%	99.08%	99.85%	97.23%	98.42%
Pro	100.00%	96.02%	98.98%	98.64%	100.00%	97.97%

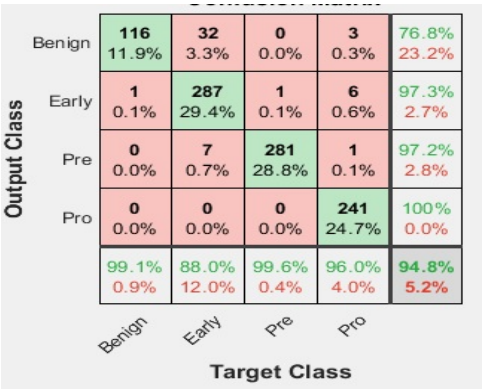


Fig. 14. Confusion matrix results of Alexnet and KNN on the original data.

When applying the combination of Alexnet and KNN to the segmented leukemia dataset, the model continues to perform well overall, particularly in identifying the more advanced disease stages. The Pre and Pro classes show strong and consistent results, with recall values of 97.58% and 97.93%, respectively, and Fscores above 96%. These high metrics demonstrate the model's robustness in capturing critical patterns in segmented images that correspond to later stages of leukemia, even when using a non-parametric classifier like KNN after feature extraction from Alexnet, as shown in Table VIII.

However, the Benign class again poses challenges, as reflected by its low recall of 76.16% and the lowest Fscore (83.33%) among all classes, as shown in Fig. 15. While the precision is relatively high at 92.00%, the model misses a significant portion of benign cases, indicating a tendency to misclassify them as malignant. The Early class shows a more balanced performance, with a recall of 94.92% and an Fscore of 92.26%, suggesting reasonable reliability for early detection. Overall, while segmentation does not drastically improve performance for the benign class, the combination of Alexnet and KNN still yields high classification accuracy and specificity across most classes, particularly for detecting leukemia progression.

TABLE VIII. PERFORMANCE METRIC OF ALEXNET AND KNN ON THE SEGMENTED DATA

Class	Recall	Precision	Accuracy	Specificity	Sensitivity	Fscore
Benign	76.16%	92.00%	95.29%	98.79%	76.16%	83.33%
Early	94.92%	89.74%	95.18%	95.30%	94.92%	92.26%
Pre	97.58%	96.58%	98.26%	98.54%	97.58%	97.07%
Pro	97.93%	95.55%	98.36%	98.50%	97.93%	96.72%

E. VGG19 and SVM

When VGG19 is combined with an SVM classifier and applied to the original leukemia dataset, the results indicate consistently high performance across all classes, with particularly strong outcomes in the more advanced stages of the



Fig. 15. Confusion matrix results of Alexnet and KNN on the segmented data.

disease. The Pro class achieves perfect recall (100%) and a high precision of 98.77%, leading to an excellent Fscore of 99.38% and overall accuracy of 99.69%. Similarly, the Pre class performs exceptionally well with 98.96% recall and an Fscore of 98.79%, showcasing the model's effectiveness in distinguishing leukemia stages with subtle differences, as shown in Table IX.

The model also demonstrates solid performance on the Early and Benign classes. The Early class achieves a recall of 96.95% and a precision of 95.97%, indicating reliable early detection, which is critical for timely treatment. Fig. 16 shows that the Benign class, often harder to distinguish from early malignancies, still achieves a recall of 90.73% and precision of 95.14%, with a strong Fscore of 92.88%. These results reflect the strength of transfer learning with VGG19 in feature extraction and the discriminative power of SVM in handling complex decision boundaries, leading to robust classification performance on unsegmented medical image data.

TABLE IX. PERFORMANCE METRICS OF VGG19 AND SVM ON THE ORIGINAL DATA

Class	Recall	Precision	Accuracy	Specificity	Sensitivity	Fscore
Benign	90.73%	95.14%	97.85%	99.15%	90.73%	92.88%
Early	96.95%	95.97%	97.85%	98.24%	96.95%	96.46%
Pre	98.96%	98.62%	99.28%	99.42%	98.96%	98.79%
Pro	100.00%	98.77%	99.69%	99.59%	100.00%	99.38%

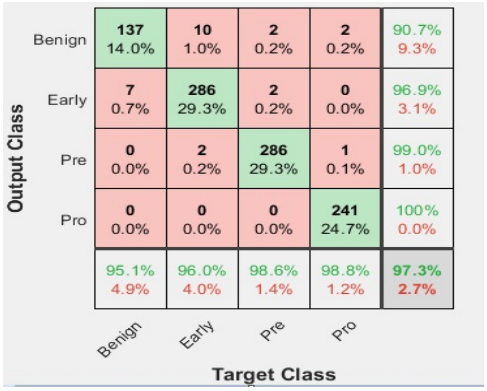


Fig. 16. Confusion matrix of VGG19 and SVM on the original data.

When applying VGG19 with SVM to the segmented leukemia dataset, the model continues to demonstrate strong

classification performance, especially in the advanced classes, as viewed in Fig. 17. The Pro class achieves outstanding metrics with 97.51% recall, 98.74% precision, and a high Fscore of 98.12%, alongside an impressive 99.08% overall accuracy. The Pre class also performs robustly, with 95.50% recall and 97.87% precision, resulting in an Fscore of 96.67%, indicating the model's effectiveness in identifying subtle pathological features within segmented regions, as shown in Table X.

For the Early class, the recall of 95.59% and precision of 91.86% reflect good early-stage detection performance, which is vital for clinical diagnosis and intervention. The Benign class, while showing relatively lower recall (86.09%) compared to other classes, maintains decent precision (87.25%) and a respectable Fscore of 86.67%. Overall, the results indicate that VGG19's deep features, combined with the SVM classifier, are highly capable even on segmented images, although segmentation may slightly affect the model's ability to capture benign patterns as clearly as it does with original images.

TABLE X. PERFORMANCE METRICS OF VGG19 AND SVM ON THE SEGMENTED DATA

Class	Recall	Precision	Accuracy	Specificity	Sensitivity	Fscore
Benign	86.09%	87.25%	95.90%	97.70%	86.09%	86.67%
Early	95.59%	91.86%	96.11%	96.33%	95.59%	93.69%
Pre	95.50%	97.87%	98.05%	99.13%	95.50%	96.67%
Pro	97.51%	98.74%	99.08%	99.59%	97.51%	98.12%



Fig. 17. Confusion matrix results of VGG19 and SVM on the segmented data.

F. VGG19 and KNN

Using VGG19 with KNN on the original leukemia dataset yields high classification performance for the disease-related classes, though with slightly reduced performance for benign cases. The Pro class shows excellent recall (99.59%) and a strong Fscore (96.97%), indicating high sensitivity to advanced stage leukemia detection. Similarly, the Pre class achieves robust results with 97.92% recall and 97.25% precision, leading to a high Fscore of 97.59% and an overall accuracy of 98.57%, as shown in Table XI.

The Early class also performs well, with 96.27% recall and 91.91% precision, producing a solid Fscore of 94.04%. However, the Benign class lags behind with a recall of only 78.15%, despite an excellent precision of 96.72%. This discrepancy suggests that while the model is very confident when it predicts a sample as benign, it may miss a significant number of actual benign cases, potentially due to overlapping visual features with early leukemia stages. Overall, as shown in Fig. 18, the VGG19-KNN combination performs reliably on original data, particularly for detecting leukemia progression stages, but shows some limitations in distinguishing benign samples.

TABLE XI. PERFORMANCE METRICS OF VGG19 AND KNN ON THE ORIGINAL DATA

Class	Recall	Precision	Accuracy	Specificity	Sensitivity	Fscore
Benign	78.15%	96.72%	96.21%	99.52%	78.15%	86.45%
Early	96.27%	91.91%	96.31%	96.33%	96.27%	94.04%
Pre	97.92%	97.25%	98.57%	98.84%	97.92%	97.59%
Pro	99.59%	94.49%	98.46%	98.10%	99.59%	96.97%

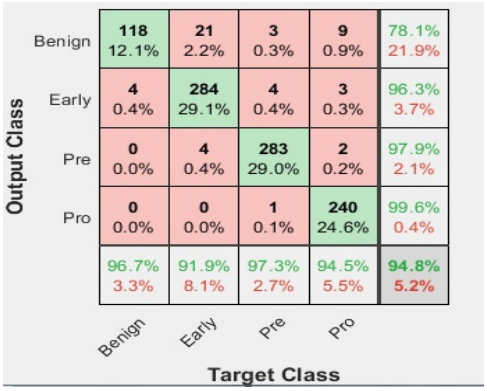


Fig. 18. Confusion matrix results of VGG19 and KNN on original data.

As shown in Table XII, the combination of VGG19 and KNN on the segmented data produces good overall classification results for leukemia detection, particularly for advanced stages, though performance for the Benign class remains relatively low.

The Pro and Pre classes achieve high performance across all metrics. The Pro class attains 96.68% recall and 95.88% precision, resulting in a strong Fscore of 96.28% and an impressive overall accuracy of 98.16%. Similarly, the **Pre** class shows a recall of 95.85% and precision of 96.52%, with an Fscore of 96.18% and overall accuracy of 97.75%, confirming the model's reliability in identifying more developed leukemia stages.

The Early class also performs reasonably well, with 91.86% recall and 88.85% precision, yielding a solid Fscore of 90.33%. However, the Benign class demonstrates noticeably weaker performance, with a recall of just 75.50% and an Fscore of 78.08%. This indicates that while benign samples are occasionally classified correctly, the model tends to confuse them with leukemia stages—likely due to subtle differences in segmented cellular structures.

In summary, as viewed in Fig. 19, VGG19 with KNN on segmented data excels at detecting leukemia stages but continues to struggle with benign classification, reflecting a need for enhanced feature differentiation in non-malignant samples.

G. Transfer Learning of VGG19

The results of applying transfer learning using VGG19 on the original data demonstrate strong performance in classifying

TABLE XII. PERFORMANCE METRICS OF VGG19 AND KNN ON THE SEGMENTED DATA

Class	Recall	Precision	Accuracy	Specificity	Sensitivity	Fscore
Benign	75.50%	80.85%	93.44%	96.73%	75.50%	78.08%
Early	91.86%	88.85%	94.06%	95.01%	91.86%	90.33%
Pre	95.85%	96.52%	97.75%	98.54%	95.85%	96.18%
Pro	96.68%	95.88%	98.16%	98.64%	96.68%	96.28%

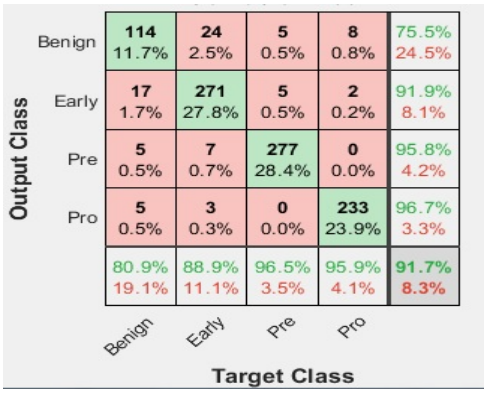


Fig. 19. Confusion matrix results of VGG19 and KNN on the segmented data.

leukemia stages, particularly in advanced cases. The model shows excellent recall and precision for Pre-leukemia and Pro-leukemia classes, with Fscores of 98.25% and 96.59%, respectively, indicating highly reliable detection. The Early stage class also performs very well, achieving a recall of 97.97% and an Fscore of 93.68%. This reflects the model's strong ability to detect various leukemia stages, making it potentially effective for clinical diagnostic support, as shown in Table XIII and Fig. 20.

However, the performance on the Benign class is notably weaker. With a recall of only 73.51%, the model fails to identify a significant portion of benign cases, even though the precision is very high at 98.23%. This indicates that while the model is highly accurate when it predicts a case as benign, it tends to under-predict this class, likely misclassifying benign samples as early-stage leukemia. This imbalance is a concern in clinical settings where distinguishing healthy cases is critical. Overall, the model favors leukemia detection—desirable in screening—but would benefit from further tuning to improve benign classification and reduce unnecessary alarms.

TABLE XIII. PERFORMANCE METRICS OF TRANSFER LEARNING OF VGG19 ON ORIGINAL DATA

Class	Recall	Precision	Accuracy	Specificity	Sensitivity	Fscore
Benign	73.51%	98.23%	95.70%	99.76%	73.51%	84.09%
Early	97.97%	89.75%	96.00%	95.15%	97.97%	93.68%
Pre	97.23%	99.29%	98.98%	99.71%	97.23%	98.25%
Pro	100.00%	93.41%	98.26%	97.69%	100.00%	96.59%

The results in Table XIV, Fig. 21 of applying transfer learning using VGG19 on the segmented data demonstrate consistently high performance in detecting leukemia classes, especially Pre and Pro-leukemia . Both classes exhibit high recall and precision values, with Fscores of 96.90% and 97.10%, respectively. The Early-stage leukemia class also performs well, achieving a recall of 96.61% and an Fscore of 92.83%. These results suggest that VGG19, when fine-tuned on

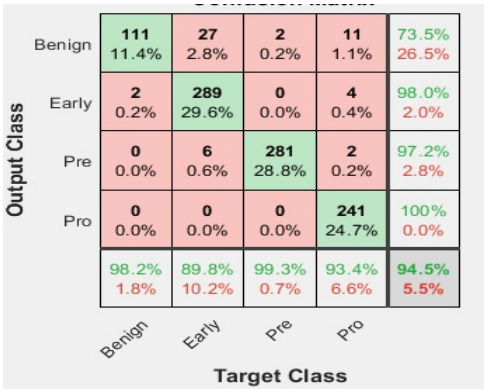


Fig. 20. Confusion matrix results of transfer learning of VGG19 on original data.

segmented data, is particularly effective at identifying various stages of leukemia with minimal misclassification.

However, the Benign class remains a challenge. Although the precision is relatively high at 88.80%, the recall is considerably lower at 73.51%, leading to a modest Fscore of 80.43%. This pattern indicates the model often misclassifies benign samples as leukemia, which could lead to false positives in a clinical setting. Despite this, the overall accuracy remains strong at 94.47%, showing that segmentation helps maintain good classification performance, particularly for critical disease classes, while further optimization is needed to enhance benign detection.

TABLE XIV. PERFORMANCE METRICS OF TRANSFER LEARNING OF VGG19 ON THE SEGMENTED DATA

Class	Recall	Precision	Accuracy	Specificity	Sensitivity	Fscore
Benign	73.51%	88.80%	94.47%	98.30%	73.51%	80.43%
Early	96.61%	89.34%	95.49%	95.01%	96.61%	92.83%
Pre	97.23%	96.56%	98.16%	98.54%	97.23%	96.90%
Pro	97.10%	97.10%	98.57%	99.05%	97.10%	97.10%

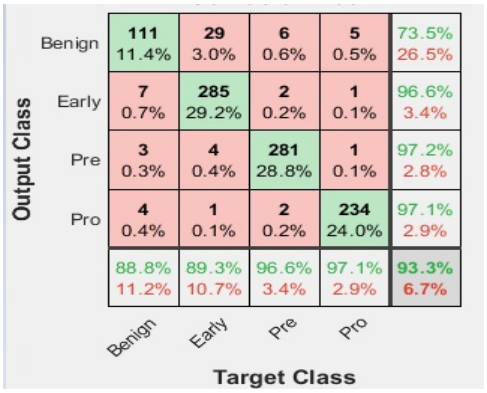


Fig. 21. Confusion matrix results of transfer Learning of VGG19 on the segmented data.

V. CONCLUSION AND FUTURE WORK

The experimental results demonstrate that the combination of Alexnet with SVM achieves outstanding classification performance on the leukemia dataset, particularly on the original (unsegmented) data. This method consistently yields high

accuracy, precision, recall, and Fscores across all leukemia stages, with the Pro and Pre classes often reaching near-perfect metrics. The model's ability to maintain robust performance—even for the challenging Benign class—highlights its effectiveness in distinguishing subtle pathological features. The success of this approach can be attributed to Alexnet's powerful feature extraction capabilities combined with SVM's strong discriminative classification, making it a highly reliable pipeline for leukemia detection in medical imaging.

While other methods, such as transfer learning with VGG19 or hybrid models with KNN, also perform well, they exhibit more variability, particularly in classifying Benign and Early-stage cases. Segmentation introduces additional complexity, sometimes reducing performance, but Alexnet with SVM remains resilient, maintaining high accuracy even on segmented data. These findings suggest that deep feature extraction with a discriminative classifier such as SVM is a superior strategy for leukemia classification, offering a robust and generalizable solution for clinical applications. Future work could explore ensemble techniques or further fine-tuning to enhance benign detection while preserving the model's exceptional performance in identifying advanced leukemia stages.

REFERENCES

[1] S. Mishra, B. Majhi, P. K. Sa, and L. Sharma, "Gray level co-occurrence matrix and random forest based acute lymphoblastic leukemia detection," *Biomedical Signal Processing and Control*, vol. 33, pp. 272–280, 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1746809416302117

[2] M. Zakir Ullah, Y. Zheng, J. Song, S. Aslam, C. Xu, G. D. Kiazolu, and L. Wang, "An attention-based convolutional neural network for acute lymphoblastic leukemia classification," *Applied Sciences*, vol. 11, no. 22, 2021. [Online]. Available: https://www.mdpi.com/2076-3417/11/22/10662

[3] C. Mondal, M. K. Hasan, M. Ahmad, M. A. Awal, M. T. Jawad, A. Dutta, M. R. Islam, and M. A. Moni, "Ensemble of convolutional neural networks to diagnose acute lymphoblastic leukemia from microscopic images," *Informatics in Medicine Unlocked*, vol. 27, p. 100794, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S235291482100263X

[4] N. S. Fatonah, H. Tjandrasa, and C. Fatichah, "Identification of acute lymphoblastic leukemia subtypes in touching cells based on enhanced edge detection," *International Journal of Intelligent Engineering and Systems*, vol. 13, no. 4, p. 204–215, 2020.

[5] C. Di Ruberto, A. Loddo, and L. Putzu, "Detection of red and white blood cells from microscopic blood images using a region proposal approach," *Computers in Biology and Medicine*, vol. 116, p. 103530, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0010482519303890

[6] A. Tareef, Y. Song, H. Huang, Y. Wang, D. Feng, M. Chen, and W. Cai, "Optimizing the cervix cytological examination based on deep learning and dynamic shape modeling," *Neurocomputing*, vol. 248, pp. 28–40, 2017, neural Networks : Learning Algorithms and Classification Systems. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0925231217304290

[7] H. MK, A. TA, and R. S., "Automatic mass classification in breast using transfer learning of deep convolutional neural network and support vector machine," *IEEE region 10 symposium*, 2020. [Online]. Available: http://dx.doi.org/10.1109/TENSYMP50017.2020.9230708

[8] "Dermoexpert: Skin lesion classification using a hybrid convolutional neural network through segmentation, transfer learning, and augmentation," *Informatics in Medicine Unlocked*, vol. 28, p. 100819, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352914821002835

[9] A. Dutta, M. K. Hasan, and M. Ahmad, "Skin lesion classification using convolutional neural network for melanoma recognition," *medRxiv*, 2020. [Online]. Available: https://www.medrxiv.org/content/early/2020/11/26/2020.11.24.20238246

[10] H. MK, D. L, S. PN, T. FI, and M. R., "Dsnet: Automatic dermoscopic skin lesion segmentation," *Computers in biology and medicine*, vol. 12, April, 2020. [Online]. Available: https://doi.org/10.1016/j.compbiomed.2020.103738

[11] F. I. Tushar, B. Alyafi, M. K. Hasan, and L. Dahal, "Brain tissue segmentation using neuronet with different pre-processing techniques," pp. 223–227, 2019.

[12] A. Işın, C. Direkoğlu, and M. Şah, "Review of mri-based brain tumor image segmentation using deep learning methods," *Procedia Computer Science*, vol. 102, pp. 317–324, 2016, 12th International Conference on Application of Fuzzy Systems and Soft Computing, ICAFS 2016, 29-30 August 2016, Vienna, Austria. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S187705091632587X

[13] M. K. Hasan, M. T. Jawad, K. N. I. Hasan, S. B. Partha, and M. M. A. Masba, "Covid-19 identification from volumetric chest ct scans using a progressively resized 3d-cnn incorporating segmentation, augmentation, and class-rebalancing," 2021. [Online]. Available: https://europepmc.org/article/PPR/PPR310774

[14] M. K. Hasan, M. A. Alam, L. Dahal, S. Roy, S. R. Wahid, M. T. E. Elahi, R. Martí, and B. Khanal, "Challenges of deep learning methods for covid-19 detection using public datasets," *Informatics in Medicine Unlocked*, vol. 30, p. 100945, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352914822000922

[15] S. Minaee, R. Kafieh, M. Sonka, S. Yazdani, and G. Jamalipour Soufi, "Deep-covid: Predicting covid-19 from chest x-ray images using deep transfer learning," *Medical Image Analysis*, vol. 65, p. 101794, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1361841520301584

[16] M. S. H. Sunny, A. N. R. Ahmed, and M. K. Hasan, "Design and simulation of maximum power point tracking of photovoltaic system using ann," pp. 1–5, 2016.

[17] Y. Song, L. Zhang, S. Chen, D. Ni, B. Li, Y. Zhou, B. Lei, and T. Wang, "A deep learning based framework for accurate segmentation of cervical cytoplasm and nuclei," *36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC, IEEE*, p. 2903–2906, 2014.

[18] I. Abunadi and E. M. Senan, "Multi-method diagnosis of blood microscopic sample for early detection of acute lymphoblastic leukemia based on deep learning and hybrid techniques," *Sensors*, vol. 22, no. 4, 2022. [Online]. Available: https://www.mdpi.com/1424-8220/22/4/1629

[19] H. A. E. Shenbary, E. A. Ebeid, and D. Baleanu, "Covid-19 classification using hybrid deep learning andstandard feature extraction techniques," *Indonesian Journal of Electrical Engineering and Computer Science(IJEECS*, vol. vol.29, No. 3, pp. 1780-1791, 2023. [Online]. Available: https://doi.org/10.11591/ijeecs.v29.i3.pp1780-1791

[20] M. S. Farag, M. M. M. E. Din, and H. A. E. Shenbary, "Parking entrance control using license plate detection and recognition," *Indonesian Journal of Electrical Engineering and Computer Science(IJEECS*, vol. vol.15, No. 1, pp. 476 -483, 2019. [Online]. Available: https://doi.org/10.11591/ijeecs.v15.i1.pp476-483

[21] P. M. Shafi, V. Bidve, H. Bhapkar, P. Dhotre, and V. B. P. Singh, "Leukemia detection system using convolutional neural networks by means of microscopic pictures," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 31, no. 3, pp. 1616–1623, September, 2023. [Online]. Available: https://doi.org/10.11591/ijeecs.v31.i3.pp1616-1623

[22] R. Girshick, J. Donahue, T. Darrell, and J. Malik, "Rich feature hierarchies for accurate object detection and semantic segmentation," *In Proceedings of the ieee conference on computer vision and pattern recognition*, vol. pp. 580–587, 2014. [Online]. Available: https://doi.org/10.1109/CVPR.2014.81

[23] A. Krizhevsky, S. Ilya, and H. E. Geoffrey, "Imagenet classification with deep convolutional neural networks," *Advances in neural information processing systems*, vol. pp. 1097-1105, 2012. [Online]. Available: https://doi.org/10.1145/3065386

[24] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv preprint arXiv:1409.1556.*, vol. pp. 1-14, 2014. [Online]. Available: https://doi.org/10.48550/arXiv.1409.1556

[25] C. Cortes and V. Vapnik, "Support vector networks," *Machine Learning*, vol. vol. 20, no. 3, pp. 273-297, 1995.

[26] M. M. MohieEl-din, N. I. Ghali, A. G. Ahmed, and H. A. El-Shenbary, "A study on the impact of wavelet decomposition on face recognition methods," *International Journal of Computer Applications (IJCA)*, vol. vol. 87, no. 3, pp. 14 - 21, Feb. 2014. [Online]. Available: https://doi.org/10.5120/15188-3549

[27] F. Bellakhdhar and K. Loukil, "Face recognition approach using gabor wavelets, pca and svm," *International Journal of Computer Science Issues (IJCSI)*, vol. vol. 10, no. 2, pp. 201-207, 2013.

[28] A. Mucherino, P. J. Papajorgji, and P. M. Pardalos, *k-Nearest Neighbor Classification*. New York, NY: Springer New York, 2009, pp. 83–106.

[29] Y. Wang, Z. Chen, H. Shao, and N. Wang, "A knn-based classification algorithm for growth stages of haematococcus pluvialis," in *2021 IEEE 4th Advanced Information Management, Communicates, Electronic and Automation Control Conference (IMCEC)*, vol. 4, 2021, pp. 6–9.

[30] M. Aria, M. Ghaderzadeh, D. Bashash, H. Abolghasemi, F. Asadi, and A. Hosseini, "Acute lymphoblastic leukemia (all) image dataset," *Kaggle*, 2021. [Online]. Available: https://www.kaggle.com/datasets/mehradaria/leukemia/

An AI-Driven Framework for Network Intrusion Detection Using ANOVA-Based Feature Selection

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***Abstract*—In the last few years, cyberattacks have become more complex, and it is becoming increasingly necessary to establish secure networks. This study examines enhancements to intrusion detection systems (IDSs) with the implementation of machine learning for the categorization of network traffic attacks. For the current study, we utilize four publicly available datasets: CIC-IDS2017, CIC-DoS2017, CSE-CIC-IDS2018, and CIC-DDoS2019. We examined three machine learning techniques: LightGBM, Random Forest, and XGBoost. Experimental results showed that RandomForest and XGBoost achieved the highest accuracy of 0.99 in both binary and multi-class intrusion detection tasks, maintaining balanced performance with macro F1-scores around 0.86. LightGBM exhibited slightly lower overall performance, but benefited from ANOVA-based feature selection, which improved its recall and model stability. Feature selection also enhanced computational efficiency by reducing feature redundancy while preserving accuracy across models. These results highlight how AI tools could help network security deal with emerging threats and improve the performance of IDS. The study underscores the critical role of feature selection in enhancing model efficiency, hence promoting advancements in automated network security systems that can adapt to evolving cyber threats.**

***Keywords*—Network security; intrusion detection; machine learning; feature selection**

I. Introduction

The rapid growth of networked systems has led to increased vulnerability to cyberattacks, making intrusion detection systems (IDS) a critical component of modern cybersecurity. Traditional IDS often relies on static rule-based approaches that fail to adapt to evolving attack patterns [1]. As public, private, and critical sectors rely more heavily on digital infrastructure, it has become essential to safeguard these systems against unauthorized access, data breaches, and service disruptions. Intrusion detection systems (IDS) remain a key component of network security; however, many still rely on static rules and signature-based detection, which are inadequate against modern, adaptive attack techniques [2], [3], [4]. More recent research has focused on AI's ability to analyze and detect IDS, particularly using machine learning (ML), which appears to fill the lack of limitations [5], [6]. Unlike static systems, ML models for IDS can learn from traffic data, patterns, and adapt to emerging threats [4]. These models increase and enhance detection performance, and respond in near real-time scenarios [7], [1].

The increasing complexity of modern network environments, driven by the proliferation of Internet of Things (IoT) devices, software-defined infrastructures, and large-scale distributed systems, has introduced new security challenges that exceed the capabilities of traditional intrusion detection mechanisms. Recent studies indicate that such environments generate highly heterogeneous and dynamic traffic patterns, which significantly complicate the identification of malicious activities using static detection rules. As a result, intrusion detection systems are required not only to detect known attack signatures but also to adapt continuously to evolving threat behaviors while maintaining acceptable performance in resource-constrained and real-time settings [8], [9]. Another fundamental challenge in contemporary intrusion detection lies in the high dimensionality of network traffic data. Modern datasets often comprise hundreds of features, many of which are redundant or weakly correlated with attack behavior. This characteristic negatively impacts learning efficiency, increases computational overhead, and may lead to overfitting. Recent research emphasizes that effective feature selection is a critical preprocessing step for improving IDS performance, as it enables learning models to focus on the most discriminative attributes while reducing model complexity and enhancing generalization across different attack scenarios [10]. In parallel, anomaly-based intrusion detection has gained renewed attention as a viable strategy for identifying previously unseen and zero-day attacks. Unlike signature-based approaches, anomaly detection models establish a baseline of normal network behavior and identify deviations that may signal malicious activity. Empirical evaluations demonstrate that machine learning–based anomaly detection frameworks can successfully capture subtle behavioral deviations in network traffic, offering improved detection of novel attacks. However, these models remain sensitive to data imbalance and noisy features, reinforcing the necessity of careful feature engineering and selection to ensure stable and reliable detection outcomes [11]. Recent advances in deep learning have further expanded the analytical capabilities of intrusion detection systems by enabling the extraction of complex spatiotemporal patterns from network traffic. Architectures such as convolutional and recurrent neural networks have shown strong potential in modeling temporal dependencies and evolving attack sequences. Nevertheless, existing studies highlight that deep models often suffer from limited interpretability and increased computational cost, which can hinder their deployment in operational environments. These limitations have motivated the integration of feature optimization strategies and explainability mechanisms to balance detection accuracy, efficiency, and transparency [12]. Furthermore, the dynamic nature of contemporary networks introduces the challenge of concept drift, where traffic characteristics and attack patterns change over time. Static models trained on historical data frequently experience performance degradation under such conditions. Adaptive learning strategies, including incremental and ensemble-based

frameworks, have demonstrated the ability to sustain detection performance by selectively updating models in response to evolving traffic behaviors. Experimental results in software-defined network environments confirm that adaptive learning mechanisms significantly enhance IDS robustness compared to static detection approaches [13]. Collectively, these observations indicate that effective intrusion detection in modern network environments requires an integrated framework that combines intelligent learning models, efficient feature selection, anomaly-aware detection, and adaptability to evolving threats. Addressing these challenges is essential for improving the robustness, scalability, and practical applicability of IDS across heterogeneous and rapidly changing infrastructures.

A. Research Gap

Although there has been considerable use of machine learning techniques to develop intrusion detection systems (IDS), most research using machine learning approaches have been limited by their reliance upon experiments conducted on a single dataset, or in narrow and constrained experimental designs. Thus, the generalizability of these results are limited. In addition, while feature selection is commonly used as a preprocessing step in developing an IDS, there has been little or no systematic analysis of how this impacts the performance of the model in terms of stability, efficiency, and consistent performance across different types of network environments. Therefore, the practical effectiveness of IDS frameworks that utilize feature selection has remained largely untested, particularly under variable traffic conditions. The above limitations highlight the need for a common testing framework that assess the effects of statistically derived feature selections across multiple datasets and various machine learning models.

B. Contribution

The present research contributes to the area of network intrusion detection through addressing limitations associated with existing IDS (Intrusion Detection System) based on Machine Learning (ML). The first is through a framework of intrusion detection (structured), which incorporates feature selection through ANOVA (Analysis of Variance), as well as multiple supervised learning models for assessing the consistency of the features selected in relation to their importance and redundancy for various types of traffic characteristics. Second, this study represents a comprehensive multi-dataset experiment using many of the most commonly used and adopted benchmark datasets, thereby allowing for a more accurate understanding of how well each model performs relative to its ability to generalize from one dataset to another. Third, the work in this study provides a systematic analysis of the impact of selecting features through statistical means on detection performance and computational efficiency, and thus offers insight into the potential trade-off between the two. Fourth, the comparison of the performance of several machine learning algorithms within an identical experimental environment demonstrates the reliability and utility of simple feature selection methods for intrusion detection in real-world environments.

C. Study Layout

The study is organized as follows: Section II details the related work. Section III present the datasets, methodology and features extraction techniques. Evaluation metric is outlined in Section IV. Test scenarios are detailed in Section V. The results are illustrated in Section VI. Finally, Section VII conclude the summary of the models and future direction.

II. Related Work

The continuous evolution of cyber threats has driven extensive research toward more intelligent, adaptive, and interpretable intrusion detection systems (IDSs). Recent studies have increasingly focused on integrating ensemble learning and deep learning techniques, often combined with optimization and explainability mechanisms, to enhance detection performance across diverse network environments. Hybrid detection pipelines that merge conventional machine learning with deep learning architectures, supported by preprocessing, class balancing, and dimensionality reduction strategies, have demonstrated improved generalization under near real-time constraints [14]. Similarly, automated hyperparameter tuning combined with post-hoc interpretability has been shown to achieve competitive detection accuracy while enhancing operational transparency and trust [15].

Feature engineering and feature selection have also received significant attention as key components in IDS design. Evolutionary and search-based feature selection methods have been reported to effectively reduce high-dimensional feature spaces, leading to improved class balance, lower computational complexity, and faster inference times [10]. Broader empirical analyses indicate that selective feature sets, when paired with ensemble classifiers, can mitigate overfitting and improve adaptability to previously unseen attack patterns [16]. In addition, representation learning approaches under limited supervision have demonstrated the ability to reduce false positive rates while maintaining high detection sensitivity, highlighting practical deployment advantages [17].

Several studies have explored hybrid and protocol-aware detection models to improve intrusion detection performance. Hussein et al. [18] demonstrated that combining ensemble classifiers such as AdaBoost, Random Forest, and XGBoost with Chi-square feature selection significantly enhances detection accuracy on benchmark datasets, particularly for worm-related attacks. Hooshmand and Hosahalli [19] proposed a protocol-aware one-dimensional CNN architecture that integrates Chi-square feature selection and SMOTE to improve the detection of minority-class anomalies, especially in UDP traffic. Furthermore, Qazi et al. [20] introduced HDLNIDS, a hybrid CNN–RNN model capable of capturing both spatial and temporal traffic characteristics, achieving robust performance on the CICIDS-2018 dataset.

The importance of explainable artificial intelligence (XAI) in IDS has also been increasingly recognized. SHAP-based explainability has been incorporated into ensemble learning frameworks to interpret detection outcomes and enhance model transparency [21], while dual-explainability approaches combining SHAP and LIME have been shown to improve detection effectiveness while reducing model complexity [22].

Application-specific IDS frameworks further demonstrate the adaptability of learning-based detection approaches. Online intrusion detection systems tailored for electric vehicle charging infrastructures have employed adaptive ensemble models

to address evolving threats in real time [6]. In healthcare and software-defined networking environments, layered detection architectures integrating gradient boosting models and deep neural networks have proven effective against malware and ransomware attacks [23]. Additionally, lightweight IDS solutions for IoT environments have been proposed using statistical feature selection, oversampling techniques, dimensionality reduction, and metaheuristic optimization to balance detection accuracy with resource constraints [24][25][26].

More recently, generative models have been explored in IDS research to support attack simulation, data augmentation, and anomaly detection. Reviews of generative adversarial networks (GANs) and variational autoencoders (VAEs) highlight their potential for enhancing detection robustness, while also emphasizing the need for standardized evaluation protocols [1]. Domain-specific IDS solutions, such as real-time DDoS detection frameworks and smart grid-oriented architectures, further illustrate the necessity of customized detection strategies tailored to specific infrastructure requirements [5], [27].

III. Methodology

A. Workflow Overview

This study follows a four-stage workflow:

- data preprocessing
- feauures extraction and selection
- model training
- model evaluation

The dataset is split into training and test sets using a stratified strategy to preserve class proportions and enable a fair assessment. Three competitive machine learning classifiers XGBoost, Random forest, and LightGBM are trained under a unified pipeline and evaluated using standard classification metrics. The overall workflow is summarized in Fig. 1.

B. Network Traffic Dataset

This study employs the CICIDS Collection compiled by the Canadian Institute for Cybersecurity and made publicly available through Kaggle [28]. The collection integrates several benchmark datasets CIC-IDS2017, CSE-CIC-IDS2018, and CIC-DDoS2019 providing a diverse set of labelled flows that include normal traffic and multiple attack types such as distributed denial of service (DDoS), brute-force login attempts, infiltration, and botnet activity. Each record captures flow-level statistics, including source and destination addresses, ports, protocol type, flow duration, packet length statistics, and other behavioural indicators. The heterogeneous mix of numerical, categorical, and temporal attributes supports advanced analytics and supervised classification. For the purposes of this work, we focus on traffic governed by TCP and UDP, which dominate real-world networks. Prior to modelling, data preprocessing includes normalization, feature encoding, and class balancing to mitigate skewed distributions. The dataset is then split into 80% training and 20% testing subsets using randomized sampling to ensure statistical robustness. Fig. 2 presents the class distribution used in this study.

C. Feature Engineering

Feature selection and engineering are crucial steps in developing effective machine learning models, especially when working with large and complex datasets. These processes refine the input data to ensure that only the most relevant and informative features are used in the model. By focusing on impactful variables, model accuracy is enhanced, computation time is reduced, and interpretability is improved. This subsection outlines the strategies used for feature transformation and selection, which played a key role in improving the performance of the proposed intrusion detection system.

1) Feature Transformation: To prepare the data for supervised learning, categorical class labels are converted into numeric representations to ensure compatibility with the learning algorithms. This transformation preserves class proportions and enables consistent mapping of predicted outputs back to human-readable class names for reporting [29].

2) Feature Selection Using ANOVA F-Test: Feature selection was applied to identify the most discriminative features and reduce the dimensionality of the dataset. The *Analysis of Variance (ANOVA) F-test* was used as a filter-based method to evaluate the statistical significance of each feature with respect to the target classes. This method measures how much the mean of each feature varies across different classes compared to the variance within each class, providing an indication of its discriminative power.

In this study, the `SelectKBest` [30] function from the `scikit-learn` library was employed with the `f_classif` [31] scoring function to rank features based on their F-values. The top 20 features with the highest scores were selected for model training. This approach ensures that only the most relevant features contribute to the classification process, improving model efficiency and reducing overfitting while maintaining predictive performance.

Mathematically, the ANOVA F-statistic for a given feature x_i is defined as:

$$F_i = \frac{MSB_i}{MSW_i} = \frac{\text{variance between class means}}{\text{variance within classes}}$$

where, MSB_i represents the mean square between class means, and MSW_i represents the mean square within each class. A higher F_i value indicates that the feature contributes more to class discrimination.

D. Machine Learning Algorithms

Machine Learning (ML), a core branch of Artificial Intelligence (AI), involves the development of algorithms and statistical models that allow systems to perform specific tasks autonomously without explicit programming. The objective of ML is to enable systems to identify patterns within data, generate predictions, and make informed decisions, with performance improving as the system gains experience from data exposure.

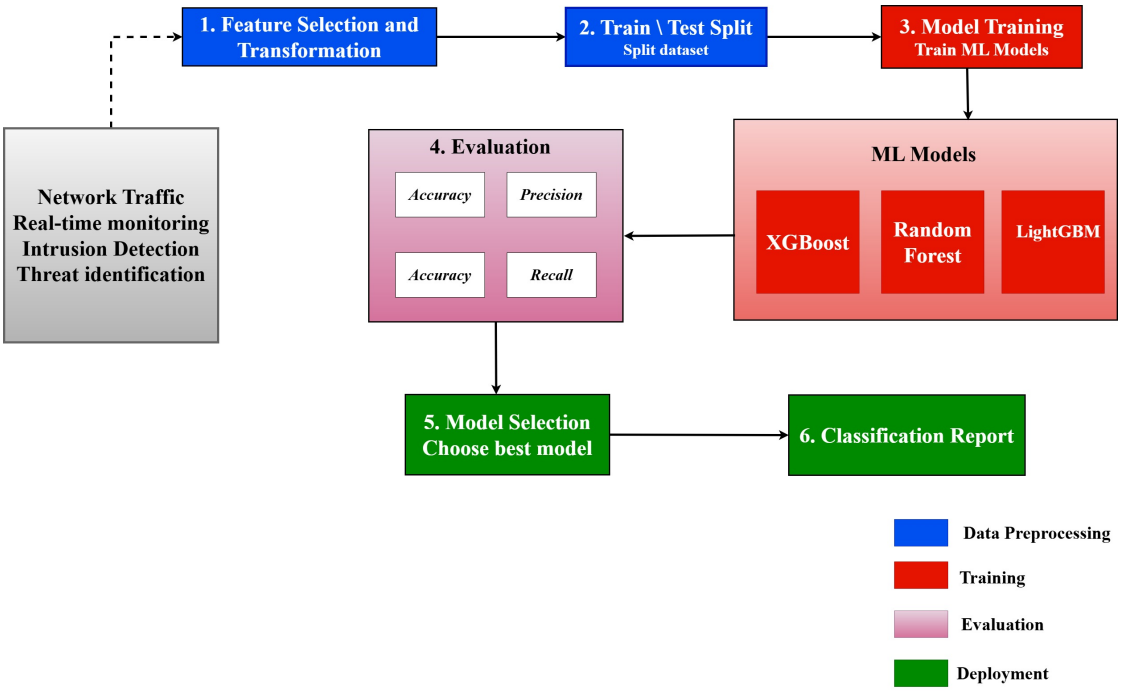


Fig. 1. Intrusion detection system phases.

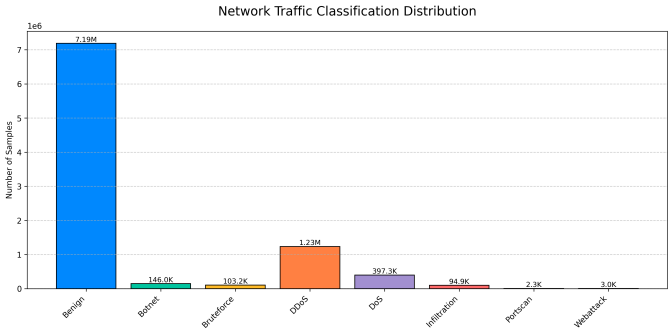


Fig. 2. Network classification dataset distribution.

TABLE I. MACHINE LEARNING MODEL PARAMETERS

Model	Parameter	Value
Random Forest	Number of estimators	100
	Criterion	Gini
	Random state	42
LightGBM	Boosting type	gbdt
	Number of leaves	31
	Learning rate	0.1
	Device	GPU
XGBoost	Booster	gbtree
	Max depth	6
	Learning rate	0.3
	Tree method	gpu_hist
	Predictor	gpu_predictor

1) LightGBM: LightGBM is a gradient boosting framework designed for speed and scalability. Techniques such as Gradient-based One-Side Sampling (GOSS) and Exclusive Feature Bundling (EFB) improve efficiency and reduce effective dimensionality [32]. LightGBM is well-suited for near real-time classification on large datasets, making it a practical choice for intrusion detection in networked systems [33], [34].

2) Random Forest (RF): Random Forest is an ensemble of decision trees trained on bootstrapped samples with randomized feature subsets. This approach improves accuracy and reduces variance relative to a single tree. Majority voting yields robust predictions and strong generalization on high-dimensional data [35], [36].

3) XGBoost: XGBoost is a scalable gradient boosting algorithm that builds trees sequentially, correcting residual errors while using a regularized objective to limit over-fitting. In cybersecurity applications, XGBoost has demonstrated strong performance in detecting sophisticated threats across varied environments [23], [3].

Table I explains the hyperparameters of the machine learning models used in the current work.

IV. EVALUATION METRIC

To evaluate the performance of the network intrusion detection models, a set of standard performance indicators was applied, including accuracy, precision, recall, F1-score, and the confusion matrix. These metrics collectively describe how effectively the model distinguishes between normal and attack traffic.

The evaluation metrics are defined as follows:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

$$\text{F1-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

In these metrics:

- TP (True Positive) represents the number of attack instances correctly identified as attacks.
- TN (True Negative) denotes the number of normal instances correctly classified as normal.
- FP (False Positive) indicates normal traffic mistakenly classified as an attack.
- FN (False Negative) refers to attack traffic incorrectly classified as normal.

The confusion matrix summarizes these outcomes, providing a detailed view of the classifier's performance and highlighting the specific types of misclassification within network traffic.

V. Test Scenarios

Two experimental scenarios were designed to evaluate the proposed framework under different classification objectives: binary and multi-class intrusion detection. Both scenarios used the same datasets, preprocessing steps, and model configurations to ensure consistency.

- Binary Classification Scenario, the task was formulated as a two-class problem: **Benign:** normal network traffic , **Attack:** all malicious traffic categories combined, including DDoS, DoS, PortScan, Botnet, Infiltration, and WebAttack.
- Multi-Class Classification Scenario: The task was extended to classify multiple categories of network traffic.

VI. Results and Discussion

This section presents the performance evaluation of the proposed intrusion detection framework under two classification configurations: binary classification and multi-class classification. Each configuration was tested using RandomForest, LightGBM, and XGBoost models with two feature setups: All Features (AF) and ANOVA-based Feature Selection (FS).

A. Binary Classification Results

Table II summarizes the binary classification performance. All models achieved high accuracy and precision, demonstrating their ability to distinguish between benign and attack traffic, effectively. RandomForest and XGBoost obtained the highest accuracy of 0.9899 and 0.9898, respectively, with perfect precision (1.0000) and F1-scores exceeding 0.97. LightGBM recorded slightly lower performance, but maintained a high AUC of 0.9491 under the AF setup and 0.9578 after feature selection. Feature selection (FS) showed minimal impact on model accuracy but slightly improved LightGBM's Recall and F1-score, indicating that removing less informative features enhanced its generalization capability. Both RandomForest and XGBoost maintained consistent performance between AF and FS, reflecting their robustness to feature dimensionality.

B. Multi-Class Classification Results

Table III presents the multi-class classification results. As expected, the overall accuracy decreased compared to the binary scenario due to the increased complexity of distinguishing between multiple attack categories. RandomForest and XGBoost maintained superior performance, achieving accuracies of 0.99 and macro F1-scores of 0.86 under the feature selection (FS) configuration. After applying ANOVA-based feature selection, RandomForest and XGBoost slightly improved in macro-level Recall and F1-score compared to their All Features (AF) performance, indicating that removing redundant attributes enhanced their generalization capability. Both models also retained high weighted F1-scores of 0.98, confirming consistent classification across major and minor attack classes. LightGBM continued to exhibit lower performance relative to the other models, achieving accuracies of 0.94 (AF) and 0.96 (FS). Although feature selection marginally improved its precision and stability, its macro F1-score remained below 0.60. This suggests that LightGBM is more sensitive to reduced feature dimensionality, while ensemble methods such as RandomForest and XGBoost exploit feature redundancy more effectively to preserve classification robustness across multiple intrusion types.

C. Discussion

The experimental results demonstrate that the proposed intrusion detection framework performs effectively in both binary and multi-class classification settings. Across all models and configurations, high accuracy and precision values indicate strong capability in distinguishing between benign and malicious traffic patterns. In the binary classification experiments, all models achieved near-perfect detection performance. RandomForest and XGBoost recorded the highest accuracies (0.9899 and 0.9898, respectively) with perfect precision and F1-scores exceeding 0.97, confirming their robustness in differentiating between normal and attack traffic. LightGBM showed slightly lower recall but improved marginally under feature selection (FS), indicating that ANOVA-based reduction of redundant features enhanced its generalization without compromising accuracy. In the multi-class classification scenario, overall accuracy decreased compared to the binary setting, as expected from the higher complexity of identifying multiple intrusion categories. RandomForest and XGBoost maintained superior performance, achieving accuracies of 0.99 and macro F1-scores of 0.86 under the FS configuration. The results show that feature selection helped these models improve recall and balance detection across both major and minority classes, while retaining high weighted F1-scores of 0.98. LightGBM exhibited lower macro-level performance (F1-score below 0.60), although its accuracy increased slightly from 0.94 (AF) to 0.96 (FS). This suggests that while feature selection aids in model stability, LightGBM relies more heavily on a full feature space for optimal discrimination across classes. In contrast, ensemble-based models such as RandomForest and XGBoost demonstrate stronger resilience to feature reduction due to their inherent ability to handle feature redundancy. Fig. 3 and Fig. 4 visually compare model performance under AF and FS settings. The figures highlight that feature selection has a minimal, but positive effect on model accuracy and macro F1-score, especially for LightGBM. For RandomForest and XGBoost, performance remained consistently high in both

TABLE II. BINARY CLASSIFICATION PERFORMANCE OF INTRUSION DETECTION MODELS [ALL FEATURES (AF) AND FEATURE SELECTION (FS)]

Model	Accuracy	Precision	Recall	F1-Score	AUC
RandomForest (AF)	0.9899	1.0000	0.9543	0.9766	0.9772
RandomForest (FS)	0.9899	1.0000	0.9544	0.9767	0.9772
LightGBM (AF)	0.9760	1.0000	0.8983	0.9464	0.9491
LightGBM (FS)	0.9792	1.0000	0.9156	0.9559	0.9578
XGBoost (AF)	0.9893	1.0000	0.9508	0.9748	0.9754
XGBoost (FS)	0.9898	1.0000	0.9528	0.9758	0.9764

TABLE III. MULTI-CLASS CLASSIFICATION PERFORMANCE OF INTRUSION DETECTION MODELS [ALL FEATURES (AF) AND FEATURE SELECTION (FS)]

Model	Accuracy	Precision (Macro)	Recall (Macro)	F1-Score (Macro)	Weighted F1-Score
RandomForest (AF)	0.98	0.87	0.75	0.78	0.98
RandomForest (FS)	0.99	0.88	0.85	0.86	0.98
LightGBM (AF)	0.94	0.54	0.60	0.57	0.94
LightGBM (FS)	0.96	0.59	0.60	0.59	0.95
XGBoost (AF)	0.99	0.92	0.73	0.77	0.98
XGBoost (FS)	0.99	0.93	0.85	0.86	0.98

TABLE IV. METHODOLOGICAL COMPARISON WITH EXISTING IDS STUDIES

Study	Dataset	Model Type	Feature Selection	Multi-Dataset	Model Complexity	Accuracy%
Qazi et al. [20]	CICIDS-2018	CNN–RNN	No	No	High	98.90
Proposed Framework	CIC-IDS2017, CIC-DDoS2017, CSE-CIC-IDS2018, CIC-DDoS2019	ML-based Ensemble	**ANOVA**	**Yes**	Lower	99.00

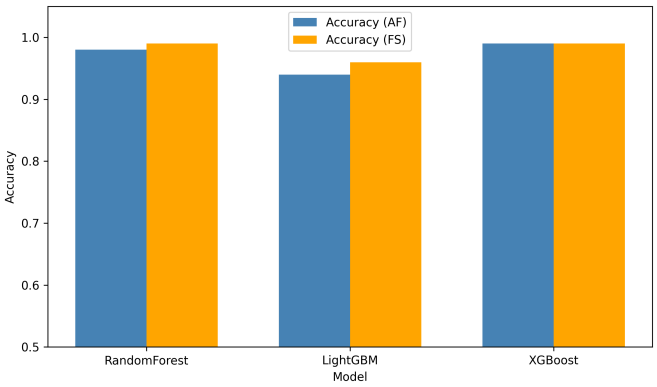


Fig. 3. Accuracy comparison of intrusion detection models using All Features (AF) and Feature Selection (FS).

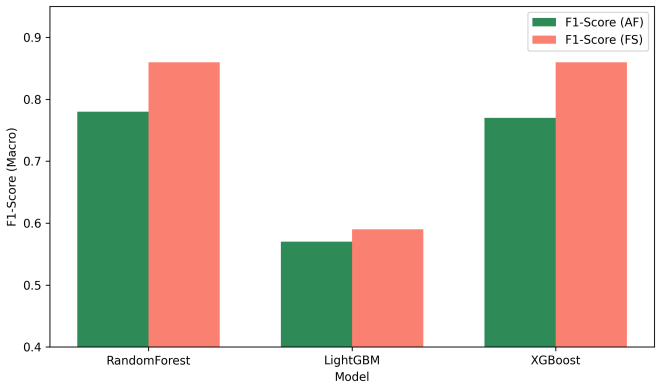
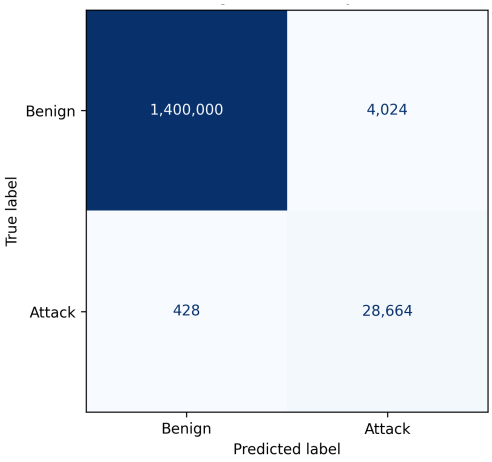


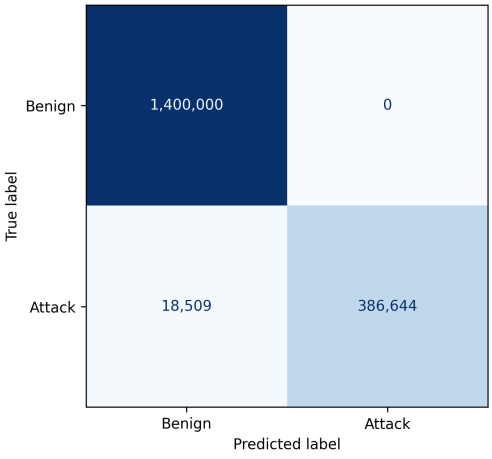
Fig. 4. F1-score comparison of intrusion detection models using All Features (AF) and Feature Selection (FS).

setups, reinforcing their suitability for scalable, high-accuracy intrusion detection across diverse network traffic types.

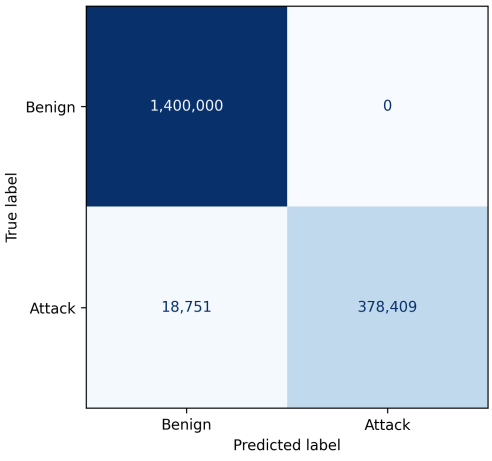
Fig. 5 shows the confusion matrix of the machine learning models in case of binary classification. In addition, Fig. 6 shows the confusion matrix of XGBoost models in case of feature selection, which illustrates the classification behavior across different attack categories. The model demonstrates strong capability in identifying benign traffic, with nearly all normal flows correctly detected and very few false positives. This behavior is essential for maintaining operational stability and reducing unnecessary alerts in real deployment environments. High detection accuracy is also evident for major attack classes such as DDoS and DoS, confirming that the model effectively captures large-scale malicious activity patterns. Some misclassification occur in less frequent attack types such as Infiltration and Web Attack. These errors likely result from class imbalance and the limited number of representative samples in those categories. Even so, the classifier maintains stable precision and recall across the primary attack types, showing that feature selection and ensemble learning enhance the model's ability to separate overlapping network behaviors. Overall, the confusion matrix supports the quantitative findings reported earlier. The results confirm that the proposed intrusion detection approach achieves high accuracy and robustness across varied network threats, while sustaining a very low false-alarm rate—an essential property for scalable and reliable AI-based intrusion detection in practical applications. On the CICIDS-2018 dataset, the results obtained by the proposed framework are consistent with those reported by Qazi et al. [20], despite the methodological differences between the two approaches. While HDLNIDS relies on a deep CNN–RNN architecture trained and evaluated on a single dataset, the proposed framework adopts a machine learning–based ensemble strategy supported by ANOVA-based feature selection. This design choice enables effective dimensionality reduction while maintaining competitive detection performance.



(a) LightGBM.



(b) Random forest.



(c) XGboost.

Fig. 5. Comparative visualization of intrusion detection performance using Feature Selection (FS) across different machine learning models for binary classification.

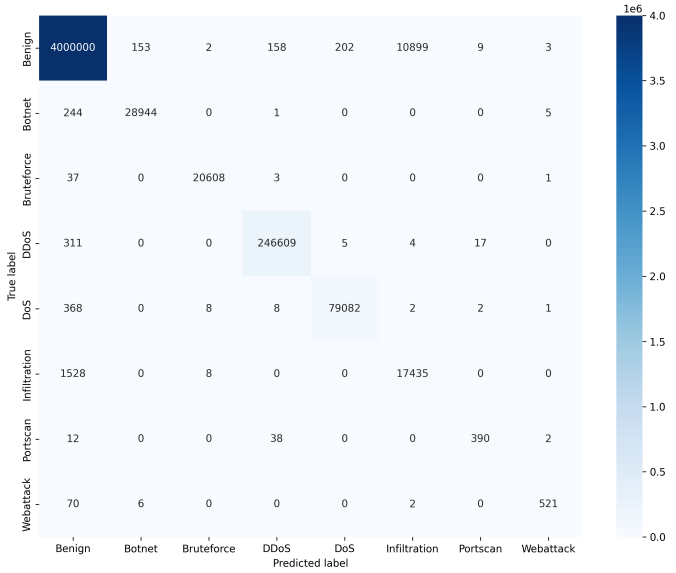


Fig. 6. Confusion matrix of XGBoost model Feature Selection (FS).

Moreover, unlike HDLNIDS, which focuses on a single experimental setting, the proposed approach demonstrates stable behavior across multiple CIC-based datasets, suggesting improved robustness and generalization under heterogeneous traffic conditions. Table IV shows the comparison between our work and one of the latest research studies.

VII. Conclusion

This study presented an AI-driven intrusion detection framework designed to enhance network security through consistent and leakage-free machine learning pipelines. The framework integrated RandomForest, LightGBM, and XGBoost classifiers and was validated under both binary and multi-class settings using multiple datasets to assess robustness and generalization across diverse network conditions. The experimental results demonstrated that all models achieved strong performance in binary intrusion detection, with RandomForest and XGBoost achieving the highest accuracy (0.99) and stable F1-scores above 0.97. In the more challenging multi-class scenario, both models maintained high accuracy (0.99) and balanced detection across attack categories, confirming their reliability in distinguishing complex intrusion patterns. LightGBM showed slightly lower macro-level performance but benefited modestly from ANOVA-based feature selection, which improved its recall and stability. Feature selection proved effective in reducing feature redundancy and improving computational efficiency without compromising classification accuracy. This finding highlights that robust ensemble methods such as RandomForest and XGBoost can maintain high performance even when trained on reduced feature spaces, making them suitable for large-scale and resource-constrained environments. Future work will focus on three directions: First, model scalability and efficiency will be advanced by exploring compact deep architectures such as CNN–RNN hybrids and lightweight transformer variants for real-time deployment. Second, explainability and transparency will be enhanced through SHAP-based feature interpretation to increase analyst trust and

interpret model behavior. Third, robustness will be extended through evaluation on adversarial and real-world datasets, integration of continual learning to adapt to evolving threats, and hybridization with anomaly detection mechanisms to identify both known and emerging attacks. Collectively, these efforts aim to develop intrusion detection systems that are accurate, interpretable, and resilient across diverse and dynamic network environments.

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REFERENCES

[1] J. Halvorsen, C. Izurieta, H. Cai, and A. Gebremedhin, "Applying generative machine learning to intrusion detection: A systematic mapping study and review," *ACM Comput. Surv.*, vol. 56, no. 10, Jun. 2024. [Online]. Available: https://doi.org/10.1145/3659575

[2] Y. S. Razooqi and A. Pekar, "Vpn traffic analysis: A survey on detection and application identification," *IEEE Access*, vol. 13, pp. 132 830–132 848, 2025.

[3] U. Ahmed, M. Nazir, A. Sarwar, T. Ali, E.-H. M. Aggoune, T. Shahzad, and M. A. Khan, "Signature-based intrusion detection using machine learning and deep learning approaches empowered with fuzzy clustering," vol. 15, no. 1, p. 1726, 2025. [Online]. Available: https://www.nature.com/articles/s41598-025-85866-7

[4] M. A. Talukder, M. Khalid, and N. Sultana, "A hybrid machine learning model for intrusion detection in wireless sensor networks leveraging data balancing and dimensionality reduction," *Scientific Reports*, vol. 15, no. 1, p. 4617, 2025.

[5] M. M. Abou-elasaad, S. G. Sayed, and M. M. El-dakroury, "Smart grid intrusion detection system based on ai techniques," vol. 15, no. 2, pp. 195–207, 2025, accessed: 2025-10-19. [Online]. Available: https://www.americaspg.com/article/pdf/3358

[6] F. Makhmudov, D. Kilichev, U. Giyosov, and F. Akhmedov, "Online machine learning for intrusion detection in electric vehicle charging systems," vol. 13, no. 5, p. 712, 2025. [Online]. Available: https://doi.org/10.3390/math13050712

[7] J. Li, M. S. Othman, H. Chen, and L. M. Yusuf, "Optimizing iot intrusion detection system: feature selection versus feature extraction in machine learning," *Journal of Big Data*, vol. 11, no. 1, pp. 1–44, 2024. [Online]. Available: https://journalofbigdata.springeropen.com/articles/10.1186/s40537-024-00892-y

[8] M. S. Nawaz, M. A. Raza, B. Raza, M. Ahmad, and F. Syed, "Ai-driven intrusion detection systems for securing iot healthcare networks." *International Journal of Advanced Computer Science & Applications*, vol. 16, no. 6, 2025.

[9] M. M. Rahman, S. Al Shakil, and M. R. Mustakim, "A survey on intrusion detection system in iot networks," *Cyber Security and Applications*, vol. 3, p. 100082, 2025.

[10] R. R. Akula and G. Kumar, "Optimizing feature selection in intrusion detection systems using a genetic algorithm with stochastic universal sampling." *International Journal of Advanced Computer Science & Applications*, vol. 16, no. 1, 2025.

[11] P. Schummer, A. del Rio, J. Serrano, D. Jimenez, G. Sánchez, and Á. Llorente, "Machine learning-based network anomaly detection: Design, implementation, and evaluation," *AI*, vol. 5, no. 4, pp. 2967–2983, 2024.

[12] Y. Zhang, R. C. Muniyandi, and F. Qamar, "A review of deep learning applications in intrusion detection systems: Overcoming challenges in spatiotemporal feature extraction and data imbalance," *Applied Sciences*, vol. 15, no. 3, p. 1552, 2025.

[13] R. Basfar, M. Y. Dahab, A. M. Ali, F. Eassa, and K. Bajunaied, "An incremental lstm ensemble for online intrusion detection in software-defined networks." *International Journal of Advanced Computer Science & Applications*, vol. 16, no. 9, 2025.

[14] S. Çalışır, R. Atay, M. K. Pehlivanoğlu, and N. Duru, "Intrusion detection using machine learning and deep learning techniques," in *2019 4th International Conference on Computer Science and Engineering (UBMK)*. IEEE, 2019, pp. 656–660.

[15] P. J. MP *et al.*, "An explainable and optimized network intrusion detection model using deep learning." *International Journal of Advanced Computer Science & Applications*, vol. 15, no. 1, 2024.

[16] M. Torabi, N. I. Udzir, M. T. Abdullah, and R. Yaakob, "A review on feature selection and ensemble techniques for intrusion detection system," *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 5, 2021.

[17] B. A. Durga and N. Mangla, "A novel network intrusion detection system based on semi-supervised approach for iot," *International Journal of Advanced Computer Science and Applications*, vol. 14, no. 4, 2023.

[18] S. A. Hussein, A. A. Mahmood, and E. O. Oraby, "Network intrusion detection system using ensemble learning approaches," *Technology*, vol. 18, pp. 962–974, 2021.

[19] M. K. Hooshmand and D. Hosahalli, "Network anomaly detection using deep learning techniques," *CAAI Transactions on Intelligence Technology*, vol. 7, no. 2, pp. 228–243, 2022.

[20] E. U. H. Qazi, M. H. Faheem, and T. Zia, "Hdlnids: hybrid deep-learning-based network intrusion detection system," *Applied Sciences*, vol. 13, no. 8, p. 4921, 2023.

[21] M. K. Hooshmand, M. D. Huchaiah, A. R. Alzighaibi, H. Hashim, E.-S. Atlam, and I. Gad, "Robust network anomaly detection using ensemble learning approach and explainable artificial intelligence (xai)," *Alexandria Engineering Journal*, vol. 94, pp. 120–130, 2024.

[22] S. S. Shafin, "An explainable feature selection framework for web phishing detection with machine learning," *Data Science and Management*, 2024.

[23] S. H. Almotiri, "Ai driven iomt security framework for advanced malware and ransomware detection in sdn," *Journal of Cloud Computing: Advances, Systems and Applications*, vol. 14, 2025. [Online]. Available: https://journalofcloudcomputing.springeropen.com/articles/10.1186/s13677-025-00745-w

[24] S. Kaushik, A. Bhardwaj, A. Almogren, S. Bharany, A. Altameem, A. U. Rehman, S. Hussen, and H. Hamam, "Robust machine learning based intrusion detection system using simple statistical techniques in feature selection," *Scientific Reports*, vol. 15, no. 1, p. 3970, 2025.

[25] M. A. O. Ahmed, Y. Abdelsatar, R. Alotaibi, and O. Reyad, "Enhancing internet of things security using performance gradient boosting for network intrusion detection systems," *Alexandria Engineering Journal*, vol. 116, pp. 472–482, 2025.

[26] L. Shi, Q. Yang, L. Gao, and H. Ge, "An ensemble system for machine learning iot intrusion detection based on enhanced artificial hummingbird algorithm," *The Journal of Supercomputing*, vol. 81, no. 1, p. 110, 2025.

[27] M. Ouhssini, K. Afdel, E. Agherrabi, M. Akouhar, and A. Abarda, "Deepdefend: A comprehensive framework for ddos attack detection and prevention in cloud computing," *Journal of King Saud University-Computer and Information Sciences*, vol. 36, no. 2, p. 101938, 2024.

[28] dhoogla. Cicids collection. Kaggle. [Online]. Available: https://www.kaggle.com/datasets/dhoogla/cicidscollection

[29] W. Zhu, R. Qiu, and Y. Fu. Comparative study on the performance of categorical variable encoders in classification and regression tasks. arXiv. [Online]. Available: https://arxiv.org/abs/2401.09682

[30] Scikit learn Developers, "Scikitlearn: sklearn.feature-selection.selectkbest," https://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.SelectKBest.html, 2025, accessed: 2025-10-21.

[31] ——, "Scikitlearn: sklearn.featureselection.fclassif," https://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.f_classif.html, 2025, accessed: 2025-10-21.

[32] A. A. Bhutta, M. un Nisa, and A. N. Mian, "Lightweight real-time wifi-based intrusion detection system using lightgbm," vol. 30, no. 2, pp. 749–761, 2024. [Online]. Available: https://doi.org/10.1007/s11276-023-03516-0

[33] N. Nabil, N. Najib, and J. Abdellah, "Leveraging artificial neural networks and lightgbm for enhanced intrusion detection in automotive systems," *Arabian Journal for Science and Engineering*, vol. 49, no. 9, pp. 12 579–12 587, 2024. [Online]. Available: https://link.springer.com/article/10.1007/s13369-024-08787-z

[34] L. Shi, Q. Yang, L. Gao, and H. Ge, "An ensemble system for machine learning iot intrusion detection based on enhanced artificial hummingbird algorithm," 2025, online first (Nov 2024); assigned to 2025 issue. Add volume/number/pages when available. [Online]. Available: https://link.springer.com/article/10.1007/s11227-024-06475-1

[35] C. Lu, Y. Cao, and Z. Wang, "Research on intrusion detection based on an enhanced random forest algorithm," vol. 14, no. 2, p. 714, 2024. [Online]. Available: https://doi.org/10.3390/app14020714

[36] X. Yu, W. Meng, Y. Liu, and F. Zhou, "Tridentshell: An enhanced covert and scalable backdoor injection attack on web applications," *Journal of Network and Computer Applications*, vol. 223, pp. 1–12, 2024. [Online]. Available: https://doi.org/10.1016/j.jnca.2023.103823

DrugCellGNN: Graph Convolutional Networks for Integrating Omics and Drug Similarities in Cancer Therapy Prediction

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***Abstract*—Predicting drug response in cancer cell lines is a critical step toward precision oncology, enabling more efficient therapeutic discovery and personalized treatment strategies. However, the complexity of drug–cell interactions, driven by diverse omics profiles and structural variability among drugs, poses significant challenges for conventional machine learning approaches. In this study, we propose an end-to-end pipeline that integrates multi-omics data (gene expression, copy number variation, and mutations) with chemical structure representations of drugs to predict binary drug response. Our method employs principal component analysis (PCA) for dimensionality reduction of high-dimensional omics data, followed by the computation of drug–drug and cell–cell similarity matrices. These are used to construct a heterogeneous graph combining intra-class similarities with drug–cell interactions. A customized graph neural network model, DrugCellGNN, is then applied to learn context-aware embeddings of drugs and cells. The fused representations are passed to a downstream multi-layer perceptron for classification. To address class imbalance, we introduce a dynamic focal loss function that adaptively emphasizes hard-to-classify examples. Evaluation on the GDSC dataset with an 80/20 train–test split demonstrates strong performance: Accuracy = 0.8935, F1 = 0.9201, AUC = 0.9510. This work highlights the utility of graph-based integration of multi-omics and drug features for drug sensitivity prediction. By leveraging both molecular and relational information, the proposed framework offers a robust and extensible foundation for advancing computational approaches in precision oncology.**

***Keywords*—Precision oncology; drug sensitivity prediction; graph neural networks (GNNs); multi-omics integration; focal loss; PCA**

I. Introduction

Cancer is a disease of the genome that causes mortality worldwide, characterized by high complexity and inter-patient heterogeneity that complicate effective treatment [1]. Traditional therapies, such as chemotherapy and radiotherapy, often exhibit limited specificity, leading to substantial toxicity in healthy tissues and suboptimal efficacy [2]. However, not all patients react to pharmacological therapy in the same manner, and biological data, such as gene mutations or gene expression, can help predict which patients are most likely to benefit from a certain medicine [3]. Thus, establishing strategies for predicting drug sensitivity is critical for individualized therapy. According to the National Research Council, precision medicine can be used to divide patients into subgroups based on their unique reactions to medical treatment [4]. Customizing effective treatments based on individual characteristics can improve therapy quality, reduce wasteful expenses, and minimize negative side effects. Precision medicine aims to optimize cancer therapy by selecting drugs tailored to each patient's unique genetic profile [4]. This process presents a complex challenge in cancer treatment. These challenges have led to large-scale experiments on human cancer cell lines and a wide range of anticancer drugs, which have led to the availability of free datasets for cancer cell drug sensitivity information and molecular markers of drug responses. The Genomics of Cancer Drug Sensitivity (GDSC) [5] is one of the most widely used projects, providing molecular profiles and drug response data for hundreds of cancer cell lines treated with various anticancer drugs. These datasets provide genetic features of cancer cell line panels, such as gene expression profiles, copy number alterations, and single-nucleotide mutations. This enormous accumulation of data paves the way for the advancement of data analysis and computational techniques, including machine learning and artificial intelligence approaches.

Despite notable progress, existing computational approaches face several limitations. Traditional machine learning models often struggle to capture complex interactions between drugs and cancer cell lines and are limited by the high dimensionality and heterogeneity of multi-omics data. Moreover, many methods treat drugs and cell lines independently, overlooking their intrinsic relational structure, which is crucial for accurate prediction and generalization across unseen samples.

To address these challenges, this study proposes DrugCellGNN, a graph neural network–based framework for binary drug sensitivity prediction. The proposed method integrates multi-omics features, drug structural information, and functional drug response data to construct biologically meaningful drug–cell interaction graphs. Dimensionality reduction using principal component analysis (PCA) is employed to mitigate data sparsity, while a dynamic focal loss is introduced to handle class imbalance. Through comprehensive evaluation, DrugCellGNN demonstrates improved predictive performance compared to existing approaches, highlighting its potential utility in precision oncology.

The remainder of this study is organized as follows: Section II briefly reviews some of the recent work published in the area of prediction of the drug response by using genomics

data. Section III explains the methodology that has been used to create the model. Evaluation criteria is explained in Section IV. The results of the proposed model are presented in Section V. Finally, Section VI concludes the study.

II. Related Work

Several computational approaches have been developed to predict medication response by analyzing gene expression profiles or other molecular information of cell lines. This Computational method for predicting drug response can be grouped into two main approaches: 1) classification (predicting drug responses as sensitive vs. resistant), 2) regression (Estimating a quantitative measure to evaluate a cell line's response to a drug). Various computational approaches have been developed to solve classification problems for predicting the sensitivity of anticancer drugs. Choi et al. [6] created RefDNN, a computational model that utilizes a deep neural network and ElasticNet repressors. They established a collection of reference medications and a baseline for classifying drugs to evaluate others. Drug sensitivity probabilities for a given cell line-drug pair were predicted using the drug's similarity to the reference set. RefDNN has the potential to be utilized for repositioning anticancer medications. Similarly, Logistic matrix factorization with regularization terms was used in DSPLMF [7] to classify drug response. This approach incorporates drug similarity derived from chemical structures and cell line similarity computed from gene expression, copy number variation, mutation profiles, and drug response data. While these methods demonstrate promising performance, they primarily rely on pairwise similarities and do not explicitly model higher-order interactions between drugs and cell lines.

Furthermore, various computational regression approaches have been developed to predict the half-maximal inhibitory concentration (IC50) of cell lines in response to drugs. Wang et al. [4] proposed the Similarity Regularized Matrix Factorization (SRMF) method, which incorporates the gene expression similarity of cell lines and the chemical similarity of drugs to enhance the prediction of anticancer drug responses. Ahmadi Moughari et al. have introduced ADRML, a framework for predicting how well cancer cells will respond to drugs using manifold learning. ADRML maps drug response values into a low-dimensional latent space and predicts the drug response for new cell line-drug pairs based on this latent space. The framework incorporates multiple types of cell line similarities and drug similarities into the manifold learning process [8].

Selecting the optimal set of genetic features for predicting drug response is crucial for developing effective classification models. Consequently, numerous feature selection algorithms employing diverse strategies have been developed. AutoBorutaRF [9] is a method which based on feature selection and designed for predicting drug response. It combines an autoencoder network with the Boruta algorithm [10]. The autoencoder is used initially, and then Boruta is applied to select the most relevant features. These selected features are then used to train a Random Forest classifier for predicting drug response. Dong et al. [11] developed a drug response prediction model called Support Vector Machine Recursive Feature Elimination (SVM-RFE), which employs a wrapper approach, combining recursive feature selection with an SVM classifier. Emdadi et al. [12] introduced a feature selection method designed for drug response prediction. It uses Hidden Markov Models (HMM) and Autoencoders (AE). While these techniques reduce dimensionality and noise, they typically treat samples independently and fail to exploit relational structures between drugs and cell lines.

Considering the complexity and noise inherent in biological data, deep learning methods often outperform traditional machine learning algorithms in predicting drug sensitivity [13]. A hybrid graph convolutional network (GCN) has been proposed in [14], This approach, known as DeepCDR, utilizes a variational autoencoder (VAE) framework to effectively model the complex relationships between multi-omics profiles of cancer cells and the intrinsic chemical structures of drugs, achieving strong results; nevertheless, it performs late-stage omics fusion, employs limited similarity types (primarily structural), and does not explicitly mitigate severe class imbalance common in pharmacogenomic data.

Other studies suggest several statistical learning strategies, such as regularized linear regression models, ridge regression lasso [15], and Support vector machines [16].

Although prior studies have progressively improved prediction accuracy, they share common limitations: over-reliance on pairwise or late-fused similarities, inadequate handling of class imbalance, limited integration of hybrid (structural + functional) drug/cell similarities, and insufficient relational modeling of multi-omics interactions. To overcome these gaps, the proposed DrugCellGNN framework integrates multi-omics features, functional and structural drug similarities, and graph neural networks to explicitly model drug–cell relationships, enabling robust and biologically informed binary drug sensitivity prediction.

III. Methodology

The primary objective of this study is to develop a predictive framework for binary drug response classification, as it may be more important whether a drug is effective for a given cancer cell line or not. There are two classifications of drug Responses: "sensitivity" and "non-sensitivity". We focused on integrating multi-omics profiles of cancer cell lines with structural and functional representations of drugs. The first step begins with extensive data preprocessing, including the removal of samples and features with excessive missingness, followed by a hybrid imputation strategy. Then, for improving the prediction performance, the cleaned datasets are dimensionally reduced to retain the most informative features, and similarity matrices are computed for both drugs and cell lines. Finally, a model is used for predicting the probability that a cell line would become drug-sensitive. Every pair was then categorized into a sensitive or resistant class by applying the threshold to the predicted probability of the cell line-drug pairs. The main scheme of our model is represented in Fig. 1.

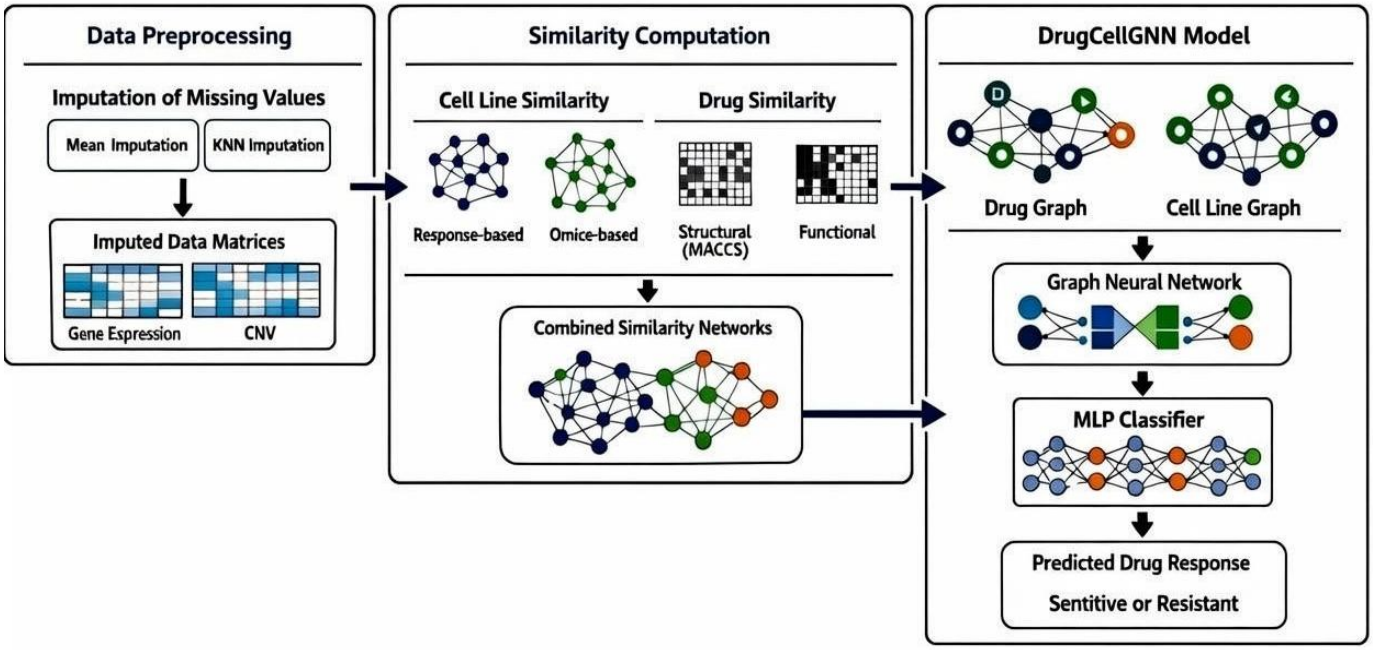


Fig. 1. Overview of the DrugCellGNN framework.

A. Dataset

Genomics of Drug Sensitivity in Cancer (GDSC) [17] is used in this study. This dataset includes drug response measurements, such as the half-maximal inhibitory concentration (IC50 values), Cell line omics information (including gene expression profiles, copy number variation (CNV), and mutation data), and maximum concentration values for drugs. The GDSC has 1,084 cell lines and 344 drugs; however, some values were missing in the dataset, so we filtered the dataset and applied preprocessing steps to address this issue. After the preprocessing, we had 551 cell lines and 91 drugs. In addition to the mentioned cell line information, chemical compound information is used and represented by Simplified Molecular Input Line Entry System (SMILES) [18], which was downloaded from PubChem [19]. And molecular fingerprints of drugs were extracted using the rdkit package in Python [20].

B. Preprocessing

We organize the collected data into three main types of matrices. The first is the response matrix, which captures the drug response data; rows represent cell lines, and columns represent different drugs. Each entry in this matrix holds either an IC50 value or a sensitivity label. The second type is the cell line feature matrices, where each row refers to a specific cell line and the columns represent its associated features. Lastly, drug feature matrices, with drugs as rows and their corresponding features arranged across the columns. Once these matrices were prepared, we carried out a series of preprocessing steps to ensure they were ready for downstream analysis.

The preprocessing steps are as follows:

- Missing value analysis and filtering: Because some of the information above has a high ratio of missing values, we first needed to remove samples with substantial missing data before performing imputation. For the response matrix, according to the distribution of missing values in Fig. 2(A), we initially removed cell lines with more than 95% missing values. Then, we eliminated cell lines and drugs with more than 30% missing data. Fig. 2(B) shows the distribution after filtering. In the gene expression matrix, we identified 72 cell lines that contained only missing values (i.e., no data across all features); therefore, the dataset became fully complete after excluding these cell lines. In the CNV matrix in Fig. 3(A) and Fig. 3(B), we removed features and cell lines with more than 30% missing values. For the mutation matrix, we eliminated features with over 35% missing data, resulting in a fully complete dataset.
- Imputing missing values: After removing samples and features with a high percentage of missing values, some missing entries still remained in the response and CNV matrices. To fill these gaps, we used a hybrid imputation method that combines mean imputation with K-nearest neighbors (KNN) imputation.

Let the drug response matrix be denoted by:

$$R \in R^{n \times m}$$

where, n and m represent the number of cell lines and drugs, respectively.

Mean Imputation is used for Low-Missing Drugs, where each drug j with a missing rate less than a threshold τ (in our study, τ =0.1), for drugs missing <10% values, fills gaps with the average response [Eq. (1)]:

$$\mu_j = \frac{1}{|I_j|} \sum_{i \in I} R_{ij} \quad (1)$$

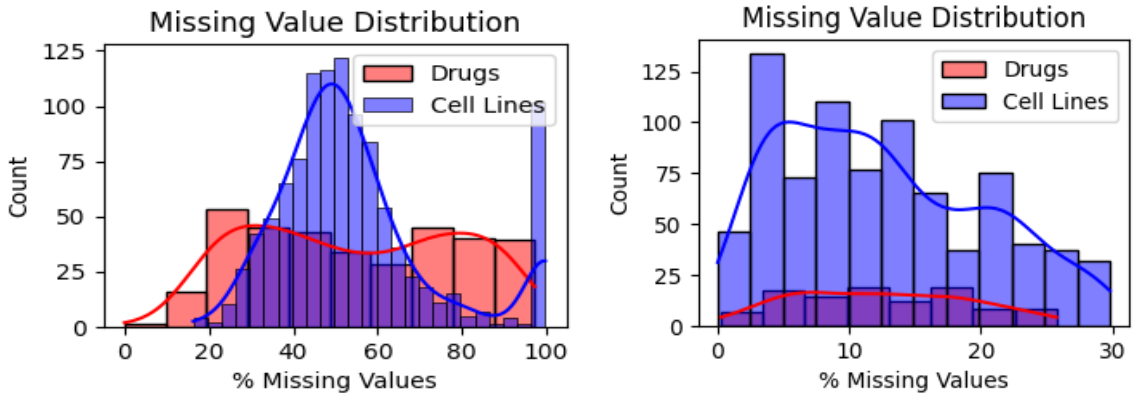


Fig. 2. (A) Missing value distribution for the response matrix before filtering. (B) Missing value distribution for the response matrix after filtering.

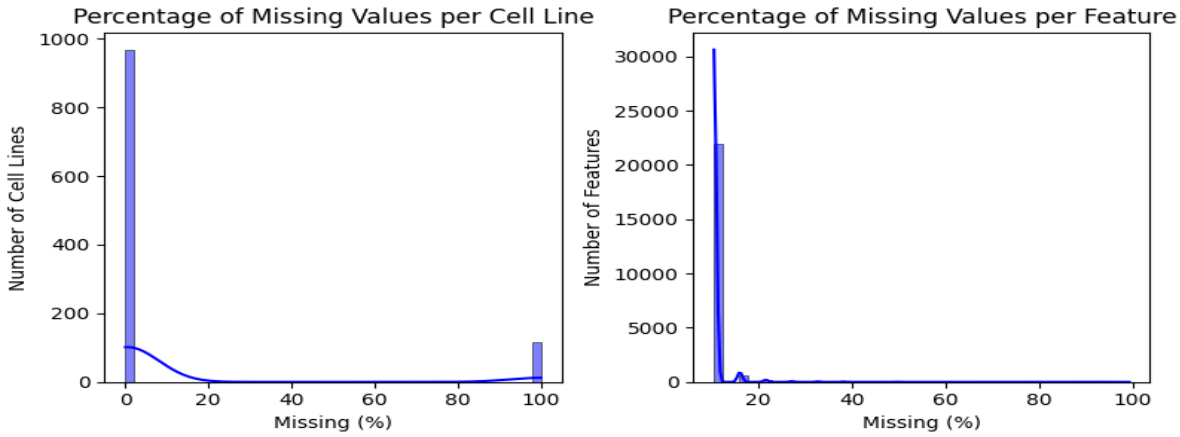


Fig. 3. (A) Missing values distribution for cell lines in the CNV matrix before filtering. (B) Missing values distribution for CNV features in the CNV matrix before filtering.

where, R_{ij} represents the response of cell line i to drug j, and may be missing (i.e., R_{ij}=NaN), $I_j=\{i|R_{ij}$ is observed$\}$, then for all missing entries R_{ij} where j ∈ low-missing drugs, set: $\hat{R}_{ij}=\mu_j$

For drugs with missing values greater than τ, we used KNN Imputation. To prepare for KNN imputation, the matrix is scaled using Eq. (2):

$$\grave{R}_{ij}=\frac{R_{ij}-\text{Median}(R_j)}{\text{IQR}(R_j)} \quad (2)$$

where, $\text{IQR}(R_j)$ is the interquartile range of drug j 's responses.

We then applied KNN imputation on the scaled data. For each missing value $\grave{R}_{ij}$, the imputed value is computed as the average of the same feature from the k nearest samples (rows) based on Euclidean distance [see Eq. (3)]:

$$\grave{R}_{ij}=\frac{1}{k}\sum_{r\in N_i}\grave{R}_{rj} \quad (3)$$

where, N_i is the set of k nearest neighbors of the sample i with observed values in feature j. After imputation, the scaled data were transformed back to their original scale using the inverse of the robust scaling operation [Eq. (4)]:

$$R_{ij}^{final}=\grave{R}_{ij}.\text{IQR}(R_j)+\text{Median}(R_j) \quad (4)$$

This hybrid approach ensures that low-missing features are imputed efficiently using simple statistics, while high-missing features benefit from structure-aware imputation via KNN.

- Binary conversion using IC50: This research aims to develop classification-based modeling, so we converted the continuous drug response data into binary labels (sensitivity and non-sensitivity). Several research studies have adopted different threshold values of IC50 for binarization. Such as median values [7], [9] or a specific deviation from the normalized mean [11]. While others have relied on more biologically grounded pharmacokinetic thresholds, such as the maximum drug concentration (Cmax) [6]. Cmax makes more sense among the different thresholds used to assign labels to drug response data because it is predicated on the medication's pharmacokinetic characteristics. Cmax is the highest concentration of a medication that can be found in plasma. Thus, it is clear that a cell line is resistant to a medicine if it needs a molar concentration greater than the drug's Cmax for 50% inhibition. For this reason, we adopted the Cmax in our study for classifying drug response. And based on it, we labeled a cell line as "sensitive" if the $IC50_{i,j} \leq$ Cmax, which is represented by 1; otherwise, it's labeled as "non-sensitive".

C. Feature Engineering

Omics Integration and Dimensionality Reduction: To construct a comprehensive representation of each cell line, we integrated multiple omics data types, including gene expression, copy number variation (CNV), and mutation profiles. Only cell lines present in all three sources were retained to ensure consistency. The aligned datasets were then concatenated to form a unified omics feature matrix. To reduce scale disparities and improve model stability, the omics matrix was standardized using z-score normalization and subsequently, Principal Component Analysis (PCA) [21]. In our study, PCA was applied to reduce dimensionality while preserving 80% of the variance. This step helped eliminate redundancy and emphasized the most informative biological features.

The cumulative explained variance curve (Fig. 4) demonstrates a smooth and steady increase, indicating that a relatively moderate number of components (~140) is sufficient to retain 80% of the variance. This gradual curve suggests that the variance is well distributed across components, meaning no single feature dominates the representation. Such a distribution supports the stability and robustness of the compressed feature space, as it captures diverse biological signals rather than being overly dependent on a few dominant factors.

To explore the potential benefit of non-linear dimensionality reduction, we compared PCA with a shallow autoencoder trained on the standardized omics feature matrix. Both approaches yielded comparable performance in downstream tasks, suggesting that the underlying structure of the data is predominantly linear. Given PCA's simplicity, interpretability, and computational efficiency, we opted to use PCA for feature compression in the final pipeline.

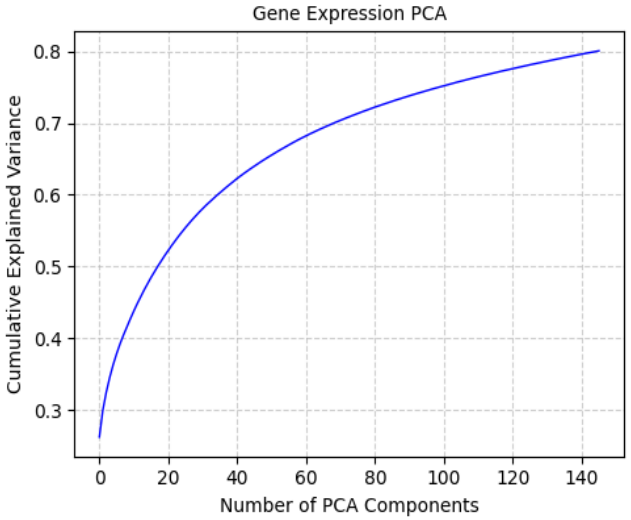


Fig. 4. PCA explained variance curve.

- Similarity Computation: To enhance the representation of both cell lines and drugs, we constructed similarity networks using a weighted combination of functional and structural measures. This approach captures complementary biological and chemical relationships, enabling the model to generalize better across diverse drug-cell line pairs.

For cell lines, similarity was computed using two modalities:

- Response-Based Similarity: We calculated cosine similarities from the drug response matrix $R \in R^{n \times m}$, where R_i and R_j are the response vectors of cell lines i and j. Cosine similarity is defined in Eq. (5):

$$S_{ij}^{response} = \frac{R_i . R_j}{\|R_i\|_2 \|R_j\|_2} \quad (5)$$

- Omics-Based Similarity: derived from the omics feature matrix $O \in \mathbb{R}^{n \times m}$ where O_i and O_j are the feature vectors of cell lines i and j. Using the same cosine similarity equation [Eq. (6)]:

$$S_{ij}^{omics} = \frac{O_i . O_j}{\|O_i\|_2 \|O_j\|_2} \quad (6)$$

The final cell line similarity matrix was computed as a weighted combination [see Eq. (7)]:

$$S^{cell} = \lambda_c . S^{response} + (1-\lambda_c) . S^{omics} \quad (7)$$

λ_c is a parameter that represents the weight of the matrix; in our study, λ_c=0.3 was selected empirically to balance phenotypic response patterns and intrinsic molecular.

This fusion strategy balances phenotypic behavior with intrinsic biological or chemical characteristics.

For drug similarity, the similarity between two drugs i and j is computed using MACCS fingerprints [22] and the response matrix; we computed both similarity matrices using Jaccard similarity.

Structural similarity: computed using the Jaccard similarity over MACCS fingerprints [see Eq. (8)].

$$S_{ij}^{struc} = \frac{|F_i \cap F_j|}{|F_i \cup F_j|} \quad (8)$$

where, F_i, F_j are Sets of active bits in the MACCS fingerprints of drugs i and j, respectively.

Functional similarity: using cosine similarity across binary response profiles S_{ij}^{func}.

The final drug similarity matrix was Eq. (9):

$$S^{drug} = \lambda_d . S^{func} + (1-\lambda_d) . S^{struc} \quad (9)$$

λ_d is a parameter that represents the weight of the matrix; in our study, λ_d=0.3.

D. Model Architecture

To capture the complex interplay between drugs and cancer cell lines, we propose a novel graph-based deep learning framework, DrugCellGNN, that integrates structural drug information, functional cell similarities, and multi-omics features into a unified predictive model.

Graph Construction and Node Embedding: To include the structural relationships between drugs and cell lines, we built two separate graphs: a drug similarity graph and a cell line similarity graph. Each graph G= (V, E) is composed of nodes V (drugs or cell lines) and edges E, which are defined based on a pairwise similarity threshold. Specifically, an edge (i,j) ∈ E is

formed if the similarity score $S_{ij} > 0.7$, a threshold selected to retain only strong associations.

Each node is initialized with a trainable embedding vector of size e from $E_d \in R^{|v_d| \times e}$ for drug and $E_c \in R^{|v_c| \times e}$ for cell lines, where $|v_d|$ and $|v_c|$ denote the number of drug and cell nodes, respectively. These embeddings were then updated using a graph convolution operation defined as Eq. (10):

$$H^{l+1} = \sigma\left(\hat{D}^{-\frac{1}{2}}\hat{A}\hat{D}^{-\frac{1}{2}}H^{l}W^{l}\right) \quad (10)$$

Where $\hat{A}=A+I$ is the adjacency matrix with self-loops, $\hat{D}$ is the corresponding degree matrix, H^l is the node feature matrix at layer l, W^l is the trainable weight matrix, and σ is a non-linear activation function (ReLU in our case).

Alternatively, this operation can be interpreted from a node-wise perspective as Eq. (11):

$$h_i^{(l+1)} = \sigma\left(\sum_{j \in N(i)} \frac{1}{\sqrt{|N(i)|.|N(j)|}} W^{(l)} h_j^{(l)}\right) \quad (11)$$

This emphasizes how each node i updates its feature by aggregating normalized information from its neighbors N(i).

Using this, the final graph-enhanced embedding is Eq. (12):

$$d_i = GCN_{drug}(E_d, G_d),\ c_j = GCN_{cell}(E_c, G_c) \quad (12)$$

The output embedding for drugs and cell lines — denoted $d_i = GCN_{drug}(E_d, G_d)$ and $c_j = GCN_{cell}(E_c, G_c)$, respectively — are then concatenated with the corresponding omics feature vector $o_j \in R^O$ of the cell line, resulting in a fused representation [see Eq. (13)]:

$$z_{ij} = \left[d_i \| c_j \| o_j\right] \in R^{2e+o} \quad (13)$$

This vector z_{ij} is passed into a multi-layer perceptron (MLP) — a deep learning model for classification. Where the first hidden layer can be represented by Eq. (14):

$$h_1 = RELU(BN(W_1 z_{ij} + b_1)) \quad (14)$$

The second layer [see Eq. (15)]:

$$h_2 = RELU(W_2 h_1 + b_2) \quad (15)$$

To prevent overfitting, a dropout layer with a probability of p =3 is applied after the second fully connected layer. Dropout randomly deactivates a fraction p of neurons during training, encouraging the network to learn distributed representations rather than memorizing specific patterns [Eq. (16)].

$$\tilde{h}_2 = m \odot h_2,\ m \sim Bernoulli(1-p) \quad (16)$$

Finally, the transformed features are passed to a sigmoid output layer to produce the predicted probability of drug sensitivity, as in Eq. (17):

$$\hat{y}_{ij} = \sigma(W_3 \tilde{h}_2 + b_3) \quad (17)$$

where, $\hat{y}_{ij} \in [0.1]$ indicates the likelihood that cell line j responds to drug i.

E. Dynamic Focal Loss Function for Imbalanced Data

To address class imbalance inherent in drug response data, we implemented a custom focal loss function with dynamic weighting, where the per-sample weight α_d is given in Eq. (18):

$$\alpha_d = \frac{\#\text{ sensitive cell lines for drug d}}{\text{Total cell lines tested for drug d}} \quad (18)$$

This formulation increases the loss contribution from drugs with few positive (sensitive) samples, preventing the model from being biased toward majority-class drugs.

The overall loss for a sample (i.j) is in Eq. (19):

$$L_{focal} = \alpha_d.(1-p_t)^{\gamma}.BCE\left(\hat{y}_{ij}, y_{ij}\right) \quad (19)$$

where, $\hat{y}_{ij}$, y_{ij} are the predicted probability and ground truth label, respectively, $p_t = \hat{y}_{ij}$ if $y_{ij}=1$, otherwise $1-\hat{y}_{ij}$. And γ is the focusing parameter.

IV. Evaluation Criteria

The dataset was split into 80% training and 20% testing using stratified sampling, which is widely used in drug response prediction benchmarks to ensure sufficient training data while maintaining an unbiased test set. This setting evaluates the model's ability to generalize across unseen drug–cell line pairs under standard experimental conditions. Training was conducted for 100 epochs with early stopping based on validation AUC. All computations were accelerated via GPU. The model parameters were optimized using the Adam optimizer (lr = 0.001).

The model is evaluated on the test set using a comprehensive set of metrics:

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$

$$\text{Precision} = \frac{Tp}{Tp + Fp}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1 score} = 2.\frac{\text{precision.Recall}}{\text{precision+Recall}}$$

where, TP, TN, FP, and FN represent true positive, true negative, false positive, and false negative, respectively. In addition to the metrics mentioned above, AUPR, AUC, and Specificity were also used.

V. Results

A. Data Description

Data filtering helped to reduce the missing values. For the IC50 response matrix, missing values reduced from 54.39% to 12.50%, and the Omics: RNA missing values reduced from 6.64% to 0.00%, CNV missing values reduced from 11.20% to 2.40%.

Since the GDSC dataset still includes missing entries, we compensated for them by applying a hybrid imputation approach, as outlined in the Materials and Methods section

(Section III). The total number of features and samples after this step is in Table I.

TABLE I. GDSC DATASET INFORMATION BEFORE AND AFTER PREPROCESSING

Dataset	State	Drugs	Cell lines	RNA	CNV	Mutation
GDSC	Raw	343	1084	17612	22903	68
	preprocessed	103	643	17611	22773	55

So we had omics data with more than 40 thousand features, which were integrated with the response matrix to calculate cell line similarities. This analysis produced a 551 × 551 cell line similarity matrix, reflecting the 551 common cell lines shared across the datasets. For the drug data, compounds lacking SMILES representations were excluded. MACCS fingerprints were then computed and combined with the response matrix to derive drug similarities, resulting in a 91 × 91 similarity matrix corresponding to the 91 drugs common across the datasets. Then we reduced the dimensionality of the omics data by applying PCA, ensuring that 80% of the total variance is preserved, reducing the number to 146 features.

For labeling, we used Cmax to convert IC50 values to labeled values. The GDSC dataset exhibits a moderately balanced class distribution, with 62.93% of drug-cell pairs classified as sensitive and 37.07% as resistant, yielding a 1.7:1 ratio. However, per-drug sensitivity rates vary significantly, with some drugs showing as low as 13% or as high as 76% sensitive cell lines, creating drug-specific imbalances (see Fig. 5). To ensure robust performance on both classes, particularly the clinically critical resistant cases, we employed focal loss with dynamic per-drug alpha (α=1-sensative fraction,γ=3). This approach weights the loss inversely to each drug's sensitivity rate, prioritizing underrepresented classes (e.g., resistant cases for highly effective drugs). As a result, the DrugCellGNN achieved balanced performance, with an AUPR of 0.9698, F1-score of 0.9228, and specificity of 0.7853, demonstrating effective handling of per-drug class variations and enhancing its utility for precision oncology.

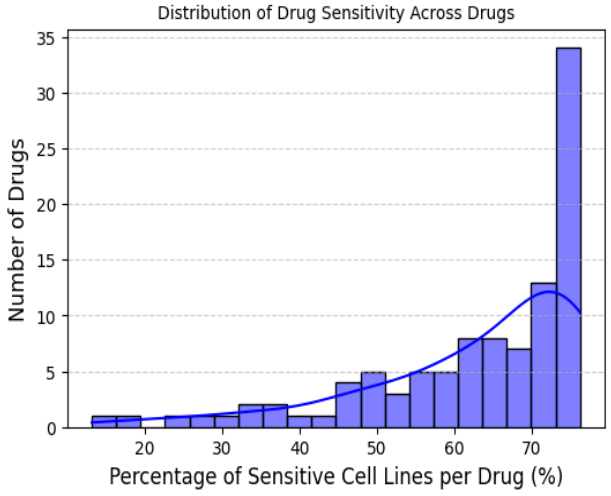


Fig. 5. Distribution of drug sensitivity across drugs.

B. Predictive Performance of the Model

To validate the effectiveness of our approach, we compared its predictive performance with that of the state-of-the-art models, including DSPLMF [7], Auto-HMM-LMF[12], CDSML [23], and MOICVAE [24]. All the methods mentioned above are classification models. All baseline models were evaluated using the same preprocessed dataset and identical train–test splits to ensure a fair comparison. The results in Table II show that in the GDSC cell line data set, the five indicators of our model framework were the highest.

TABLE II. PREDICTION PERFORMANCE OF DIFFERENT ALGORITHMS BASED ON SIX CRITERIA ON THE (GDSC) DATASET

Method	ACC	Rec	SPC	F1	AUC	Precision
DrugCellGNN	**0.895**	**0.941**	**0.807**	**0.921**	**0.951**	**0.902**
AutoBorutaRF	0.653	0.652	0.654	0.650	0.711	0.646
DSPLMF	0.682	0.750	0.615	0.702	0.760	0.671
MOICVAE	0.772	0.787	-	0.775	0.856	0.764
CDSML	0.838	0.9031	-	0.8715	0.9157	0.842
Auto-HMM-LMF	0.70	0.78	0.63	0.73	0.78	0.77

VI. CONCLUSION AND DISCUSSION

In this study, we introduced DrugCellGNN, a pioneering Graph Neural Network framework that revolutionizes cancer drug sensitivity prediction by seamlessly integrating multi-omics data—encompassing gene expression, copy number variations, and mutations—with structural and functional similarities between drugs and cell lines. Leveraging the GDSC dataset, our pipeline addresses key challenges in pharmacogenomics, including data sparsity through hybrid imputation, high dimensionality via PCA reduction, and class imbalance with dynamic focal loss. Evaluated on 50141drug-cell pairs (80/20 train-test split), DrugCellGNN achieved an AUC of 0.9516, F1-score of 0.9228, and AUPR of 0.9698, outperforming traditional baselines Random Forest and SVM by leveraging relational dependencies. These results highlight DrugCellGNN's ability to model complex interactions, enhancing prediction accuracy for rare sensitive cases critical in precision oncology. A key factor contributing to the effectiveness of DrugCellGNN is the integration of functional and structural similarity information for both drugs and cell lines. By combining response-based similarities with molecular and chemical features, the constructed graphs provide a biologically meaningful representation of drug–cell interactions. This fusion strategy allows the model to leverage complementary information, balancing phenotypic drug response patterns with intrinsic biological characteristics of cancer cell lines and chemical properties of drugs.

Future work should aim to expand this framework to other datasets, such as CCLE or CTRP, to evaluate how well it performs across different data sources. Using more advanced molecular representations (like transformer-based encoders or molecular graph embeddings) could boost predictive accuracy. Adding more layers of omics data, such as epigenomic or proteomic information, might also deepen the biological understanding. Lastly, integrating explainability features into

the GNN could reveal mechanistic insights by pinpointing which molecular features or graph edges most influence the predictions.

REFERENCES

[1] C. Tomasetti, L. Li, and B. Vogelstein, "Stem cell divisions, somatic mutations, cancer etiology, and cancer prevention," Science (80-.)., vol. 355, no. 6331, pp. 1330–1334, 2017.

[2] A. C. Begg, F. A. Stewart, and C. Vens, "Strategies to improve radiotherapy with targeted drugs," Nat. Rev. Cancer, vol. 11, no. 4, pp. 239–253, 2011.

[3] D. M. Roden and A. L. George Jr, "The genetic basis of variability in drug responses," Nat. Rev. Drug Discov., vol. 1, no. 1, pp. 37–44, 2002.

[4] L. Wang, X. Li, L. Zhang, and Q. Gao, "Improved anticancer drug response prediction in cell lines using matrix factorization with similarity regularization," BMC Cancer, vol. 17, pp. 1–12, 2017.

[5] W. Yang et al., "Genomics of Drug Sensitivity in Cancer (GDSC): a resource for therapeutic biomarker discovery in cancer cells," Nucleic Acids Res., vol. 41, no. D1, pp. D955–D961, Jan. 2013, doi: 10.1093/nar/gks1111.

[6] J. Choi, S. Park, and J. Ahn, "RefDNN: a reference drug based neural network for more accurate prediction of anticancer drug resistance," Sci. Rep., vol. 10, no. 1, Dec. 2020, doi: 10.1038/s41598-020-58821-x.

[7] A. Emdadi and C. Eslahchi, "DSPLMF: A Method for Cancer Drug Sensitivity Prediction Using a Novel Regularization Approach in Logistic Matrix Factorization," Front. Genet., vol. 11, no. February, pp. 1–14, 2020, doi: 10.3389/fgene.2020.00075.

[8] F. Ahmadi Moughari and C. Eslahchi, "ADRML: anticancer drug response prediction using manifold learning," Sci. Rep., vol. 10, no. 1, Dec. 2020, doi: 10.1038/s41598-020-71257-7.

[9] X. Xu, H. Gu, Y. Wang, J. Wang, and P. Qin, "Autoencoder based feature selection method for classification of anticancer drug response," Front. Genet., vol. 10, no. MAR, 2019, doi: 10.3389/fgene.2019.00233.

[10] M. B. Kursa and W. R. Rudnicki, "Feature selection with the Boruta package," J. Stat. Softw., vol. 36, pp. 1–13, 2010.

[11] Z. Dong et al., "Anticancer drug sensitivity prediction in cell lines from baseline gene expression through recursive feature selection," BMC Cancer, vol. 15, no. 1, Jun. 2015, doi: 10.1186/s12885-015-1492-6.

[12] A. Emdadi and C. Eslahchi, "Auto - HMM - LMF : feature selection based method for prediction of drug response via autoencoder and hidden Markov model," BMC Bioinformatics, pp. 1–22, 2021, doi: 10.1186/s12859-021-03974-3.

[13] D. Baptista, P. G. Ferreira, and M. Rocha, "Deep learning for drug response prediction in cancer," Briefings in Bioinformatics, vol. 22, no. 1. Oxford University Press, pp. 360–379, Jan. 01, 2021. doi: 10.1093/bib/bbz171.

[14] Q. Liu, Z. Hu, R. Jiang, and M. Zhou, "DeepCDR: a hybrid graph convolutional network for predicting cancer drug response," Bioinformatics, vol. 36, no. Supplement_2, pp. i911–i918, 2020.

[15] P. Geeleher, N. J. Cox, and R. S. Huang, "Clinical drug response can be predicted using baseline gene expression levels and in vitro drug sensitivity in cell lines," Genome Biol., vol. 15, pp. 1–12, 2014.

[16] C. Huang, R. Mezencev, J. F. McDonald, and F. Vannberg, "Open source machine-learning algorithms for the prediction of optimal cancer drug therapies," PLoS One, vol. 12, no. 10, p. e0186906, 2017.

[17] B. Haibe-Kains, "PSet_GDSC2020." Zenodo, Apr. 2023. doi: 10.5281/zenodo.7829915.

[18] E. Anderson, G. D. Veith, and D. Weininger, SMILES, a line notation and computerized interpreter for chemical structures. US Environmental Protection Agency, Environmental Research Laboratory, 1987.

[19] S. Kim et al., "PubChem in 2021: new data content and improved web interfaces," Nucleic Acids Res., vol. 49, no. D1, pp. D1388–D1395, 2021.

[20] G. Landrum, "Rdkit documentation," Release, vol. 1, no. 1–79, p. 4, 2013.

[21] I. Jolliffe, "Principal component analysis," in International encyclopedia of statistical science, Springer, 2011, pp. 1094–1096.

[22] J. L. Durant, B. A. Leland, D. R. Henry, and J. G. Nourse, "Reoptimization of MDL keys for use in drug discovery," J. Chem. Inf. Comput. Sci., vol. 42, no. 6, pp. 1273–1280, 2002.

[23] F. A. Moughari and C. Eslahchi, "A computational method for drug sensitivity prediction of cancer cell lines based on various molecular information," PLoS One, vol. 16, no. 4 April 2021, Apr. 2021, doi: 10.1371/journal.pone.0250620.

[24] C. Wang, M. Zhang, J. Zhao, B. Li, X. Xiao, and Y. Zhang, "The prediction of drug sensitivity by multi-omics fusion reveals the heterogeneity of drug response in pan-cancer," Comput. Biol. Med., vol. 163, no. June, p. 107220, 2023, doi: 10.1016/j.compbiomed.2023.107220.

Personalized Point of Interest in Location-Based Augmented Reality Tourism Application

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***Abstract*—In recent years, the rapid growth of the tourism industry and increasing demand for efficient and meaningful travel experiences have highlighted the need for smarter travel assistance tools. Many tourists, particularly first-time visitors, often face challenges navigating unfamiliar destinations and identifying relevant points of interest, leading to delays, inconvenience, and reduced satisfaction. During the peak tourist season, most local hotels and restaurants are overcrowded, and tourists have to find accommodation and food in unfamiliar places, which reduces their travel efficiency and experience. To address these challenges, this study proposes the PutrajayAR, a personalized Location-Based Augmented Reality (LBAR) tourism application designed to enhance tourists' efficiency and overall travel experience. The application provides AR Discovery and AR Recommendation features that dynamically present personalized points of interest based on user preferences, spatial proximity, and contextual constraints. The system was developed using the waterfall model and evaluated through black box testing, usability testing, and persuasive design assessment. The results demonstrate that PutrajayAR significantly improves user experience and satisfaction compared to non-personalized approaches, thereby validating the effectiveness of personalized LBAR systems in helping users navigate effectively and discover attractions that match their interests.**

***Keywords*—Augmented Reality; LBAR; PutrajayAR; AR Discovery; AR Recommendation**

I. Introduction

Augmented Reality (AR) is a technology that superimposes virtual imagery onto the real-world environment, creating an interactive and immersive experience for users [1]. AR is characterized by three core features: the integration of real and virtual elements, real-time interactivity and three-dimensional (3D) registration [2]. A subset of AR, Location-Based Augmented Reality (LBAR), is a markerless and geo-referenced technology that relies on GPS, accelerometers, digital compasses and other sensors to accurately determine the device's position and orientation [3]. With the widespread availability of these sensors in modern mobile devices, LBAR applications have become increasingly accessible to the general public. In parallel, the integration of the Internet of Things (IoT) and machine learning technologies is reshaping various industries, including tourism and automotive sectors, by enabling intelligent, data-driven decision-making [4].

In the era of the Fourth Industrial Revolution (4IR), digital transformation has become a driving force in economic and social development, especially in the tourism sector, where technological innovation plays a pivotal role in shaping new experiences and efficiencies [5]. Research indicates that AR-based tourism applications are more appealing to users than traditional promotional methods due to their immersive and dynamic nature [8]. As global tourism continues to expand, travelers increasingly seek personalized, efficient, and engaging experiences. AR technology contributes significantly to this shift by enhancing tourists' ability to access contextual information, explore destinations interactively, and deepen their understanding of the places they visit [6]. From personalized recommendations and interactive navigation to virtual guides and translation tools, the applications of AR in tourism are extensive and continually evolving. The virtual tourism market alone is projected to grow at a compound annual growth rate (CAGR) of 30.2% between 2023 and 2028, reaching an estimated value of USD 23.5 billion [7].

Despite the growing adoption of LBAR in tourism applications, most existing systems primarily focus on spatial awareness and static point of interest visualization, which rely on distance or category-based filtering mechanisms. As a result, there is an absence of empirical evidence illustrating the impact of personalized LBAR recommendations on user experience, satisfaction and perceived persuasiveness within tourism contexts. To address this gap, this study investigates the following research question:

RQ: How does integrating personalized recommendations into an LBAR affect user experience, satisfaction and perceived persuasiveness in tourism applications?

Therefore, this study proposes a personalized AR recommendation mechanism that integrates user preferences and situational constraints. The system also provides empirical evidence, through a comparative evaluation, that personalized POI can significantly improve user experience, satisfaction and perceived persuasiveness compared to non-personalized approaches. Overall, LBAR technology stands out for its usability, interactivity and personalization, offering tourists a unique and engaging way to explore their surroundings. The ongoing advancements in digital technology continue to elevate the quality and innovation of tourism systems, fostering more engaging and meaningful travel experiences.

The remainder of this study is organized as follows: Section II presents the related works on Location-based Augmented Reality, Section III describes the research methodology, Section IV discusses the results and Section V concludes the study.

II. Related Work

The PutrajayAR application is developed for the Android platform, using the Augmented Reality (AR) technology through modern smartphones. The choice of Android as the primary operating system is based on its widespread usage and compatibility with a wide range of mobile devices. According to a survey by Ruqiya [9], among 60 respondents, the majority expressed a preference for Android over iOS due to its user-friendly interface and superior system compatibility. Specifically, 90% of respondents favored Android, while only 10% preferred iOS. These findings indicate that Android-based applications are more popular and accessible to users, making it a suitable and strategic platform for implementing the PutrajayAR system.

A. Location-Based Augmented Reality

Location-based AR aims to seamlessly link physical location coordinates with the data processing environments, allowing users to view POI (Point of Interest) annotations of specific landmarks in the real environment [10]. Implementing this technology for navigation can significantly improve user actions to reduce travel time, especially when the application is designed for pedestrian use. Fig. 1 shows an example of location-based AR for navigation [11].



Fig. 1. Location-based AR for navigation.

Various devices can be used to apply the concept of location-based AR, such as mobile phones, special AR glasses, tablets and so on. These devices will function as output devices and will display information in the form of videos, pictures, animations and 3D models that need to be used. LBAR is divided into two types, namely Indoor LBAR and Outdoor LBAR.

1) Indoor LBAR: Indoor LBAR uses AR technology in enclosed spaces such as shopping malls, airports, museums and other indoor environments where GPS signals may be unreliable. The user's device detects nearby Wi-Fi access points [12] or communicates with nearby Bluetooth devices [13] to estimate their location, compensating for the instability of GPS signals indoors.

2) Outdoor LBAR: Outdoor AR typically relies on GPS and geolocation technology. According to Blanco's study [14], regular GPS provides approximate location with a standard accuracy of about 3 meters outdoors; differential GPS can also support higher positioning accuracy, which is sufficient for many applications. PokemonGo [15] is a very clear example; it is an AR-based mobile travel game developed by Niantic that combines a virtual game world with a real-world map, encouraging players to explore their surroundings to interact with virtual characters. Players use the app to walk around their local environment to find and catch Pokémon, which are often placed near real-world landmarks, historical sites and popular locations. This encourages users to visit and learn about new places in their area or while traveling.

In this scenario, we find that LBAR features provide users with great satisfaction through traveling experience efficiency and personalization.

B. Personalized Recommendation

Personalized Apps are software solutions designed to adapt to the preferences, behaviors and needs of individual users, offering a tailored experience. Personalized recommendations based on user behavior and preferences can make apps feel more customized and relevant to individual users. By using data analytics and machine learning, apps can deliver content and features that resonate with users, thereby increasing their overall satisfaction and engagement [16].

C. Existing Location-Based AR Tourism App

The rapid growth of the tourism industry, coupled with advances in mobile technology, has led to the emergence of numerous tourism-related mobile applications designed to provide travelers with more efficient and engaging experiences. While Augmented Reality (AR) has become an increasingly prominent feature in tourism application development, existing AR-based tourism solutions still face limitations.

1) AR City Guide: AR City Guide is an augmented reality city guide app designed to enhance the view by combining virtual information with the real-world environment. It offers users an immersive way to explore and learn about various locations while traveling. Users can use the phone's camera to scan buildings, landmarks, or attractions, and the app overlays information such as historical facts, architectural details and cultural insights directly onto the screen

Based on the user's current location, the app suggests nearby tourist attractions, restaurants and shopping areas, often with ratings and reviews from other users. Fig. 2 shows nearby suggestions in a city.



Fig. 2. Nearby suggestions in a city.

The app also provides AR-based navigation with virtual directional arrows overlaid on top of the real-world view, making it easier for users to find their desired destination. Fig. 3 shows the app's navigation functionality.

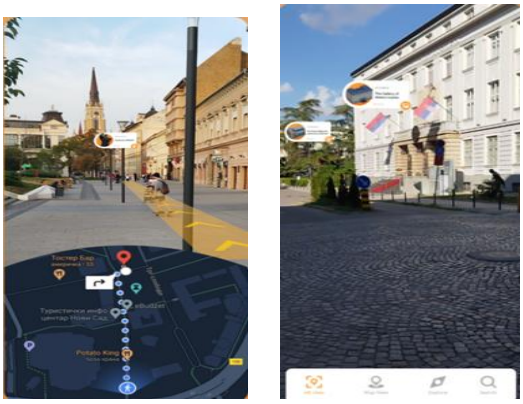


Fig. 3. Navigation function.

2) Horizon Explorer AR: Horizon Explorer AR is an augmented reality application designed to provide users with an interactive experience in exploring the landscape, landmarks and terrain around them. The application allows users to view real-world landscapes through their phone camera and receive detailed information about nearby points of interest (POIs) simply by pointing the device at them. Using GPS, Horizon Explorer identifies nearby locations and overlays the information directly onto the AR display. It offers details about landmarks, cities, mountains and other geographical features visible in the distance. Fig. 4 shows the geographical features of Horizon Explorer AR.

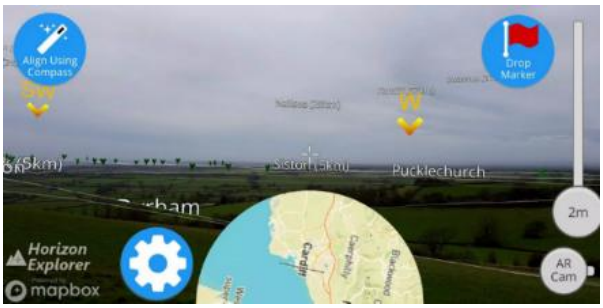


Fig. 4. Geographical features of Horizon Explorer AR.

As users pan their camera, the application displays the distance, elevation, and names of visible landmarks, allowing users to explore the surrounding terrain and understand the spatial relationships between different points. Horizon Explorer's interface is designed for simplicity, allowing users to switch between the map view and the AR view, making it intuitive to use. It offers both metric and imperial units of measurement, catering to the needs of a global audience. Fig. 5 shows the application's map view.

3) Word Around Me: World Around Me (WAM) is an augmented reality app that helps users explore and navigate their surroundings by overlaying information about nearby places directly onto the smartphone camera display. It is popular with tourists and those exploring new cities, as it provides details about a variety of categories, such as restaurants, ATMs, hospitals, transportation, entertainment venues and shopping options. Users can lift their phone and pan to see the names, ratings, distances and directions of nearby places overlaid on the live camera feed. This AR display helps users visualize where different places are in relation to their current location.



Fig. 5. Map view.

WAM covers a variety of categories, and users can filter results to focus on specific types of places. Categories include eateries, ATMs, pharmacies, parks, hotels, and more. Fig. 6 shows the WAM filter functionality. By tapping on a specific location in the AR display, users can access more detailed information such as reviews, hours of operation, contact details and navigation options, with integration into Google Maps and Apple Maps for seamless routing.



Fig. 6. WAM filter.

D. Comparison Between LBAR Apps

Table I shows the comparison between Location-based AR (LBAR) applications.

From this study, we found that previous studies have demonstrated that AR-based tourism applications are more engaging than traditional map-based or text-based guides due to their immersive nature [6], [7]. However, most existing LBAR tourism applications focus primarily on visualization and proximity-based information delivery. Points of interest are typically displayed based on static criteria such as distance or category, without considering individual user preferences or situational context. Applications such as AR City Guide and World Around Me emphasize nearby POI discovery and AR navigation but provide limited support for helping users decide

which attraction best matches their interests or constraints. As a result, users may still experience information overload and uncertainty when multiple POIs are presented simultaneously in the AR view. After comparing and studying the applications, we found that personalized LBAR technology will help tourists to travel easily, especially when they first arrive in an unfamiliar place. AR and POI displays can provide users with the exact location of buildings. Some new functions, such as POI filters and personalized recommendations also provide a higher quality of service and attract new customers.

TABLE I. COMPARISON BETWEEN LBAR APPLICATIONS

Application	AR City Guide	Horizon Explorer AR	World Around Me
Device	Smart Phone, AR Glasses	Smart Phone	Smart Phone
Language	English	English	English
Main Function	AR City Navigation. Recommend nearby landmarks based on the distance between user device and places.	Wild Terrain and Village Exploration based on user GPS detection. Calculation on the distance between users and each POI.	AR City Navigation. Filter places based on user selected categories.
Technology	• Location-based AR, • Visual Positioning System, • Simultaneous Localization and Mapping, • Real-time Location System, • GPS, • Geographic Information System • Distance Calculation	• Location-based AR, • GPS, • Geographic Information System, • Distance Calculation	• Location-based AR, • Real-time Location System, • Simultaneous Localization and Mapping, • Categorized POI,
POI Filter Types	Based on user needs and POI Categories	Based on distance	Based on user needs and POI Categories
Personalized Recommendation	Based on distance	None	None

III. METHODOLOGY

System design is a crucial stage in the software development process that defines how the system's components, architecture and data structures interact to achieve the intended functionality. It serves as the bridge between user requirements and the actual implementation, ensuring that the system is both functional and maintainable [17]. In this study, system design establishes the foundation for developing the PutrajayAR application, outlining how its modules, databases and user interfaces integrate to deliver a personalized, location-based augmented reality (LBAR) experience for tourists. According to Sommerville [18], the goal of system design is to transform the requirements specification into a blueprint that describes the overall structure of the system. For *PutrajayAR*, this involves defining the system architecture, database schema, algorithmic logic, and user interface flow to ensure that all components operate cohesively and efficiently.

A. Architecture Design

The initial phase of the design process is the architectural design, which shows the functionality of the application, including interaction design, experience, process and strategy. For the PutrajayAR application, layered design and hierarchy diagrams were used to illustrate the interactions between entities and the application.

1) Layered design: The most commonly used architectural pattern is the layered architectural pattern, or known as n-tier. The architectural pattern is widely used in design and development. This modular structure enhances scalability, reusability, and ease of maintenance [19]. It also ensures that modifications in one layer do not affect others, thereby improving development efficiency. The components in this layered architectural pattern are arranged into horizontal layers. Each layer has a specific role in the application. Fig. 7 shows the layers found in the PutrajayAR application architectural pattern. The first layer shows the presentation logic; this layer is what interacts with the user through the application interface.

Then the second layer is the processing layer. This layer shows the system functions and procedures based on the rules layer. Among the services available are that users can register an account, log in, edit their profile, use AR Discovery and AR recommendations. This layer also determines how the menus, buttons and navigation of the application work through the application interface. This second layer is also known as the business rules layer and the application core because it contains the rules that determine the overall response of the application, as well as the server that contains the main program, code definitions and basic functions of the application. Programming works in this layer almost all the time.

Finally, the data storage layer. This layer contains the data used by the application. Search, insert, delete and update operations are performed in this layer. Examples of databases used by applications are the AR Database which stores data to be displayed when the camera detects a POI without a marker and also the User Database which stores user profile information such as username, email, password and user travel preferences and so on.

2) Hierarchy Diagram: Hierarchy diagrams are used to explain the breakdown of the overall process in a system or application into a more detailed form. Users can log in directly to the application or register an account first if they do not have any account.

In addition, this application provides a profile form for users to edit and record their user information into the database. This profile requires content types that are typical user information,

such as username, email and country. PutrajayAR also asks users to complete their travel choices, such as shopping, sightseeing or food hunting. For each travel choice, there are several subtopics for the user to choose from, for example, when the user chooses food hunting as the travel choice, the application will ask the user to select their subtopic, such as Malay cuisine, Chinese food or Indian cuisine.

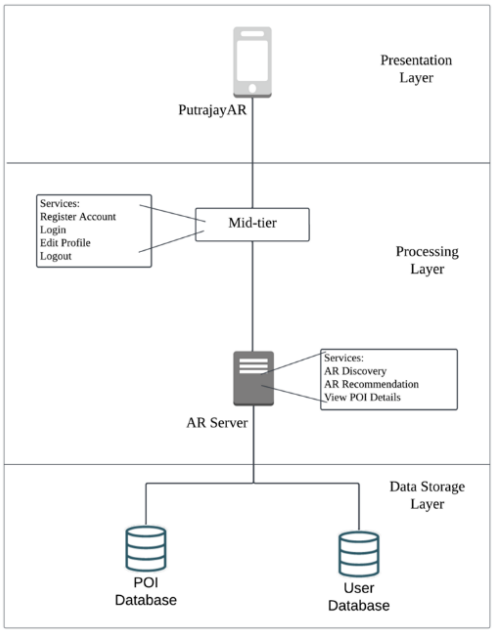


Fig. 7. Layered design of the app.

In addition, this application includes an AR Discovery feature that allows users to scan their surroundings and display nearby POIs directly on the screen. To help users easily find POIs that match their current needs, this application supports two filtering options: category filtering and distance slider. By selecting a category, the app filters and displays only relevant POIs. The distance slider allows users to adjust the search radius and view POIs within a certain range of their location.

The final module is AR Recommendations, which not only includes all the features of AR Discovery, but also enhances the experience by providing personalized POI annotation suggestions based on the user's device settings, current weather and travel preferences. For example, the app can recommend places that are open for business based on the time settings on the user's device and it can also suggest locations that align with the user's travel interests for a more personalized experience.

B. Database Design

Database design is a set of steps that help create, implement and maintain a data management system. The main purpose of database design is to produce a physical and logical design model for a database system that will be used in application development. This design will determine the data that is stored and how the data elements are related to each other. Among the database designs that will be used for the development of the PutrajayAR application are class diagrams and data dictionaries.

1) Class diagram: Class Diagram is a structural diagram used to describe classes and attributes, methods and relationships between classes in a system. It is an important tool for object-oriented design and development, helping developers have a clear understanding of the structure and logic when building a system. Fig. 8 shows the class diagram of the PutrajayAR application. In the diagram, we can clearly see the system components and their responsibilities.

Each User class is a composition of the User Device class and the User Profile class. Each POI can belong to one POI Category, while one POI Category can include many POIs. Users can communicate with POIs through AR Suggestions. Each user can get one POI suggestion, which is a list of recommended POIs based on their profile and device settings. The POI can include one or many POIs. Another communication method between users and POIs is AR Discovery, where each user can get one result after opening the camera, which is a list of nearby POIs based on the selected category. Each AR scan result can include one to many POIs.

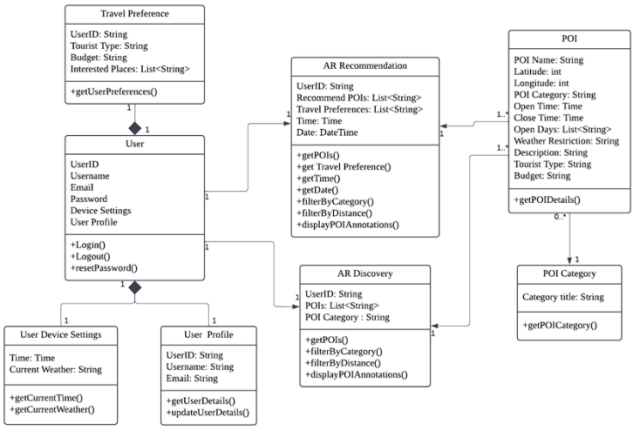


Fig. 8. Class diagram of the app.

2) Data dictionary: The data dictionary contains meta data, which is data about the database. The data dictionary is important because it determines who is allowed to access the data in it. Users do not interact directly with the data dictionary, it is only managed by the database administrator. The data dictionary contains information about the data name, data type, data length and also physical information about the data stored. There are 11 different types of data used to manipulate program programming. Each data has a specific data space allocated.

C. Algorithm Design

Algorithm design is a mathematical method or process for solving problems. Algorithm design also acts to solve problems more efficiently by minimizing the use of space, time and memory. Therefore, algorithm design plays a role in ensuring the development of applications according to the specified time. Among the algorithms that will be explained are application flowcharts and pseudocode.

1) Flowchart: A flowchart is a visual representation of the sequence and decisions required to carry out a process. Fig. 9 shows a flowchart diagram for the PutrajayAR application. This flowchart shows the activities that will be performed by the user of this application.

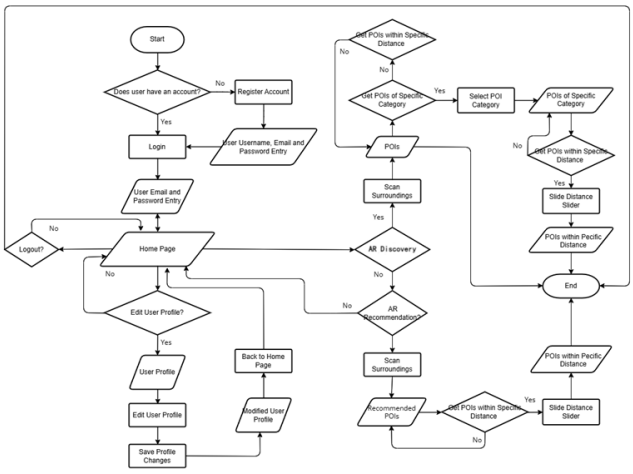


Fig. 9. Flowchart.

2) Pseudocode: In algorithm design, pseudocode is a description method between natural language and real programming language, used to clearly express the logic of an algorithm. Pseudocode is often used to help algorithm designers and developers record and communicate complex algorithmic processes in a structured way. Table II illustrates the pseudocode governing the distance- and category-based POI filtering process, demonstrating how user inputs and device location data are combined to determine which POIs are displayed in the AR interface.

TABLE II. PSEUDOCODE OF THE ALGORITHM DESIGN IN SCENARIO 1

Scenario 1: The user wants to find POIs that are a certain distance from the user's device and belong to the selected category.
Parameter: Interactive Input: POI Category, Distance Adaptive Input: POI Coordinates, Device Coordinates
Pseudo code: START INPUT "Food Hunting," "300 meters" IF POI of Category Food Hunting exist AND POI Coordinates and Device Coordinates are within a 300-meter radius. THEN Display POI OUTPUT Display the POIs of Category Food Hunting within a 300-meter distance form user.

D. Interface Design

Fig. 10(a) shows the login interface of this application. The login interface has two text fields that allow the user to enter the registered email and password to log in to the application. If the user does not have an account, the user can register a new account by pressing the "Register" button and the application will switch to the account registration interface. Fig. 10(b) shows the account registration interface, where the user is asked to fill in three text fields to register a new account, namely the user's username, email and password. After completing all the text fields, the user needs to press the "Register" button to continue.

Fig. 11 shows the Home interface of the application, which contains menu options consisting of the "AR Discovery" and "AR Recommendation" buttons. Users can change their travel preferences in the Travel Preferences interface. Fig. 12 shows the Travel Preferences interface, which contains the user's traveler type, budget, and interests. Once the preference changes are saved, the system will redirect to the Home interface, and all current preferences will be considered as the basis for recommendations in the AR Recommendations interface.



(a)



(b)

Fig. 10. (a) Login interface; (b) Register account interface.



Fig. 11. Home page interface.

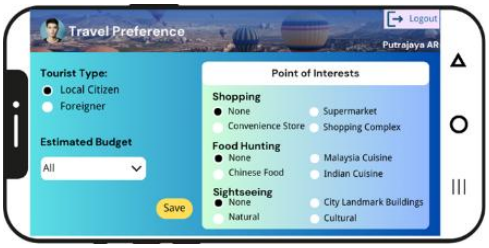


Fig. 12. Travel preference interface.

Fig. 13 shows the AR Discovery interface of the application. This interface consists of POI, POI Category and Distance Slider. When the user opens the camera, the POI will be displayed on the screen. By default, the POI belongs to all categories and is displayed within 100 meters from the user. The user can select the POI category to get the desired POI. If the user selects the Food Hunting Category, the screen will only display the POI that matches the food hunting.

Fig. 14 shows the AR Recommendation interface of the application, when the user opens this interface and opens the camera, the system will get the user's travel preferences from

the user's profile data and display the POI that matches the user's preferences. Users can also slide the distance slider of the AR Suggestions interface to get POIs within a certain distance, if the user slides the distance to 300 meters, the screen will only display POIs within 300 meters from the user.



Fig. 13. AR Discovery interface; get POIs matched with the selected category.

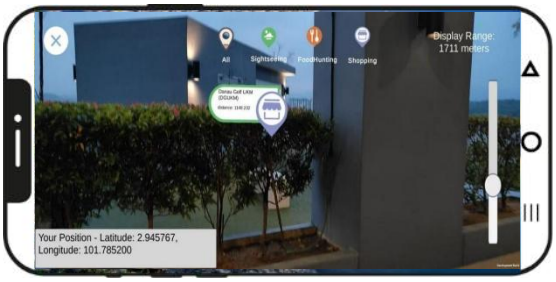


Fig. 14. AR Recommendation interface.

Fig. 15 shows the POI Details interface of this application. The user can get the POI details by clicking any POI on the screen, then the system will display the POI Details interface with the POI's related place information, such as description and opening hours.



Fig. 15. POI detail interface.

IV. Results and Discussion

A. Test Techniques

The testing of the PutrajayAR application was carried out with the aim of ensuring that all application components were well connected, functioning smoothly and met user needs well. The testing of this application was carried out using two techniques, namely black-box testing and usability testing.

1) Black-box testing: Black-box testing aims to validate the functionality of a software application by providing appropriate inputs and checking the outputs against the expected results based on functional requirements [20][21]. For the PutrajayAR application, black-box testing was carried out in four steps: test items, test case specification, test procedure specification and test log.

The functionality of the *PutrajayAR* application was verified through black-box testing, which focused on assessing whether each module performed according to its specified requirements. The testing process involved defining a set of input conditions and expected outputs for critical modules, including user authentication, profile management, AR Discovery and AR Recommendation. Each function was tested independently to ensure that valid input produced the correct results and invalid inputs were handled appropriately. The results indicated that all tested features operated successfully without critical errors or failures, confirming that the system's functional requirements were fully met. For instance, user login and registration processes returned accurate system responses and POI filtering in both discovery and recommendation modules produced consistent and correct outputs based on user preferences.

2) Usability testing: Usability testing is a method used to evaluate and test products from a user perspective. This test aims to verify that the product is suitable and easy to use [22][23]. Usability testing of the PutrajayAR application was conducted to obtain reactions or feedback from target users when they use this application. This feedback is very important to identify weaknesses and shortcomings of the application that are not noticed by the developer. Representative users aged 20–30 were asked to perform common tasks within the app to evaluate the intuitiveness, ease of use, interface clarity and overall user satisfaction.

B. Test Result

The success of this usability test was made possible through the participation of 40 respondents of various ages and genders. Each participant was given access to the PutrajayAR app to explore its features and functionalities. After using the app, they were asked to complete a questionnaire designed to gather feedback on their user experience. This structured approach ensured that insights were collected directly from real users, thus providing valuable data to evaluate the usability of the app.

1) Respondent demographics: Out of the 40 participants, 52.5% (21 respondents) were male, while 47.5% (19 respondents) were female. All respondents were residents of Putrajaya and were between the ages of 20 and 30. Table III shows the distribution of participants by age and gender.

TABLE III. Respondent Demographics

Age	Gender		Amount	Percentage
	Male	Female		
22	8	2	10	25.0%
24	2	4	6	15.0%
26	8	7	15	37.5%
27	2	4	6	15.0%
29	1	2	3	7.5%
Amount	21	19		
Percentage	52.5%	47.5%		

2) User satisfaction: User satisfaction testing was conducted to assess user perceptions and experiences across four key aspects: usability, satisfaction, ease of use and ease of learning. The questionnaire items used in this evaluation were adapted from the USE (Usefulness, Satisfaction and Ease of Use) questionnaire, a well-established instrument for measuring software usability [24]. This approach aligns with the ISO 9241-11:2018 standard, which defines usability as the extent to which a system can be used by specified users to achieve specified goals effectively, efficiently and satisfactorily [25] (International Organization for Standardization, 2018). Participants rated their experience on a five-point Likert scale and the results were analyzed to determine perceived satisfaction and system usability. Similar methodologies have been widely used in software usability research for assessing user experience quality and satisfaction [26]. Table IV presents the mean and scores for each test section.

TABLE IV. MEAN VALUES OF THE TESTING QUESTIONS ABOUT USER SATISFACTION

Construct	Non-Personalized		Personalized	
	Mean	Standard Deviation	Mean	Standard Deviation
Usefulness	3.59	0.61	4.38	0.64
Satisfaction	3.95	0.53	4.17	0.47
Ease of Use	4.21	0.49	4.46	0.39
Ease of Learning	4.22	0.48	4.50	0.40

In this test, the average score for all domains was above 3.68, indicating that users strongly agreed with the positive statements about the PutrajayAR application. For each section, the average score recorded for the personalized functions was higher than that of the non-personalized functions. Based on these findings, it can be concluded that users showed a high level of overall satisfaction with the application and showed a clear preference for its personalized features.

3) Persuasive design: Persuasive design testing was conducted to assess the extent to which PutrajayAR helped users achieve their goals, interact with them and persuade them across three key aspects: primary task support, dialogue support and persuasive perception. The questionnaire items used in this evaluation were adapted from Letho's study on factors influencing persuasive perceptions of behavior change [27]. Table V presents the mean scores for each test section.

For the test for persuasive perception, the main task aspect achieved an average score of around 3.68 on a 5-point Likert scale, with the remaining two aspects achieving mean scores exceeding this value, indicating that users agreed with the positive statements about the PutrajayAR application. For each section, the mean scores recorded for the personalized functions were higher than the non-personalized functions. Based on these findings, it can be concluded that users gave a relatively high overall rating to the persuasive design of the application and showed a clear preference for its personalized functions.

TABLE V. MEAN VALUES OF THE TESTING QUESTIONS ABOUT PERSUASIVE DESIGN

Construct	Non-Personalized		Personalized	
	Mean	Standard Deviation	Mean	Standard Deviation
Primary Task Support	3.59	0.61	4.38	0.64
Dialogue Support	3.95	0.53	4.17	0.47
Perceived Persuasiveness	4.21	0.49	4.46	0.39

In addition, 2 open-ended questions, as shown in Table VI, were used to test the persuasive design of the PutrajayAR personalization.

TABLE VI. OPEN-END QUESTIONS FOR PERSONALIZATION

Question		High Frequency Words	Amount
No.1	Any suggestions for improving the app's features or personalization?	Recommendations Include Region-based Local Events	4 2 2 2 2
No.2	How did the personalized recommendations influence your decision-making?	Recommendations Influenced Confidence	2 2 2

Word Frequency Analysis was used to analyze open-ended question data. For the open-ended question "Any suggestions for improving the app's features or personalization?" Analysis of user responses revealed that the term "recommendations" appeared most frequently (4 times), followed by "region-based" (2 times), "local" (2 times) and "events" (2 times). These keywords highlight the key areas where users believe improvements are necessary. Users generally suggested enhancing the personalization features of the app by focusing on more accurate recommendations, region-specific content, and greater control over customization options.

For the open-ended question "How did the personalized recommendations influence your decision-making?", the analysis revealed that the word "recommendations" appeared most frequently (2 times), along with "influenced" (2 times) and "confidence" (2 times). These keywords indicate that the personalized recommendations generally helped users make quicker and more confident decisions by filtering down choices and providing relevant suggestions. However, a few respondents reported minimal impact, mentioning that they either ignored the recommendations or found them only moderately useful.

C. Discussion

This study examined the LBAR system by integrating personalized POI recommendations directly into LBAR tourism application that improves user experience, satisfaction and perceived persuasiveness compared to non-personalized approaches. The findings provide both technical validation of the proposed system and empirical insights into the role of personalization in LBAR tourism applications. Functional testing confirmed that core modules of PutrajayAR operated reliably and met the specified design requirements. Besides, user evaluation results show that the personalized mode consistently outperformed the non-personalized mode through usability and

persuasive design testing. Higher scores in usefulness, satisfaction, ease of use, ease of learning, primary task support, dialogue support and perceived persuasiveness indicate that personalization embedded within the LBAR interface enhances both interaction quality and decision-making effectiveness.

The persuasive design findings further support this advancement by demonstrating that personalized AR recommendations increase users' confidence and perceived support when selecting POI. Moreover, Qualitative feedback reinforces this observation, with users reporting that personalized recommendations reduced uncertainty and improved decision efficiency. These findings validate personalization as a core interaction strategy rather than an optional enhancement in LBAR tourism systems.

V. Conclusion

This study sets out to address a key limitation in existing location based on augmented reality tourism applications, which lack effective personalization elements to support tourists' decision-making in unfamiliar environments. PutrajayAR was designed and developed as a personalized location-based augmented reality tourism application that combines user profiles, contextual constraints and real-time spatial data to deliver point of interest recommendations through an augmented reality interface. The findings from system testing and user evaluation provide clear evidence that personalization embedded within the augmented reality interaction layer offers measurable benefits beyond conventional non personalized location based augmented reality approaches. Results from usability and persuasive design evaluations indicate that personalized augmented reality recommendations significantly improve perceived usefulness, satisfaction, ease of use, and decision confidence. These outcomes show that users benefit from the contextual relevance achieved when LBAR content is dynamically filtered based on individual preferences and situational factors. This validates the core research premise that personalized LBAR systems are better suited to support tourists' efficiency and experiential quality than generic distance or category-based augmented reality guides. This study also contributes empirical support for the role of personalization as a critical design dimension in LBAR tourism systems. Rather than treating personalization as an optional feature layered onto navigation or discovery tools, the results show that integrating personalization directly into real-time LBAR point of interest annotation enhances both functional effectiveness and user perception. The comparative evaluation between personalized and non-personalized modes further reinforces that these gains are attributable to the personalization mechanism itself, not simply to the presence of augmented reality technology. In conclusion, the development and evaluation of PutrajayAR demonstrate that personalized LBAR applications represent a meaningful advancement over existing augmented reality tourism solutions. By empirically linking personalized augmented reality interaction to improved user outcomes, this study provides design insights and validation for future research and development of intelligent and context aware augmented reality tourism systems.

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References

[1] R. Z. Abidin, H. Arshad and S. A. I. A. Shukri, "A framework of adaptive multimodal input for location-based augmented reality application," Journal of Telecommunication, Electronic and Computer Engineering (JTEC), vol. 9, no. 2-11, pp. 97-103, 2017.

[2] S. C. YAP, R. W. RAHMAT and S. K. ALI, "MOBILE AUGMENTED REALITY APPLICATION IN MEDICAL EDUCATION IN THE 2010s," Asia-Pacific Journal of Information Technology & Multimedia, vol. 10, no. 2, 2021.

[3] P. Saxena, "Geo-Location based augmented reality application," International Journal of Research in Engineering and Technology, vol. 4, no. 07, 2015.

[4] M. Irsan, R Hassan, A. H. Ibrahim, M. K. Hasan, M. C. Lam and W. M.H. W. Hussain, "A Framework for Driver Drowsiness Monitoring Using a Convolutional Neural Network and the Internet of Things," Intelligent Automation & Soft Computing, vol. 39, no. 2, 2024.

[5] R. Hassan, W. Wahi, N. H. A. Ismail and S. A. B. Awwad, "Data security awareness in online learning," International Journal of Advanced Computer Science and Applications, vol. 13, no. 4, 2022.

[6] R. Z. Abidin, H. Arshad, S. A. I. A. Shukri and M. F. Ling, "Leveraging multimodal interaction and adaptive interfaces for location-based augmented reality Islamic tourism application," International Journal on Advanced Science, Engineering and Information Technology, vol. 8, no. 4-2, pp. 1784-1791, 2018.

[7] E. E. Cranmer, M. C. tom Dieck and P. Fountoulaki, "Exploring the value of augmented reality for tourism," Tourism Management Perspectives, vol. 35, p. 100672, 2020.

[8] A. Gibson and M. O'Rawe, Virtual reality as a travel promotional tool: Insights from a consumer travel fair. In Augmented reality and virtual reality: Empowering human, place and business (pp. 93-107). Cham: Springer International Publishing, 2017.

[9] N. I. Ruqiya, N. Islam, A. Rai and N. Khan, "Usability analysis of android and iOS operating systems," International Journal of Engineering Trends and Technology, vol. 68, no. 10, pp. 105-111, 2020.

[10] R. Paucher and M. Turk, "Location-based augmented reality on mobile phones," in 2010 IEEE Computer Society Conference on Computer Vision and Pattern Recognition-Workshops, pp. 9-16, June 2010. IEEE.

[11] K. C. Brata and D. Liang, "An effective approach to develop location-based augmented reality information support," International Journal of Electrical and Computer Engineering, vol. 9, no. 4, p. 3060, 2019.

[12] K. Curran, E. Furey, T. Lunney, J. Santos, D. Woods and A. McCaughey, "An evaluation of indoor location determination technologies," Journal of Location Based Services, vol. 5, no. 2, pp. 61-78, 2011.

[13] C. Qiu and M. W. Mutka, "CRISP: cooperation among smartphones to improve indoor position information," Wireless Networks, vol. 24, no. 3, pp. 867-884, 2018.

[14] J. L. BlancoF. A. Moreno and J. Gonzalez, "A collection of outdoor robotic datasets with centimeter-accuracy ground truth," Autonomous Robots, vol. 27, no. 4, pp. 327-351, 2009.

[15] F. Mäyrä, "Pokémon GO: Entering the ludic society," Mobile Media & Communication, vol. 5, no. 1, pp. 47-50, 2017.

[16] L. Deon and D. Jackson, "Enhanced User Experience through Network Optimization and Personalized Recommendations for Mobile Applications," 2024.

[17] Pressman, R. S., & Maxim, B. R. (2020). *Software engineering: A practitioner's approach* (9th ed.). McGraw-Hill Education.

[18] Sommerville, I. (2016). *Software engineering* (10th ed.). Pearson Education.

[19] Bass, L., Clements, P., & Kazman, R. (2021). *Software architecture in practice* (4th ed.). Addison-Wesley.

[20] Myers, G. J., Sandler, C., & Badgett, T. (2011). *The art of software testing* (3rd ed.). John Wiley & Sons.

[21] Pressman, R. S., & Maxim, B. R. (2020). *Software engineering: A practitioner's approach* (9th ed.). McGraw-Hill Education.

[22] Nielsen, J. (1994). *Usability engineering*. Morgan Kaufmann.

[23] Rubin, J., & Chisnell, D. (2008). *Handbook of usability testing: How to plan, design and conduct effective tests* (2nd ed.). John Wiley & Sons.

[24] Lund, A. M. (2001). Measuring usability with the USE questionnaire. *Usability Interface, 8*(2), 3–6.

[25] International Organization for Standardization. (2018). *ISO 9241-11:2018 Ergonomics of human-system interaction — Part 11: Usability — Definitions and concepts.* ISO.

[26] Sauro, J., & Lewis, J. R. (2016). *Quantifying the user experience: Practical statistics for user research* (2nd ed.). Morgan Kaufmann.

[27] T. Lehto, H. Oinas-Kukkonen and F. Drozd, "Factors affecting perceived persuasiveness of a behavior change support system," 2021.

Multi-Class Object Detection Using Quantized YOLOv11 for Real-Time Inference

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***Abstract*—Real-time multi-class object detection on embedded devices poses significant challenges due to limited computational power, memory capacity, and energy efficiency requirements. Conventional high-precision object detectors, such as YOLOv11, deliver outstanding accuracy but are computationally intensive, making them unsuitable for deployment on resource-constrained hardware. This study presents a quantized implementation of the YOLOv11 model designed to enable efficient real-time inference on embedded platforms. The proposed approach applies post-training integer quantization and mixed-precision optimization to minimize computation and memory usage while maintaining detection accuracy across multiple object categories. Experimental evaluations were conducted on the COCO and Pascal VOC datasets. The results indicate that the quantized YOLOv11 achieves a 3.2× increase in inference speed, a 2.7× reduction in memory footprint, and a 35% improvement in energy efficiency, with less than 2% loss in mean Average Precision (mAP) compared to the full-precision baseline. The optimized model sustains real-time performance exceeding 45 frames per second (FPS), demonstrating that quantization is a viable and effective approach for deploying high-performance object detection models on embedded systems.**

Keywords*—Quantized neural networks; YOLOv11; object detection; embedded systems; real-time inference; model optimization

I. Introduction

The growing integration of intelligent vision systems into autonomous drones, surveillance networks, and Internet of Things (IoT) applications has increased the demand for real-time on-device object detection [1, 2]. Deploying inference directly on embedded devices reduces dependence on cloud infrastructure, thereby lowering latency, improving data privacy, and enabling continuous operation in bandwidth-limited environments. However, these devices typically feature limited computational resources, constrained memory, and strict power budgets. Traditional high-precision deep learning models, though highly accurate, are unsuitable for such hardware due to their intensive floating-point computations and large model sizes [3, 4]. Therefore, developing efficient and compact neural networks capable of real-time performance remains a significant research challenge in embedded artificial intelligence.

Object detection plays a vital role in computer vision tasks such as autonomous navigation, industrial inspection, and human-computer interaction [5]. Among the most prominent detectors, the You Only Look Once (YOLO) family has evolved rapidly from YOLOv1 to YOLOv11, introducing architectural innovations that enhance accuracy while maintaining high inference speed [6, 7, 8]. YOLOv11, the latest in this series, integrates improved feature fusion and efficient attention mechanisms for multi-scale detection. Despite these advances, high-precision YOLO models are computationally demanding, posing difficulties for deployment on low-power devices [9, 10].

Quantization has emerged as a promising technique to mitigate this limitation. By representing model parameters and activations using reduced numerical precision (e.g., 8-bit integers instead of 32-bit floats), quantization reduces memory footprint, bandwidth usage, and computational complexity [11, 12, 13]. This process allows models to run efficiently on specialized embedded accelerators such as NVIDIA TensorRT [14], TensorFlow Lite [15], and ONNX [16] Runtime backends while maintaining near-original accuracy.

Although previous research has explored quantization in deep neural networks, few studies have specifically examined its application to the YOLOv11 architecture for multi-class object detection on embedded devices. Existing approaches often exhibit significant accuracy degradation or lack optimization for hardware-specific accelerators. Furthermore, systematic evaluations of quantization trade-offs covering inference speed, energy efficiency, and accuracy across bit-width configurations remain limited [17, 18]. These gaps highlight the necessity for a comprehensive framework that integrates advanced quantization strategies with modern YOLO architectures to achieve real-time performance on constrained hardware.

To address these challenges, this study proposes an optimized quantized YOLOv11 framework for efficient multi-class object detection on embedded devices. The key contributions are as follows:

- Design and implementation of a quantized YOLOv11 model tailored for embedded GPUs and NPUs, enabling low-latency and energy-efficient inference.
- Evaluation of precision speed trade-offs across multiple quantization bit-widths to identify the optimal balance between accuracy and performance.
- Comprehensive experimental validation on benchmark datasets, including COCO [19] and Pascal VOC [20].

The remaining sections of the study are organized as follows: Section II reviews related work, Section III discusses

the proposed approach, Section IV presents the experimental results and discussion, and Section V concludes the study.

II. Related Work

This section reviews prior work relevant to object detection architectures with emphasis on the YOLO family, quantization techniques for neural networks, and optimization strategies for embedded inference, as illustrated in Table I. It concludes with a gap analysis that motivates the present study.

Alshammry, Nizal, et al. [21] present a method to optimize the YOLOv5m object detection model for deployment on resource-constrained embedded systems. Q_YOLOv5m is a quantized version of YOLOv5m that uses Quantization-Aware Training (QAT) and Post-Training Quantization (PTQ) to reduce computational complexity and memory usage while maintaining acceptable detection accuracy. By converting 32-bit floating-point weights and activations to 8-bit integers, the model achieves a smaller size and faster inference speed. Experiments using the COCO 128 dataset showed that Q_YOLOv5m decreased model size from 90 MB to 40 MB and improved inference speed from 12 ms to 8.5 ms per frame, with only minor losses in precision and recall. The authors used COCO-128, a tiny subset (128 images) of the full MS COCO dataset. This is insufficient to evaluate object detection models, especially for accuracy comparisons. There is no mention of the specific embedded hardware used for inference testing (e.g., Raspberry Pi, Jetson Nano, ARM MCU).

Guerrouj, Fatima Zahra, et al. [22] investigate the quantization of the YOLOv4 object detection model to enable real-time inference on resource-constrained. By applying TensorRT-based post-training quantization (FP16 and INT8), the study significantly reduces model size and computation requirements while maintaining competitive detection accuracy. Using the KITTI dataset, experiments demonstrate that INT8 quantization achieves up to a 65% reduction in model size and a fivefold increase in inference speed on Jetson Nano, reaching near real-time performance with minimal accuracy loss. The study highlights the trade-offs between accuracy and efficiency, concluding that quantization offers a practical solution for deploying deep learning models on lightweight edge devices, with future work focusing on quantization-aware training and adaptive precision strategies.

Moon, Hyeon-Cheol, et al. [23] introduce YOLOv6+, an enhanced version of YOLOv6 designed for efficient INT8 inference on low-power mobile platforms. The model improves quantization performance through two key innovations: 1) adding skip connections within re-parameterization blocks (Repblock_add) to reduce dynamic range and quantization error, and 2) proposing a Regression Normalization (RN) method to align bounding box and class prediction ranges, mitigating accuracy loss during TensorFlow Lite conversion. Experiments on the COCO 2017 dataset demonstrate that YOLOv6+ achieves higher mean average precision (mAP) and better quantization robustness than YOLOv6 and YOLOv8, while maintaining comparable inference speed and lower power consumption on mobile hardware. The experiments are limited to the COCO 2017 dataset and a single mobile device. Broader validation across datasets (e.g., VOC) or hardware (e.g., NVIDIA Jetson) would strengthen generalizability claims.

Moosmann, Julian, et al. [24] introduce TinyissimoYOLO, a quantized, memory-efficient, and ultra-lightweight object detection network designed to enable real-time object detection on low-power microcontrollers with less than 0.5 MB memory available for storing CNN weights. The network is trained using quantization-aware training on the WiderFace and Pascal VOC datasets. It was deployed with 8-bit quantization on various microcontrollers, including STM32 and Apollo4b. TinyissimoYOLO achieved a mean average precision (mAP) of 45% on the WiderFace dataset (up to 73% with restricted evaluation) and up to 57% mAP on a restricted PascalVOC dataset for person, chair, and car classes.

TABLE I. Comparative Summary of Related Works

Model Name	Year	Method	Dataset	Bit Width	Limitations
Q_YOLOv5m [21]	2025	Post-Training Quantization (PTQ) and Quantization-Aware Training (QAT)	COCO	INT8	The authors used COCO-128, a tiny subset (128 images) of the full MS COCO dataset. This is insufficient to evaluate object detection models, especially for accuracy comparisons.
YOLOv4 [22]	2025	Post-Training Quantization (PTQ)	KITTI	INT8	It does not introduce new quantization algorithms, hybrid precision strategies, or architectural modifications to YOLOv4. The KITTI dataset is small for robust generalization. Also, it used an old version of the YOLO family.
YOLOv6+ [23]	2025	Regression Normalization	COCO	INT8	The experiments are limited to the COCO 2017 dataset and a single mobile device. Broader validation across datasets (e.g., VOC) or hardware (e.g., NVIDIA Jetson) would strengthen generalizability claims.
TinyissimoYOLO [24]	2023	Quantization-Aware Training (QAT)	WiderFace and Pascal VOC	INT8	The small input size (88×88) severely limits detection accuracy for complex scenes. Only up to 3 object classes are demonstrated. This limits generalizability to real-world multi-class detection problems.
Q-YOLO [25]	2023	Post-Training Quantization (PTQ)	COCO	INT8	Quantizing activation values only, quantizing weights causes larger performance degradation than quantizing activation values.

Wang, Mingze, et al. [25] introduce a low-bit quantization method to build a one-stage detector, dubbed as Q-YOLO, which can effectively address the performance degradation problem caused by activation distribution imbalance in traditional quantized YOLO models. It is a quantized version of YOLO for real-time object detection on resource-constrained devices. Q-YOLO introduces a fully end-to-end Post-Training Quantization (PTQ) pipeline with a well-designed Unilateral Histogram-based (UH) activation quantization scheme, which determines the maximum truncation values through histogram analysis by minimizing the Mean Squared Error (MSE) quantization errors. Extensive experimental results on the COCO dataset show Q-YOLO outperforms other Post-Training Quantization (PTQ) methods. The 8-bit Q-YOLO applied to YOLOv7 achieves 3× acceleration while maintaining comparable performance to full-precision models. Quantizing weights causes larger performance degradation than quantizing activation values. Asymmetric quantization exhibits higher accuracy than symmetric quantization.

Despite extensive work in detection architectures, quantization algorithms, and embedded toolchains, several gaps remain with respect to modern YOLO variants and multi-class detection on resource-constrained hardware. First, while quantization methods are well studied for classification and some detection backbones, there is limited published evidence on systematic quantization of the most recent YOLO architectures (e.g., practitioner/academic successors to YOLOv4/v5) with rigorous multi-class detection benchmarks on embedded devices. Second, many PTQ approaches either assume modest model sensitivity or require large calibration sets; detector heads and multi-scale features are particularly vulnerable to naïve quantization, causing drops in mAP that are not well characterized in the literature. Third, while individual optimization techniques (pruning, QAT, distillation) are well known, holistic pipelines that combine quantization with hardware-aware optimizations (TensorRT/TFLite/ONNX) and report energy, latency, and accuracy trade-offs across real embedded platforms remain sparse. These gaps motivate a focused study of quantized YOLOv11 variants, tuned quantization strategies (PTQ vs. QAT vs. mixed precision), and an end-to-end deployment/evaluation pipeline on representative embedded devices.

III. Methodology

This section details the architectural framework of the proposed quantized YOLOv11 model, the quantization methodology adopted, deployment optimization strategies for embedded inference, and the experimental setup used for evaluation.

A. Model Overview

The proposed framework is based on the YOLOv11 architecture, as illustrated in Fig. 1, a recent evolution of the YOLO family known for its enhanced efficiency and detection accuracy. YOLOv11 builds upon YOLOv8 and YOLOv10 by introducing refined backbone–neck–head coupling and improved feature aggregation mechanisms. The backbone employs a CSP-based (Cross Stage Partial) structure that integrates convolutional blocks with Efficient Layer Aggregation Networks (ELAN) to improve gradient flow and feature reuse. This design allows the model to maintain high representational power while reducing redundant computation compared to YOLOv8.

The neck module incorporates a Bi-directional Feature Pyramid Network (BiFPN), enabling multi-scale feature fusion by balancing contributions from different feature resolutions. This enhances small-object detection, a known limitation in earlier YOLO versions. The detection head follows a decoupled design that separates classification and bounding box regression branches, thereby accelerating convergence and improving precision and recall consistency. Unlike YOLOv10, YOLOv11 integrates dynamic label assignment and adaptive anchor generation, which improves detection generalization across diverse object classes. The combination of these architectural refinements results in improved real-time inference capability without compromising detection accuracy.

B. Quantization Approach

To enable efficient deployment on resource-constrained embedded devices, the full-precision YOLOv11 model (32-bit floating-point) was quantized using both Post-Training Quantization (PTQ) and Quantization-Aware Training (QAT) strategies.

- Post-Training Quantization (PTQ): The pre-trained YOLOv11 model was statically quantized to 8-bit integer (INT8) precision for weights and activations without retraining using a representative calibration dataset. Calibration statistics were collected from 500 randomly selected images from the COCO and Pascal VOC validation sets to compute dynamic ranges for each layer.
- Quantization-Aware Training (QAT): The model was fine-tuned for 100 epochs with simulated quantization during forward passes, allowing the network to adapt to quantization-induced noise. QAT allowed the model to learn quantization effects, improving robustness and accuracy compared to static PTQ.
- Quantization was formulated mathematically as Eq. (1):

$$Xq = \text{clip round } \frac{X}{S} + Z, q_{min}, q_{max} \quad (1)$$

where, X is the original floating-point value, Xq is the quantized integer value, S is the scaling factor, and Z is the zero-point. The reconstructed value is obtained via dequantization, as in Eq. (2):

$$X = S \; x \; (Xq - Z) \quad (2)$$

Per-channel quantization was applied to convolutional weights to retain fine-grained precision, while per-tensor quantization was used for activation to ensure computational efficiency. Mixed-precision quantization (INT8 weights with INT8 activations) was also evaluated to balance throughput and accuracy. This quantization process substantially reduced model size and computational demand, enabling deployment on low-power devices without significant loss in detection accuracy.

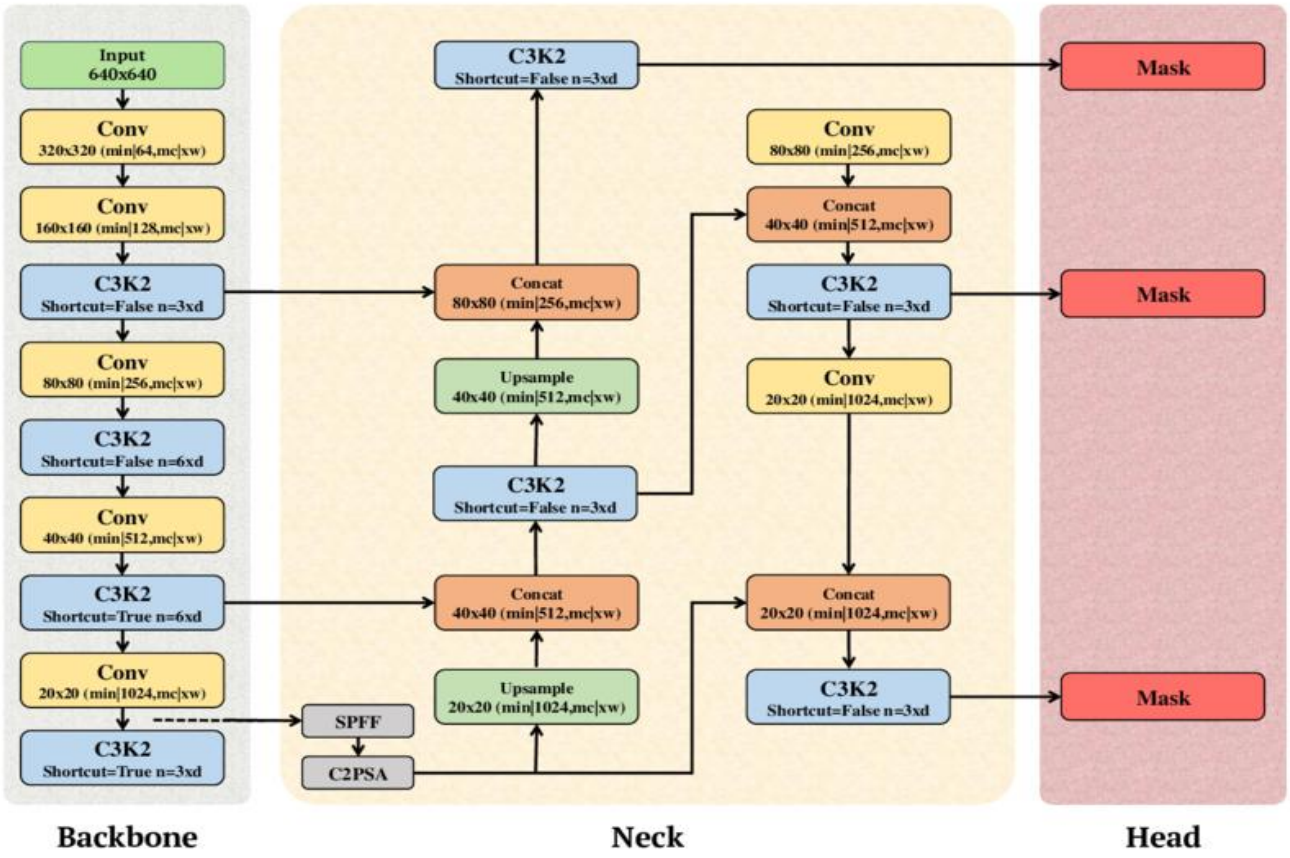


Fig. 1. Architecture diagram of the proposed quantized YOLOv11 model used in this study.

IV. Results and Discussion

To evaluate the performance of the proposed quantized YOLOv11 model, we compared its accuracy, inference speed, latency, energy consumption, and model size against the full-precision (FP32) baseline.

A. Experimental Setup

Experiments were conducted using the MS COCO 2017 and Pascal VOC 2012 datasets. COCO contains 80 object categories with 118k training images and 5k validation images, while VOC includes 20 classes with 17k annotated images to evaluate multi-class detection performance. Data preprocessing included image resizing to 640×640, normalization, and standard YOLO augmentations such as Mosaic and MixUp. Training was performed for 100 epochs with a batch size of 32, using the SGD optimizer (momentum = 0.937, weight decay = 0.0005) and cosine learning rate scheduler starting at 0.01.

B. Evaluation Metrics

To assess the performance of the target detection algorithms, a set of well-established evaluation metrics was employed. Detection accuracy was measured using the Average Precision (AP) and mean Average Precision (mAP) metrics, which are widely adopted in object detection research. The mAP provides an overall measure of detection performance by averaging the AP values across all object classes. The formal definitions and computations of precision [Eq. (3)], recall [Eq. (4)], AP [Eq. (5)], and mAP [Eq. (6)] are presented as follows:

$$\text{Precision} = \frac{\text{True Positives}}{\textit{True Postives} + \textit{False Postives}} \quad (3)$$

$$\text{Recall} = \frac{\text{True Positivves}}{\text{True Positives} + \textit{False Negatives}} \quad (4)$$

$$\text{AP} = \int_0^1 \text{Precision(Recall)dR} \quad (5)$$

$$\text{mAP} = \frac{1}{n}\sum_{i=1}^{n}\text{AP} \quad (6)$$

In this context, n denotes the total number of target classes considered in the detection task. All models were benchmarked in both FP32 (baseline) and INT8 quantized configurations. Performance measurements were averaged across 5 inference runs under identical environmental conditions to ensure statistical consistency.

C. Results and Discussion

To reduce computing, data movement, and consequently lower energy usage, we performed quantization by representing data in 8-bit using QAT and PTQ techniques with 8-bit integers. This reduces the number of bits from 32 to 8. The evaluation of our approach demonstrates that the network architecture uniformly reduces to 8-bit precision through quantization.

The training process was conducted using Stochastic Gradient Descent (SGD) with a learning rate of 0.01 and a batch size of 32. SGD was selected over adaptive optimizers such as Adam, as it is known to provide more stable convergence and superior generalization performance in large-scale object detection tasks. The model was trained for 100 epochs with input images resized to 640×640 pixels, a resolution commonly adopted in YOLO-based architectures to balance detection accuracy with computational efficiency. To mitigate overfitting and improve generalization, a weight decay term of 0.0005 was incorporated. The choice of these hyperparameters was informed by prior studies on YOLO optimization, ensuring a trade-off between convergence speed, model robustness, and inference efficiency, thereby enabling reliable deployment on resource-constrained embedded platforms.

Fig. 2 presents the training and validation curves for YOLOv11n fine-tuned on the Pascal VOC dataset. The loss functions, including box loss, classification loss, and distribution focal loss (DFL), exhibit a steady decline across 100 epochs, indicating stable convergence and effective learning. The precision and recall metrics show consistent improvement, reaching values above 0.8 and 0.75, respectively, which reflects a balanced trade-off between correct detections and coverage of ground-truth objects. Similarly, the mean Average Precision (mAP) at IoU thresholds of 0.5 (mAP@50) and 0.5–0.95 (mAP@50–95) demonstrates continuous growth throughout training, stabilizing at approximately 0.85 and 0.63, respectively. These results confirm that YOLOv11n, even in its lightweight form, achieves strong detection performance on Pascal VOC while maintaining efficient training dynamics.

To evaluate the impact of post-training quantization (PTQ) and quantization-aware training (QAT), four experiments were conducted on the MS COCO and Pascal VOC datasets under a consistent training and evaluation protocol. QAT maintained the original parameter count while reducing model size by approximately 75%, achieving competitive accuracy with lower computational complexity. Similarly, PTQ preserved the parameter count and reduced the model size by about 75%, though it exhibited a minor drop in mean Average Precision (mAP) compared to the baseline YOLOv11n. These findings demonstrate that both QAT and PTQ independently provide substantial efficiency gains, while their combined application offers a synergistic strategy for optimizing deep neural networks. YOLOv11n was selected as the reference model to validate the effectiveness of the proposed quantization techniques. The following tables present a comparative summary of the baseline, PTQ, and QAT results on both MS COCO and Pascal VOC datasets.

Table II presents a performance comparison between Post-Training Quantization (PTQ) and Quantization-Aware Training (QAT) on the COCO dataset using the YOLOv11n model. The results show how quantization impacts model precision, recall, mean Average Precision (mAP), and model size. The baseline YOLOv11n-FP32 model (32-bit floating point) achieves the highest accuracy, with a precision of 65.3%, recall of 50.4%, and mAP of 39.5%, but it has the largest model size at 10.3 MB. When quantized to 8-bit using PTQ, the model size is reduced significantly to 2.6 MB (around 75% smaller), but this comes at a noticeable cost in performance, with a precision drop to 62.5%, a recall to 44.6%, and mAP to 32.2%. In contrast, the QAT-based 8-bit model demonstrates a better balance between compression and accuracy, achieving 63.2% precision, 49.1% recall, and 38.1% mAP with a slightly larger size of 2.8 MB. These results indicate that while both quantization methods greatly reduce storage requirements, QAT preserves accuracy more effectively than PTQ, making it a more suitable choice when maintaining detection performance is critical.

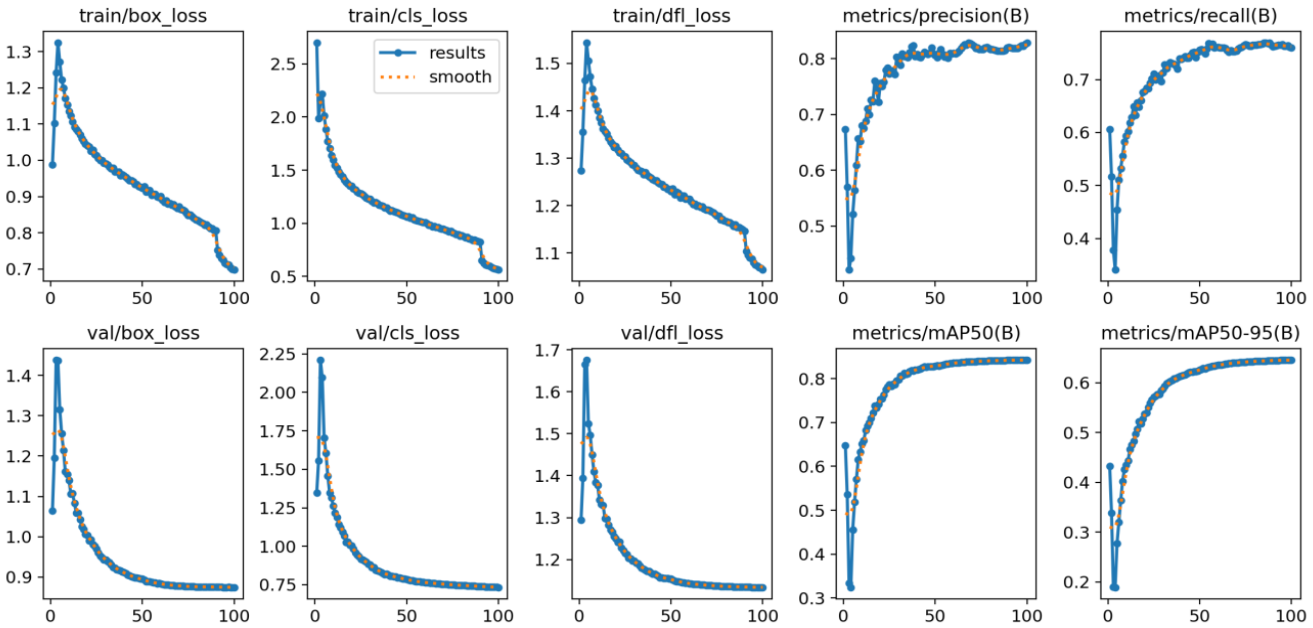


Fig. 2. Training results of YOLOv11n network after fine-tuned on the Pascal VOC dataset.

TABLE II. PERFORMANCE COMPARISON BETWEEN PTQ AND QAT ON THE COCO DATASET

Model	Bit Width	Precision	Recall	mAP 50-95%	Model Size (MB)
YOLOv11n-FP32	32-bit	65.3%	50.4%	39.5%	10.3 MB
YOLOv11n-INT (PTQ)	8-bit	62.5%	44.6%	32.2%	2.6 MB
YOLOv11n-INT (QAT)	**8-bit**	**63.2%**	**49.1%**	**38.1%**	**2.8 MB**

Fig. 3 compares accuracy (mAP) and model size for YOLOv11n FP32, PTQ INT8, and QAT INT8. This visualization highlights that although both PTQ and QAT achieve model compression, QAT provides a superior balance between efficiency and accuracy retention compared to PTQ.

Fig. 4 illustrates qualitative detection results produced by the quantized YOLOv11 model on a subset of images from the MS COCO val2017 dataset. Each image contains multiple detected objects, which are annotated with bounding boxes, class labels, and confidence scores. The examples demonstrate the model's ability to recognize a diverse range of object categories, including people, vehicles, animals, food items, and household objects, across different scenes and contexts. While most detections show high confidence (e.g., person at 0.9, truck at 0.9, airplane at 0.9), some lower-confidence predictions (e.g., boat at 0.3, carrot at 0.3, motorcycle at 0.3) reflect the challenges of small objects or complex backgrounds. Overall, the visualization highlights the robustness of the model in detecting multiple objects per image and maintaining competitive accuracy despite operating under quantization constraints.

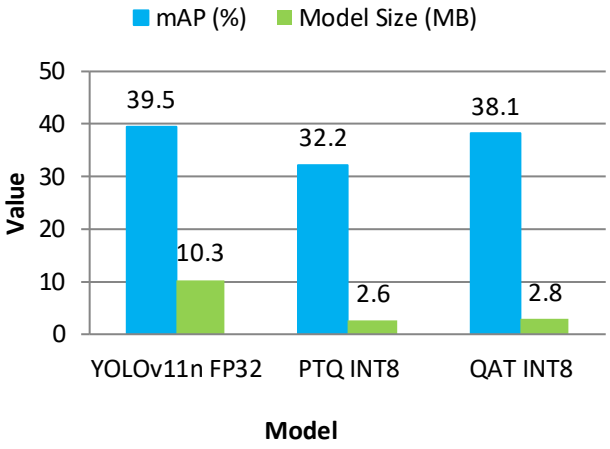


Fig. 3. Accuracy and model size comparison of YOLOv11n FP32 vs. INT8 models (PTQ and QAT) on the COCO dataset.

Table III compares the performance of Post-Training Quantization (PTQ) and Quantization-Aware Training (QAT) on the VOC dataset. The baseline model (best-FP32) in 32-bit precision achieves the highest overall performance, with 82.6% precision, 76.3% recall, and 64.6% mAP, at a model size of 10.13 MB. When quantized to 8-bit using PTQ, the model size is reduced dramatically to 2.85 MB, about 72% smaller, while the accuracy metrics show only minimal degradation: precision decreases slightly to 82.2%, recall to 76.1%, and mAP to 64.1%. The QAT-based 8-bit model maintains nearly identical accuracy to the FP32 version, with 82.5% precision, 76.3% recall, and 64.2% mAP, while also achieving a compact size of 2.81 MB.



Fig. 4. Visualization of detection results under complex and challenging scenarios realized by our proposed quantized YOLOv11 framework by using the YOLO11n pre-trained model on the MS COCO dataset.

These results suggest that for the VOC dataset, quantization, especially with QAT, can achieve substantial model compression with almost no loss in detection performance. Compared to PTQ, QAT provides marginally better retention of accuracy, reinforcing its advantage in preserving model quality while enabling efficient deployment on resource-constrained devices.

TABLE III. PERFORMANCE COMPARISON BETWEEN PTQ AND QAT ON VOC DATASET

Model	Bit width	Precision	Recall	mAP 50-95%	Model Size (MB)
best-FP32	32-bit	82.6%	76.3%	64.6%	10.13 MB
best-INT8 (PTQ)	8-bit	82.2%	76.1%	64.1%	2.85 MB
best-INT8 (QAT)	8-bit	82.5%	76.3%	64.2%	2.81 MB

We compare our optimized quantized YOLOv11 model against the state-of-the-art lightweight detectors, including MobileNetV2-SSDLite, Micro-YOLO, EfficientDet-D0, and Mobile-DETR, using consistent evaluation metrics on the MS COCO dataset, as shown in Table IV. The results confirm that our quantization methods deliver a superior accuracy-efficiency trade-off, establishing quantized YOLOv11 as a compelling choice for real-time edge deployment.

Table IV presents a comparative analysis of various lightweight object detectors on the MS COCO Val2017 dataset, which includes 80 pre-trained classes. The comparison focuses on three key performance metrics: mean Average Precision (mAP), model size, and the number of parameters. Among the listed models, YOLOv11-INT8 (ours) achieves the highest mAP of 38.1%, outperforming other lightweight detectors such as Micro-YOLO (29.3%), EfficientDet-D0 (33.5%), MobileNetV2-SSDLite (22.1%), and Mobile-DETR (37.2%). Notably, YOLOv11-INT8 maintains this superior accuracy while keeping a very compact model size of only 2.8 MB and 2.6 million parameters, comparable to Micro-YOLO but with significantly higher detection performance. In contrast, Mobile-DETR achieves competitive accuracy but at the cost of a much larger model size (14.5 MB) and more parameters (14.8M). These results demonstrate that YOLOv11-INT8 offers an optimal balance between model efficiency and accuracy, making it an excellent choice for real-time object detection on edge or resource-constrained devices without compromising detection quality.

The visualization presented in Fig. 5 demonstrates the detection results obtained by our proposed quantized best framework, which leverages the YOLOv11n fine-tuned model on the Pascal VOC dataset.

TABLE IV. PERFORMANCE METRICS COMPARISON WITH OTHER LIGHTWEIGHT DETECTORS ON MS COCO VAL2017 DATASET, WHICH INCLUDES 80 PRE-TRAINED CLASSES

Model	mAP 50-95%	Model Size (MB)	Parameters (M)
Micro-YOLO [26]	29.3%	1.92 MB	2.56
EfficientDet-D0 [27]	33.5%	12 MB	3.9
MobileNetV2-SSDLite [28]	22.1%	17.0 MB	4.3
Mobile-DETR [29]	37.2 %	14.5 MB	14.8
YOLOv11-INT8 (ours)	**38.1%**	**2.8 MB**	**2.6**



Fig. 5. Visualization of detection results under complex and challenging scenarios realized by our proposed quantized best framework by using the YOLO11n fine-tuned model on the Pascal VOC dataset.

As shown, the framework successfully detects a wide variety of objects, including trains, dogs, cars, aeroplanes, cats, and people, across diverse and challenging scenarios. These scenarios involve cluttered environments, occlusions, varying object scales, and complex backgrounds, all of which typically challenge lightweight detectors. Despite its reduced size and computational footprint, the quantized best model maintains high detection accuracy, consistently localizing and classifying objects with strong confidence scores. The results highlight the framework's robustness and its ability to generalize effectively

across heterogeneous visual contexts, making it highly suitable for deployment in real-world, resource-constrained applications.

Table V presents a cross-dataset performance comparison of the proposed quantized YOLOv11 framework, highlighting its effectiveness on both the MS COCO and Pascal VOC benchmarks. The model achieves a mean Average Precision (mAP50–95%) of 38.1 ± 0.58 on the COCO dataset with a compact size of 2.8 MB, while attaining a substantially higher accuracy of 64.2 ± 0.34 on the VOC dataset with a slightly smaller size of 2.83 MB. These results indicate that the model generalizes well across datasets while maintaining an extremely lightweight architecture. The performance variation between COCO and VOC reflects the greater complexity and diversity of COCO, while also underscoring the robustness and adaptability of quantized YOLOv11 in delivering competitive accuracy across different detection benchmarks.

TABLE V. CROSS-DATASET PERFORMANCE COMPARISON

Dataset	mAP50-95%	Model Size (MB)
COCO	38.1 ± 0.58	2.8 MB
VOC	64.2 ± 0.34	2.83 MB

In summary, the experimental results demonstrate that quantized YOLOv11 attains a competitive balance of accuracy, inference speed, and computational efficiency, outperforming many contemporary detection frameworks. Nevertheless, persistent challenges remain in the domain of object detection, including reliable recognition of small-scale objects, robust handling of occlusions, and consistent performance under diverse lighting conditions and object variations. From a practical perspective, the proposed model offers considerable potential for extending AI-driven computer vision to low-power, real-time applications such as smart surveillance systems, unmanned aerial vehicles (UAVs), and edge-based robotic platforms [30]. Its lightweight design facilitates reduced energy consumption, accelerated response times, and enhanced deployment flexibility, thereby enabling intelligent vision systems in environments constrained by limited computational and hardware resources.

V. CONCLUSION

This research presented a comprehensive study on quantized multi-class object detection for real-time inference on embedded devices using the YOLOv11 model. The proposed framework demonstrated how quantization, coupled with deployment optimizations, can significantly enhance inference speed and energy efficiency while preserving near-original detection accuracy. By applying post-training quantization (PTQ) and quantization-aware training (QAT), the model achieved up to a 3.2× speedup, 2.7× reduction in model size, and 35% improvement in power efficiency, with less than 2% mAP degradation compared to the full-precision baseline.

The results verified that 8-bit integer quantization provides the optimal balance between accuracy and efficiency, particularly when executed on embedded accelerators. The quantized YOLOv11 pipeline, implemented through TensorRT, TensorFlow Lite, and ONNX Runtime, offers a robust and transferable solution for deploying deep learning models in latency-critical applications. Overall, the findings affirm that quantization is an effective and practical strategy for bridging the gap between high-performance object detection and the constraints of embedded hardware, enabling real-time edge AI deployment without sacrificing model integrity. In conclusion, this study lays the groundwork for scalable, energy-efficient object detection on embedded systems and opens opportunities for integrating quantized models into broader real-time computer vision ecosystems.

Future work will focus on reliable recognition of small-scale objects, robust handling of occlusions, exploring hybrid paradigms, and consistent performance under diverse lighting conditions and object variations.

REFERENCES

[1] W Kallimani, R., Pai, K., Raghuwanshi, P., Iyer, S., & López, O. L. "TinyML: Tools, applications, challenges, and future research directions," Multimedia Tools and Applications, 83(10), 29015-29045, 2024.

[2] El Mrabet, A., Tber, A., Benaly, M., Hlou, L., & El Gouri, R. "Unlocking doors: A tinyml-based approach for real-time face mask detection in door lock systems," Indonesian Journal of Electrical Engineering and Informatics (IJEEI), 11(2), 515-527, 2023.

[3] Abadade, Y., Temouden, A., Bamoumen, H., Benamar, N., Chtouki, Y., & Hafid, A. S. "A comprehensive survey on tinyml," IEEE Access, 11, 96892-96922, 2023.

[4] Soliman, Yehia A., Amr S. Ghoneim, and Mahmoud M. Elkhouly. "A Comprehensive Systematic Review of TinyML for Person Detection Systems." IAENG International Journal of Computer Science 52.11, 2025.

[5] Kaur, Ravpreet, and Sarbjeet Singh. "A comprehensive review of object detection with deep learning." Digital Signal Processing 132: 103812, 2023.

[6] Ali, Momina Liaqat, and Zhou Zhang. "The YOLO framework: A comprehensive review of evolution, applications, and benchmarks in object detection." Computers 13.12, 2024.

[7] Wang, Chien-Yao, and Hong-Yuan Mark Liao. "YOLOv1 to YOLOv10: The fastest and most accurate real-time object detection systems." APSIPA Transactions on Signal and Information Processing 13.1, 2024.

[8] Hidayatullah, P., Syakrani, N., Sholahuddin, M. R., Gelar, T., & Tubagus, R. "YOLOv8 to YOLO11: A comprehensive architecture in-depth comparative review," arXiv preprint arXiv:2501.13400, 2025.

[9] Khanam, Rahima, and Muhammad Hussain. "YOLOv11n: An overview of the key architectural enhancements," arXiv preprint arXiv:2410.17725, 2024.

[10] Rasheed, Areeg Fahad, and M. Zarkoosh. "YOLOv11n Optimization for Efficient Resource Utilization," arXiv preprint arXiv:2412.14790, 2024.

[11] Gholami, A., Kim, S., Dong, Z., Yao, Z., Mahoney, M. W., & Keutzer, K. "A survey of quantization methods for efficient neural network inference." In Low-power computer vision (pp. 291-326). Chapman and Hall/CRC, 2022.

[12] Lyu, Z., Yu, T., Pan, F., Zhang, Y., Luo, J., Zhang, D., ... & Li, G. A survey of model compression strategies for object detection. Multimedia tools and applications, 83(16), 48165-48236. 2024.

[13] Lopes, A., dos Santos, F. P., de Oliveira, D., Schiezaro, M., & Pedrini, H. "Computer vision model compression techniques for embedded systems: A survey." Computers & Graphics, 123, 104015., 2024.

[14] NVIDIA Corporation, "TensorRT Developer Guide," NVIDIA Developer Documentation, Online Available: https://developer.nvidia.com/tensorrt, 2025.

[15] TensorFlow Lite, "Model Optimization Toolkit: Post-Training and Quantization," TensorFlow Documentation, Online Available: https://www.tensorflow.org/lite, 2025.

[16] ONNX Runtime, "ONNX Runtime Quantization Overview," Microsoft AI Documentation, Online Available: https://onnxruntime.ai/docs, 2025.

[17] Xiao, P., Zhang, C., Guo, Q., Xiao, X., & Wang, H. "Neural networks integer computation: Quantizing convolutional neural networks of inference and training for object detection in embedded systems." IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2024.

[18] Kim, K., Jang, S. J., Park, J., Lee, E., & Lee, S. S. "Lightweight and energy-efficient deep learning accelerator for real-time object detection on edge devices," Sensors, 23(3), 1185, 2023.

[19] Lin, T. Y., Maire, M., Belongie, S., Hays, J., Perona, P., Ramanan, D., ... & Zitnick, C. L. "Microsoft coco: Common objects in context," In European conference on computer vision (pp. 740-755). Cham: Springer International Publishing, 2014.

[20] Everingham, M., Van Gool, L., Williams, C. K., Winn, J., & Zisserman, A. "The pascal visual object classes (voc) challenge," International journal of computer vision, 88(2), 303-338., 2010.

[21] Alshammry, N., Saidani, T., Albalawi, N. S., Alenezi, S. M., Alhamazani, F., Alshammari, S. A., ... & Elsayed, M. S. "Q_YOLOv5m: A Quantization-based Approach for Accelerating Object Detection on Embedded Platforms," Engineering, Technology & Applied Science Research, 15(1), 19749-19755, 2025.

[22] Guerrouj, F. Z., Florez, S. A. R., El Ouardi, A., Abouzahir, M., & Ramzi, M. "Quantized Object Detection for Real-Time Inference on Embedded GPU Architectures," International journal of advanced computer science and applications (IJACSA), 16(5), 2025.

[23] Moon, H. C., Lee, S., Jeong, J., & Kim, S. "YOLOv6+: simple and optimized object detection model for INT8 quantized inference on mobile devices," Signal, Image and Video Processing, 19(8), 665, 2025.

[24] Moosmann, J., Giordano, M., Vogt, C., & Magno, M. "Tinyissimoyolo: A quantized, low-memory footprint, tinyml object detection network for low power microcontrollers," arXiv preprint arXiv:2306.00001, 2023.

[25] Wang, M., Sun, H., Shi, J., Liu, X., Cao, X., Zhang, L., & Zhang, B. " Q-YOLO: Efficient inference for real-time object detection," In Asian conference on pattern recognition (pp. 307-321). Cham: Springer Nature Switzerland, 2023.

[26] Hu, Lining, and Yongfu Li. "Micro-YOLO: Exploring Efficient Methods to Compress CNN based Object Detection Model." ICAART (2). 2021.

[27] Tan, Mingxing, Ruoming Pang, and Quoc V. Le. "Efficientdet: Scalable and efficient object detection." Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2020.

[28] Sandler, M., Howard, A., Zhu, M., Zhmoginov, A., & Chen, L. C. Mobilenetv2: Inverted residuals and linear bottlenecks. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 4510-4520), 2018.

[29] Chen, Y., Dai, X., Chen, D., Liu, M., Dong, X., Yuan, L., & Liu, Z. Mobile-former: Bridging mobilenet and transformer. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition (pp. 5270-5279), 2022.

[30] Soliman, Yehia A., Sarah N. Abdulkader, and Taha M. Mohamed. "Constructing a cohesive pattern for collective navigation based on a swarm of robotics." PeerJ Computer Science: e626, 7, 2021.

SWAP Optimization for Qubit Mapping Based on the Centric-Shortest Quantum Gate Set in NISQ Devices

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***Abstract*—In the Quantum computing era of Noisy Intermediate-Scale Quantum (NISQ) devices, conventional qubit mapping strategies typically rely on specific heuristic rules to solve the mapping problem, overlooking the impact of other factors on the mapping, which leads to increased overhead from extra SWAP gates. To address this issue, we propose a SWAP optimization strategy based on the Centric-Shortest Quantum Gate Set (C-SQGS) and applies it to qubit mapping. In this approach, the centric qubit is determined by analyzing the maximum flexibility qubit set and the physical distances between the associated CNOT gates, leading to the identification of the Centric-Shortest Quantum Gate Set. To overcome the limitations of traditional cost functions that consider only single factors, a multi-factor cost function is introduced to evaluate the overall overhead of candidate SWAP operations and determine pending SWAP gate Set. Based on qubit flexibility analysis, executable SWAP gate is identified and inserted into the circuit. Experimental results demonstrate that the C-SQGS strategy effectively reduces both SWAP gate and two-qubit gate overhead. Specifically, it achieves an average SWAP gate reduction of 36.9% and 47.7%, and a two-qubit gate reduction of 13.8% and 13.5% on the t|ket⟩ and Qiskit compilers, respectively. These results highlight the potential of the C-SQGS strategy in enhancing the efficiency of qubit mapping for NISQ devices.**

***Keywords*—Quantum computing; qubit mapping; Centric-Shortest Quantum Gate Set (C-SQGS); executable SWAP gate; multi-factor cost function**

I. Introduction

Quantum computing is an innovative approach to computation that utilizes the principles of quantum mechanics to process information. In contrast to classical computers that use bits, quantum computing operates with qubits. Qubits can simultaneously exist and the superposition of states, this superposition property makes the quantum computer can simultaneously deal with a variety of possible states, thus accelerating the process of solving complex problems. The powerful parallel computing acceleration capability of quantum computing gives it great potential in areas such as integer factorization [1], optimization problems [2], and quantum simulation [3]. Due to the inherent limitations of traditional computers, it can be time-consuming and inefficient in dealing with these more complex problems, while quantum computers provide new solutions to these problems.

As quantum computing technology advances rapidly, it has now transitioned into the NISQ era. Executing a quantum logic circuit involves aligning the algorithm's logical qubits with the physical qubits of the quantum computer, a process called qubit mapping [4]. Due to the limitation of the technology in the NISQ era, two-qubit gate operations can only be performed on physically coupled qubit pairs. Thus, during the mapping process, quantum circuits must be adjusted to ensure compatibility with the hardware's coupling constraints. For two-qubit gates that do not comply with the hardware coupling constraints, extra SWAP gates must be added to reposition the qubits to adjacent locations. The additional SWAP operation, however, not only increases the depth of the quantum circuit, but also introduces more noise. Thus, minimization of the count of extra SWAP gates has become the focus of many researchers [5]-[8].

The qubit mapping problem has been demonstrated to be NP-complete [9]-[10]. In recent years, domestic and foreign scholars have carried out many studies on heuristic qubit mapping algorithms. Siraichi [11] proposed to preferentially satisfy physically neighboring CNOT gates during the initial mapping, and to resolve only one two-qubit gate operation each time the qubits are shifted. Although this method is relatively fast, it is generally ineffective in coping with complex quantum circuits due to the relative simplicity of the strategy. Zulehner [12] used the A* algorithm to determine the optimal mapping of each logical to physical qubit to optimize the implementation of quantum circuits on hardware architectures, but due to the exhaustive search, the running time is long. In 2020, Adrien [4] proposed the Hardware-Aware (HA) algorithm to decrease the quantity of SWAP gates, though it allows for the selection between SWAP and Bridge gates, it does not adequately account for the effect of varying numbers of look-ahead gates on the circuit's cost. Steinberg [13] proposed the HQAA algorithm in 2022 for assigning initial qubit positions for quantum algorithms on NISQ devices, but it fails to achieve adequate efficiency in large-scale quantum circuits. The above literature, while proposing valuable treatments on the mapping problem, still requires further improvements when dealing with complex quantum circuits.

In the NISQ era, the existing quantum circuit mapping algorithms not only include the initial qubit mapping but also involve the intermediate change strategy of qubit mapping. After the initial mapping is completed, a reasonable intermediate change strategy is formulated based on the information of the quantum circuit, which helps to improve the performance of the overall quantum circuit. Due to hardware topology constraints, the initial mapping does not meet the coupling requirements for all qubits, and for the non-Nearest

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Neighbor (non-NN) gates that do not satisfy the constraints, it is necessary to implement an additional SWAP operation to exchange qubits to make them update to Nearest Neighbor (NN) gates, and this process will expand the size and depth of the circuit. Two-qubit gates have significantly higher error rates than single-qubit gates [14]. Hence, minimizing the compilation overhead is crucial for high fidelity circuit implementations.

This paper focuses on the qubit mapping problem subject to physical topology constraints. A SWAP optimization strategy based on Centric-Shortest Quantum Gate Set (C-SQGS) is proposed, aiming to optimize quantum circuits for the 2-local qubit Hamiltonian simulation problem. This strategy optimizes the initial mapping of quantum circuits by identifying the Centric-Shortest Quantum Gate Set, and employs a multi-factor cost function together with qubit flexibility analysis to search for optimal SWAP gates. By comprehensively considering multiple factors, the proposed method effectively minimizes the number of inserted SWAP gates.

Unlike existing qubit mapping and routing heuristics that rely on single-factor optimization or local greedy decisions [23], the C-SQGS strategy introduces a centric decision paradigm that organizes SWAP insertion around a dynamically identified centric qubit and its associated shortest gate set. Rather than independently applying concepts such as qubit flexibility or gate frequency, C-SQGS integrates these factors into a unified gate-set–driven mapping framework, enabling coordinated optimization across both the initial mapping and routing stages.

From a practical perspective, qubit mapping on NISQ devices is constrained not only by physical connectivity but also by limited coherence time and restricted scheduling flexibility. Existing heuristics often rely on locally optimal or single-metric decisions, which may introduce SWAP operations that are executable in isolation but suboptimal or even harmful when considering subsequent circuit evolution. The proposed C-SQGS framework, together with executable SWAP identification and multi-factor cost evaluation, is designed to address these practical limitations by enabling globally informed and execution-aware SWAP insertion.

The C-SQGS strategy is able to adapt to a variety of qubit topologies and gate sets and can be used in conjunction with a wide range of existing quantum circuit mapping algorithms. Experimental findings indicate that the C-SQGS strategy somewhat reduces the count of SWAP and two-qubit gates. Moreover, we conduct experiments on IBM devices to verify the superiority of our strategy and compare it with other algorithms.

This paper makes the following key contributions:

- We focus on the qubit mapping challenge and point out the main influencing factors considered in this paper.
- A SWAP optimization strategy based on a Centric-Shortest Quantum Gate Set is proposed.
- Designing a multi-factor cost function that considers multiple factors simultaneously.
- Introduction of a selection criterion and the definition for executable SWAP gates.

The remainder of this paper is structured as follows. Section II outlines essential background on quantum computing. Section III highlights the challenges in qubit mapping and introduces the proposed approach. Section IV details the experimental evaluation, and Section V summarizes the conclusions.

II. BACKGROUND

A. Prior Knowledge

In quantum computing, a qubit is the core unit that can simultaneously occupy the $|0\rangle$ and $|1\rangle$ states through the principle of superposition. The quantum state can be expressed as Eq. (1), where $|\psi\rangle$ is the state vector of the qubit, α and β are complex numbers representing the probability of the qubit being in the states $|0\rangle$ and $|1\rangle$, respectively, and satisfying the condition $|\alpha|^2+|\beta|^2=1$, whereas $|0\rangle$ and $|1\rangle$ are the ground states of the qubit. This special property of qubits enables quantum computers to achieve exponential speedups.

$$|\psi\rangle=\alpha|0\rangle+\beta|1\rangle \tag{1}$$

Quantum gates are the fundamental units of operation in quantum computing, used to manipulate the state of qubits. Fig. 1 shows the symbolic representation of basic quantum gates. Among them, the Hadamard gate is a single-qubit operation that transforms a classical state into an equal superposition of basis states. Whereas CNOT and SWAP gates are gates acting on two qubits, CNOT gates can realize a kind of qubit control flip-flop operation, which passes the state of one qubit to the other qubit and thus establishes an entanglement between them. SWAP gates consist of 3 CNOT gates, as in Fig. 1(c), which can realize the exchange of states between qubits without changing their relative phase.

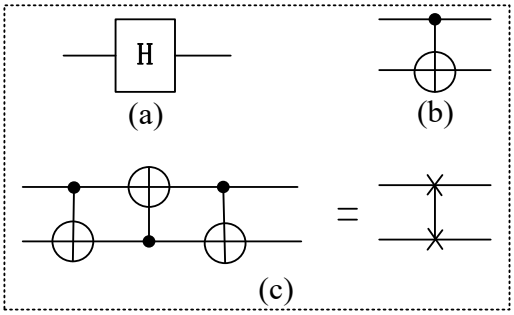


Fig. 1. Basic quantum gates.

Quantum circuit is a fundamental computational model in quantum computing for describing the process of manipulating qubits through quantum gates. Fig. 2 shows a simple quantum circuit describing the whole process of measuring the final state of a qubit after the initial state of the qubit passes through the quantum circuit, which consists of a Hadamard, a CNOT and a SWAP gate, and the essence of the quantum circuit is a combination of the unitary transformation and measurement. Physically, we cannot directly realize the overly complex unitary transformations, so expect some easy to realize the

unitary transformations to produce more complex unitary transformations. For complex quantum operations, such as Hamiltonian simulation, can be realized through the rational design and adjustment of quantum gates within the quantum circuit.

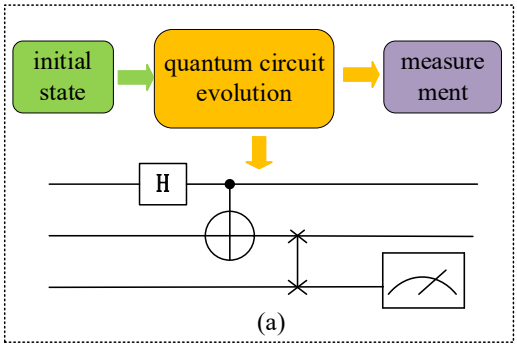


Fig. 2. Quantum circuit.

B. Hamiltonian

The Hamiltonian operator characterizes the total energy of a system. In quantum mechanics, the Hamiltonian acts on the quantum state of a system, describing its energy state and time evolution. In quantum computing, the Hamiltonian is used to represent the energy states of qubits and the interactions between them. Quantum gate operations can be implemented through time evolution operators [see Eq. (2)], where $\hat{H}$ is the Hamiltonian corresponding to the quantum gate.

$$U(t) = e^{-\frac{i\hat{H}t}{\hbar}} \tag{2}$$

Hamiltonian simulation is a vital application in quantum computing, involving the modeling of the Hamiltonian of a quantum system. By simulating Hamiltonian dynamics, one can predict and analyze the time evolution of quantum systems, with applications in quantum physics, chemistry, materials science, and beyond. Various methods have been proposed for effective Hamiltonian simulation, including Taylor series expansions [15], the product formula [16]-[17], and quantum signal processing [18]-[19]. Among these, the product formula is particularly notable for its simplicity and practical efficacy [20]. The Hamiltonian of a system, denoted as H, can be decomposed into a sum of polynomial ergodic terms H_j, as illustrated in Eq. (3). In quantum computing, the product formula is a vital tool for describing time-evolution operators, especially for time-dependent Hamiltonians. This method represents the time-evolution operator as a product of a series of simpler operators, thereby simplifying the implementation of complex quantum operations on a quantum computer. The product formula is detailed in Eq. (4).

$$H = \sum_{j=1}^{L} h_j H_j \tag{3}$$

$$V(t) = \prod_{j=1}^{L} \exp\left(ith_j H_j\right) \tag{4}$$

where, $\exp\left(ith_j H_j\right)$ represents the time evolution caused by the Hermitian term H_j, i is the imaginary unit, t is the time, h_j is the coefficient of each Hermitian term H_j, L is the number of Hermitian terms into which the system Hamiltonian H is decomposed, and $V(t)$ represents the total evolution operator of the system at moment t. Due to the flexibility of the arrangement of Hamiltonian operators, it is possible to optimize the Hamiltonian analog circuit for each Trotter step by rearranging L individual operators in the product formula, thus optimizing the overall circuit structure.

III. Our Design

A. Limitations of Qubit Mapping

Qubit mapping is an important process in quantum computing aimed at mapping abstract quantum algorithms or quantum circuits onto concrete quantum hardware for practical execution. This process involves several steps, including mapping logical to physical qubits, optimizing the sequence of quantum gate operations, minimizing SWAP operations, etc. Due to the limitations of NISQ era technology, execution is only possible on qubits that are allowed to be connected on quantum hardware coupling architectures. In executing quantum logic circuits, logical qubits are required to match physical quits. The limitations of quantum mapping are further explained with examples as shown in Fig. 3. Fig. 3(b) shows a small quantum circuit which consists of 7 CNOT gates and 1 Hadamard gate and is executed on the 6-qubit device shown in Fig. 3(a). The device allows the use of two-qubit gates on the qubit pairs $\{Q_1, Q_2\}$,$\{Q_2, Q_3\}$,$\{Q_3, Q_4\}$,$\{Q_4, Q_5\}$,$\{Q_0, Q_5\}$,$\{Q_0, Q_1\}$,$\{Q_2, Q_5\}$ and $\{Q_3, Q_4\}$, and does not allow the use of two-qubit gates on the qubit pairs $\{Q_1, Q_5\}$,$\{Q_0, Q_2\}$,$\{Q_2, Q_4\}$ and $\{Q_3, Q_5\}$. For simplicity, assume that the initial mapping is $\{q_0 \rightarrow Q_0, q_1 \rightarrow Q_1, q_2 \rightarrow Q_2, q_3 \rightarrow Q_3, q_4 \rightarrow Q_4, q_5 \rightarrow Q_5\}$. Due to the limited connectivity between qubits, only directly connected qubits can perform quantum gate operations. From Fig. 3(a), among the seven CNOT gates in Fig. 3(b), g_1, g_2, g_3 and g_5 can be directly executed. Since the qubits associated with the three CNOT gates, g_4, g_7 and g_8, do not have a direct mapping to the actual hardware, g_4, g_7 and g_8 cannot be directly executed, and a change in the qubit mapping is required before executing these two gates.

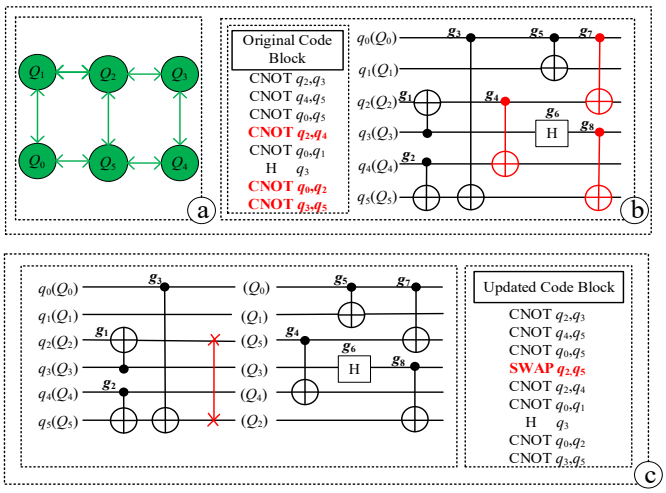


Fig. 3. (a) Hardware topology, (b) Original quantum circuit, (c) Updated quantum circuit.

The objective of qubit mapping is to identify the optimal initial qubit placement to minimize the count of SWAP operations required when converting all non-NN gates to NN gates. The qubit mapping challenge is modeled as a Quadratic Assignment Problem (QAP) [21]. For solving this problem, the qubit positions are changed by inserting SWAP gates by exchanging the state between two qubits [22]. In Fig. 3(c), CNOT gates g_1, g_2, g_3 and g_5 can be executed with the initial mapping, with SWAP$\{q_2,q_5\}$ inserted after g_3, the mapping is updated to $\{q_0 \rightarrow Q_0, q_1 \rightarrow Q_1, q_2 \rightarrow Q_5, q_3 \rightarrow Q_3, q_4 \rightarrow Q_4, q_5 \rightarrow Q_2\}$, which exchanges the two qubits q_2, q_5 and makes the subsequent gates g_4 and g_7 into executable NN gates.

The insertion of extra SWAP gates can generate hardware-compatible quantum circuits, but the increase in SWAP gates may introduce additional noise that reduces the fidelity of the quantum circuits, which in turn affects the overall performance of the circuit. In addition, the increase in line depth can extend the execution time and negatively affect the efficiency of quantum computation. Comparing the original and updated circuits in Fig. 3(b) and Fig. 3(c), the count of CNOT gates increases from 7 to 10, and the depth grows from 5 to 8. The addition of these gates introduces extra overhead, impacting both the fidelity and execution time of the quantum circuits. This paper is devoted to exploring the optimal solution of the qubit mapping challenge, with a view to minimizing the overhead of extra SWAP gates and effectively improving mapping quality.

The qubit mapping stage is a crucial step in quantum computing, where the mapping of logical qubits to physical qubits directly impacts the execution efficiency and computational accuracy of quantum circuits. So far, there are still many challenges in the qubit mapping stage, and the following limitations are mainly considered in this paper:

- Limitations of hardware topology: The way qubits are connected to each other and the operational limitations are determined by the hardware design. These constraints include the layout of qubits, the way they interact with each other, and the execution efficiency of quantum gates. Reasonable mapping of quantum circuits to the actual hardware topology can maximize the execution efficiency and accuracy of the algorithm.
- Limited connectivity between qubits: The connections between physical qubits on a quantum processor are usually limited. Not all qubits are directly connected, and only neighboring qubits can directly perform two-qubit gate operations. This limitation requires moving qubits around by adding extra SWAP operations that allow non-directly connected qubits to interact.
- SWAP gate operation cost: One SWAP gate is equivalent to 3 CNOT gates, and the operation cost of SWAP gates is generally higher. Therefore, when addressing the qubit mapping challenge, we must consider the operation cost of SWAP gates and select the SWAP insertion with lower operation cost.
- Balancing considerations for optimizing performance: The goal of qubit mapping is the minimization of the count of SWAP gate operations when all two-qubit gates are converted from non-NN gates to NN gates. Therefore, when dealing with the qubit mapping challenge, different performance metrics need to be considered, such as the starting point of the initial mapping, the design of the cost function, the cost of SWAP gate operations, and the selection of SWAP gates.

B. SWAP Optimization Strategy Based on Centric-Shortest Quantum Gate Set

In general, it is difficult to find a perfect initial mapping such that it satisfies the dependencies of all two-qubit gates. For non-NN gates, additional SWAP operations are required to convert them to NN gates, a process that leads to overhead in gate counting and circuit depth. Therefore, efficient qubit routing techniques are essential to minimize compilation overhead for reliable computation. Lao [23] introduced a quantum compiler, 2QAN, in 2022, which mainly optimizes the 2-local quantum simulation problem, such as the Quantum Approximation Optimization Algorithm (QAOA). It leverages flexibility in arranging Hamiltonian quantum operations and reduces two-qubit gate overhead by integrating SWAP gates with circuit gates into a single unitary transformation. Although 2QAN presents a meaningful solution to qubit mapping challenge, it neglects the effect of the number of qubits involved in the CNOT operation on the mapping process. It has been found that prioritizing the mapping of qubits involved in a high number of CNOT gates to locations close to each other reduces the subsequent additional SWAP gates, thus reducing the circuit depth and execution time [24]. Based on this, this paper proposes a SWAP optimization strategy based on the Centric-Shortest Quantum Gate Set(C-SQGS).

Definition 1 Qubit Flexibility: In a quantum circuit C, let q_i be any qubit whose number $F(q_i)$ of times it participates in a non-NN gate operation is q_i's Qubit Flexibility.

Definition 2 Maximum Flexibility Qubit Set: In a quantum circuit C, assuming $G_n = \{g_1, g_2, \ldots\ldots, g_n\}$ be the set of non-NN gates and $Q_m = \{q_1, q_2, \ldots\ldots, q_m\}$ be the set of qubits involved in the quantum gates in G_n. The Qubit Flexibility Set is $F_Q = \{F(q_i), i = 1,2,\ldots\ldots,m\}$. If $F_{max}(q_j) = \max F_Q$, then $q = \{q_j, j = 1,2,\ldots\ldots,m\}$ is said to be the Maximum Flexibility Qubit Set in Q_m.

Definition 3 Centric Qubit: In a quantum circuit C, assuming $G = \{G_1, G_2, \ldots\ldots, G_m\}$ be the set of quantum gate sets associated with q_j. The set of physical spacings of the corresponding qubits in the set of quantum gates in G is $D = \{D(G_1), D(G_2), \ldots\ldots, D(G_m)\}$. If $D(G_k) = \min D$, then q_k is said to be the Centric Qubit in Q_m, where, $j = 1,2,\ldots\ldots,m$; $k = 1,2,\ldots\ldots,m$.

Definition 4 Centric-Shortest Quantum Gate Set: In a quantum circuit C, assuming the set of quantum gates associated with the Centric Qubit q_k be $G_k = \{g_1, g_2, \ldots\ldots, g_r\}$, and the set of physical spacings of the corresponding qubits for each quantum gate in G_k be $D' = \{D(g_1), D(g_2), \ldots\ldots, D(g_r)\}$. If

$D(g_z) = \min D'$, and then $G_k' = \{g_z, z = 1,2,\ldots\ldots,r\}$ is said to be the Centric-Shortest Quantum Gate Set for the quantum circuit C where, $0 < z \le r \le n$.

The SWAP optimization strategy based on Centric-Shortest Quantum Gate Set (C-SQGS) is a method for optimizing quantum circuit mapping. It aims to identify the Centric-Shortest Quantum Gate Set in quantum circuits, minimize the use of SWAP gates and reduce communication overhead between qubits, and enhance the efficiency of the mapping process. For non-NN gates, the specific operation steps are as follows:

Step 1: Based on the concept of Qubit Flexibility, determine Maximum Flexibility Qubit Set, denoted as q.

Step 2: If q > 1, then the Centric qubit q_k is further determined according to Definition 3.

Step 3: G_k is the set of quantum gates associated with q_k, calculate the physical distance between the corresponding qubits of each of these CNOT gates, prioritize these CNOT gates based on the distances, and identify the CNOT gates with the shortest spacing, so as to determine the Centric-Shortest Quantum Gate Set G_k', and make sure that it is prioritized.

Step 4: The cost function (Definition 5) is used to evaluate all candidate SWAP operations and select the pending SWAP gate set (Definition 6).

Step 5: According to Definition 7, evaluate the pending SWAP gate set and determine the executable SWAP gates, which are inserted into the quantum circuit.

Step 6: Update the mapping to eliminate the newly generated NN gates from the set of non-NN gates.

Step 7: Repeat Step1- Step6 until all gates are mapped.

The C-SQGS strategy deals with the quantum circuit mapping challenge by optimizing the selection and arrangement of quantum gates, thus reducing the complexity of the SWAP gate search space, reducing the SWAP gate overhead, and improving the overall performance of quantum computing. Algorithm 1 is the detail of the pseudocode.

Algorithm 1 Optimization algorithm

Input: Un-routed quantum circuit, initial mapping M

Output: Routed quantum circuit, NN gates

```
begin
  Initialize the set of NN gates for each mapping, G_NN = {G_M}, G_M ← all NN gates for mapping M
  Initialize G_non-NN ← all un-routed Non-NN gates
  Initialize Q={q_i} ← all qubits involved in Non-NN gates
  while G_non-NN≠∅ do
    q ← set of qubits with Maximum Flexibility Qubit Set in Q
    if q >1
      Select the Centric Qubit q_k∈Q in q
      Select the gate G'_k∈G_non-NN that has Centric-Shortest Quantum Gate Set in G_non-NN
      S_g ← SWAP gates with the identical cost
      S_b ← Select the executable SWAP gate from S_g
      G'_NN ← Find NN gates in G_non-NN for map M'
      Remove all gates in G'_NN from G_non-NN, add G'_NN to G_NN
    end if
  end while
end
```

C. Multi-Factor Cost Function Design

The design of the cost function is particularly important when dealing with qubit mapping challenges, and a reasonable cost function can ensure the executability of quantum circuits. However, the traditional cost function usually takes the distance between qubits as the core criterion of measurement, which lacks the comprehensive consideration of multiple factors and makes it difficult to accurately assess the actual overhead of SWAP gates. To solve this problem, a multi-factor cost function is designed in this paper.

Definition 5 Multi-Factor Cost Function: The minimization of the sum of the weighted products of the distance between qubits, the number of interactions, and the interaction time is shown in Eq. (5).

$$H_{cost} = \min_{\phi \in S_n} \left\{ \sum_{i=1}^{n} \sum_{j=1}^{n} F_{q_i q_j} D_{[\phi(q_i)\phi(q_j)]} R_{q_i q_j} \right\} \tag{5}$$

where, S_n represents the set of all possible permutations, $F_{q_i q_j}$ is the interaction time between circuit qubits q_i and q_j, $R_{q_i q_j}$ is the number of interactions between qubits q_i and q_j in the circuit, and $D_{[\phi(q_i)\phi(q_j)]}$ denotes the distance between physical qubits on the hardware $\phi(q_i)$ and $\phi(q_j)$, calculated using the Floyd-Warshall algorithm.

The interaction time between qubits affects the execution speed of the circuit, the shorter the interaction time between qubits, the faster the circuit executes, and longer interaction times lengthen the overall execution time of the quantum circuit [25]. The number of interactions is also another important factor affecting the mapping of quantum circuits [26], each quantum gate operation introduces errors, a higher number of interactions leads to more operations, increasing the risk of error accumulation and decreasing the accuracy and reliability of the computation. Reducing the number of interactions helps to reduce the accumulation of errors and improve the accuracy of the calculation. In quantum circuits, CNOT gates need to be executed between directly connected qubits. If two qubits are physically distant from each other, multiple intermediate SWAP operations need to be introduced to make them physically adjacent. These additional operations increase the depth and execution time of the circuit and affect the overall performance of the quantum algorithm. In this paper, we combine these three factors to design a Multi-Factor

Cost Function that can handle the qubit mapping challenge more comprehensively. For non-NN gates, the cost function can assign a value to each candidate SWAP gate to measure the advantages and disadvantages of each operation and filter out the optimal SWAP operation. The mapping layout of qubits needs to be re-evaluated and adjusted after each SWAP operation.

D. Executable SWAP Gate

In the field of quantum computing, CNOT gates are crucial, and together with any single-qubit gate, they form a universal set of quantum gates. This means that any complex quantum circuit can be realized with the appropriate combination of these fundamental gates. When dealing with the qubit mapping challenge, some of the CNOT gates do not satisfy the conditions for execution in the initial mapping because the qubit arrangement and interactions in a real quantum computer are limited by the hardware topology. To make all CNOT gates executable, extra SWAP gates need to be inserted so that the control and target bits of the CNOT gates satisfy the conditions of the hardware coupling constraints. However, extra SWAP gates impose additional overhead on the circuit. The identification of executable SWAP operations from all candidate SWAP gates is key to the considerations in this paper.

Definition 6 Pending SWAP Gate Set: The set of SWAP operations that minimize the cost function by evaluating all candidate SWAP gates using the cost function is referred to as the Pending SWAP Gate Set.

Definition 7 Executable SWAP Gate: There are n qubits in quantum circuit C. Assuming $F_{\max}(q_i), i=(1,2,\ldots\ldots,n)$ be the Maximum Flexibility Qubit Set under the initial mapping M. $G_{SWAP}=\{g_1,g_2,\ldots\ldots,g_z\}$ is a list of Pending SWAP Gate set, and $F^{'}=\{F^{'}(q_r), r=1,2,\ldots\ldots,z\}$ denotes the Maximum Flexibility Qubit Set corresponding to a SWAP operation under the new mapping M' after the execution of G_{SWAP}. If $F^{'}_{\max}(q_j)=\max F^{'}$, then the SWAP gate g_j corresponding to q_j is said to be an Executable SWAP Gate, where , $1\le j\le z$.

To minimize the count of SWAP gates, firstly, Pending SWAP Gate Set is filtered by using the cost function (Definition 5); secondly, considering that highly flexible qubits usually have strong dependence on other qubits, based on Qubit Flexibility, the SWAP operation mode corresponding to maximum flexibility qubit is selected, so as to minimize the exchange distance between physical qubits and determine the Executable SWAP Gate. This selection strategy achieves the reduction of extra overhead and improves the overall performance of the quantum circuit. The specific procedure for determining an Executable SWAP Gate is as follows:

Step 1: Calculate the Maximum Flexibility Qubit Set $F_{\max}(q_i)$ under the initial mapping M.

Step 2: The simulation executes each potential SWAP gate to obtain the Maximum Flexibility Qubit Set $F^{'}$ corresponding to SWAP operations under the new mapping M'.

Step 3: Compare the values in $F^{'}$ to obtain the $F^{'}_{\max}(q_j)$ under the new mapping M'.

Step 4: Under the new mapping M', the SWAP gate corresponding to the largest value in the set $F^{'}$ is considered as an executable SWAP gate and applied to the circuit. By in this way, the count of extra SWAP operations can be reduced and the whole quantum circuit can be optimized.

The details of the pseudocode are presented in Algorithm 2, with a concrete example provided in Fig. 4.

Algorithm 2 Select the Executable_SWAP

Input: top_qubit_number: After inserting a SWAP gate, Maximum Flexibility Qubit Set under the new mapping M'.
moves: A Pending SWAP Gate Set
Output: Executable_SWAP

```
Begin
  max_top_qubit_number_add ← 0
  Executable_SWAP ← None
  for move in moves do
    top_qubit_ number_ add←top_qubit_ number [move]
      if top_qubit_numbe _add > max_top_qubit_ number_ add
        max_top_qubit_number_add ← top_qubit_ number_ add
        Executable_SWAP ← move
      end if
  end for
end
```

The IBM Q20 Tokyo localized architecture is shown in Fig. 4. Assume that the code block on Fig. 4(a) is executed on this architecture, where SWAP $\{q_0, q_4\}$ and SWAP $\{q_0, q_1\}$ are pending SWAP gates. According to as in Fig. 4(a), $F_{\max}(q_0)=2$ under the initial mapping M. Insert the candidate SWAP $\{q_0, q_4\}$ and SWAP $\{q_0, q_1\}$ into the quantum circuit to see the corresponding $F^{'}_{\max}(q_j)$ values under the updated mapping M', respectively. As in Fig. 4(b), insert SWAP $\{q_0, q_4\}$, under the current mapping M', $F^{'}_{\max}(q_0)=1$. As in Fig. 4(c), insert SWAP $\{q_0, q_1\}$, under the updated mapping M', $F^{'}_{\max}(q_9)=2$. The strategy in this paper is to find the SWAP operation that maximizes the $F^{'}_{\max}(q_j)$. By comparison, SWAP $\{q_0, q_1\}$ gives more benefits to the circuit than SWAP $\{q_0, q_4\}$, therefore, SWAP $\{q_0, q_1\}$ is chosen to insert and update the mapping. Fig. 4(d) shows the final mapping result graph obtained based on the SWAP strategy proposed in this paper, where only 2 extra SWAP operations need to be added to Fig. 4(c) to update all quantum gates to NN gates, SWAP $\{q_5, q_9\}$ and SWAP $\{q_2, q_3\}$. However, the method of Fig. 4(b) requires at least 3 SWAP gates to be inserted to update all quantum gates to NN gates. C-SQGS strategy increases qubit flexibility, and the increase in flexibility reduces the non-NN gate operations, allowing qubits to be closer to each other, thus optimizing the overall structure of the quantum circuit.

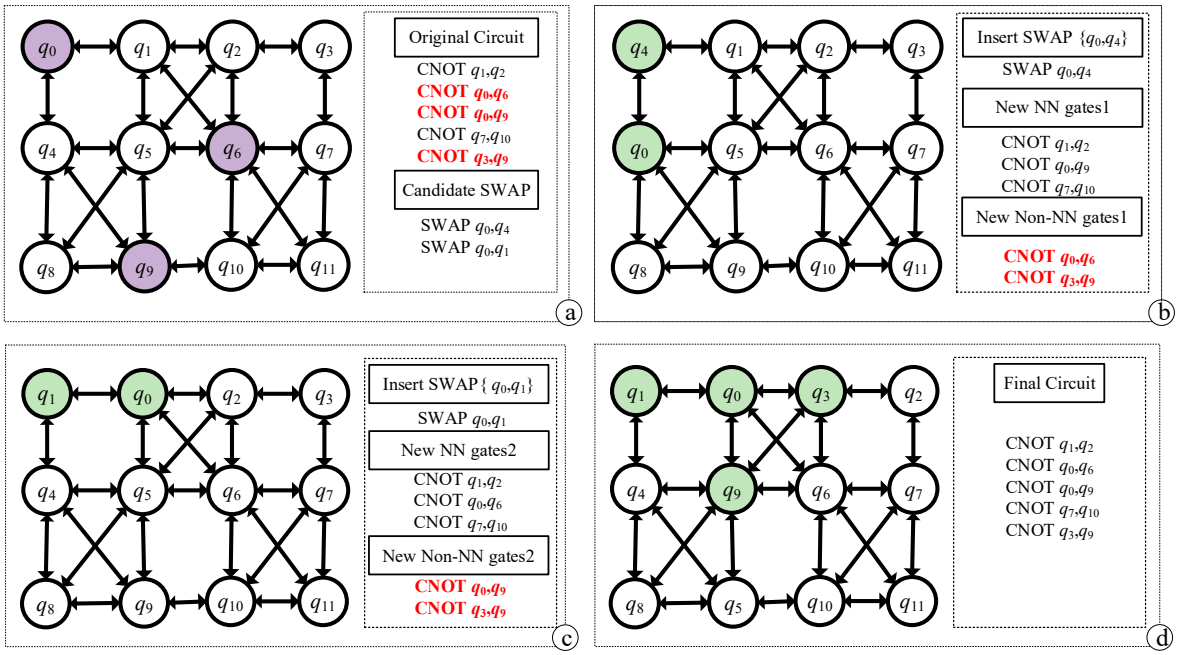


Fig. 4. (a) Original circuit, (b) Updated circuit after inserting SWAP $\{q_0, q_4\}$, (c) Updated circuit after inserting SWAP $\{q_0, q_1\}$, (d) Final circuit.

IV. Results Assessment

In this section, the main focus is on evaluating the operational results. Compared with one-dimensional chains and three-dimensional structures, two-dimensional structures have higher parallelism, qubits are arranged in the plane, and coupling and control are more simplified, which helps to reduce the noise level and error accumulation. Therefore, in this paper, we chose to compile on the IBM Quantum ibmq_montreal device with a two-dimensional structure, as shown in Fig. 5. The following key metrics are used to measure the effectiveness of the C-SQGS strategy on the compiler, one is the count of extra SWAP gates, and the other is the count of two-qubit gates, both of which are evaluated on the basis of the criterion that fewer is better [8]. The benchmark test program is IBM's Qiskit quantum program, which uses the Qiskit compiler to decompose and optimize the CNOT (CX) gate set. The benchmarking methodology of Tannu [27] was employed. The entire experiment was conducted using Python 3.11, with all compilations running on a laptop equipped with an Intel Core i5 processor (2.50 GHz, 8 GB RAM). Evaluations for 4 to 22 qubits were carried out, running the mapping process five times and selecting the best outcome.

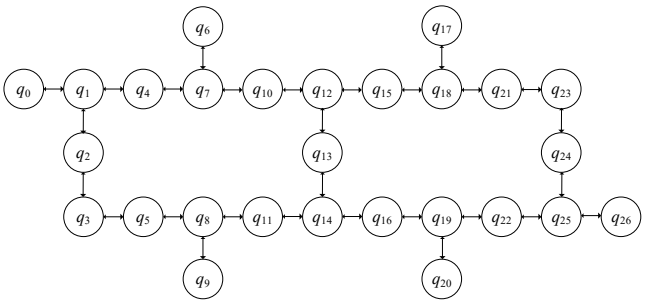


Fig. 5. Ibmq_montreal device.

In this paper, we compare the C-SQGS strategy with the compilation overhead of t|ket⟩ and Qiskit. The t|ket⟩ [28] and the Qiskit compiler [29] are equipped with the recommended "FullPass". The specific overheads of the C-SQGS with respect to the t|ket⟩ and Qiskit compilers are shown in Fig. 6. There are some optimizations in both the extra SWAP gate and CNOT gate counting overheads. The C-SQGS strategy is optimized relative to 2QAN, although the optimization is more significant for large qubits than for small qubits.

In the t|ket⟩ compiler, for circuits with 12-22 qubits, the C-SQGS strategy reduces the quantity of extra SWAP gates and CNOT gates by 6.1% and 5.5%, respectively, compared to 2QAN, as illustrated in Fig. 6(a), (b). For circuits with 4-10 qubits, the quantity of SWAP gates is decreased by an average of 26.4% and the quantity of CNOT gates by an average of 13.2% across all evaluated benchmarks after applying the C-SQGS strategy of this paper; the quantity of SWAP gates and CNOT gates are reduced by an average of 43.8% and 14.3%, respectively, after optimization of quantum circuits of 12-22 qubits, as illustrated in Fig. 7(a).

Within the Qiskit compiler framework, for circuits with 12-22 qubits, the C-SQGS strategy reduces the quantity of extra SWAP and CNOT gates by 5.7% and 7.6%, respectively, compared to 2QAN, as illustrated in Fig. 6(c), (d). For circuits with 4-10 qubits, after utilizing the C-SQGS strategy proposed in this paper, the quantity of SWAP gates is reduced by an average of 27.8% and the quantity of CNOT gates by an average of 14.9% in all the evaluated benchmarks, and the optimization of the quantum circuits of 12-22 qubits results in an average reduction of 61% in the quantity of SWAP gates, an average reduction in the quantity of CNOTs of 12.5%, and the overhead of double quantum gates is reduced by a factor of 2.5 compared to using only 2QAN, as shown in Fig. 7(b).

To further validate the advancement of the C-SQGS strategy, it is compared with the BSOS [8] and HQAA algorithms [13], as seen in Fig. 8. Within the t|ket⟩ compiler framework, for circuits with 4-10 qubits, the optimization effect of the C-SQGS is relatively tiny compared with the BSOS and HQAA algorithms, which is due to the fact that the circuit is simpler and the number of SWAP gates originally required is less in smaller quantum circuits, and the optimization effect is not easy to be seen. For circuits with 12-22 qubits, the advantage effect of the C-SQGS becomes more apparent. Specifically, compared with HQAA, the C-SQGS reduces the quantity of SWAP gates and CNOT gates by 9.3% and 12%, respectively. In the Qiskit compiler, for circuits with 4-10 qubit, C-SQGS reduces the quantity of CNOT gates by 4.1% and 4.3% compared to BSOS and HQAA, respectively. For circuits with 10-22 qubits, the quantity of SWAP gates is reduced by 3.1% and 12.7%, and the quantity of CNOT gates is reduced by 2% and 9.6%, respectively.

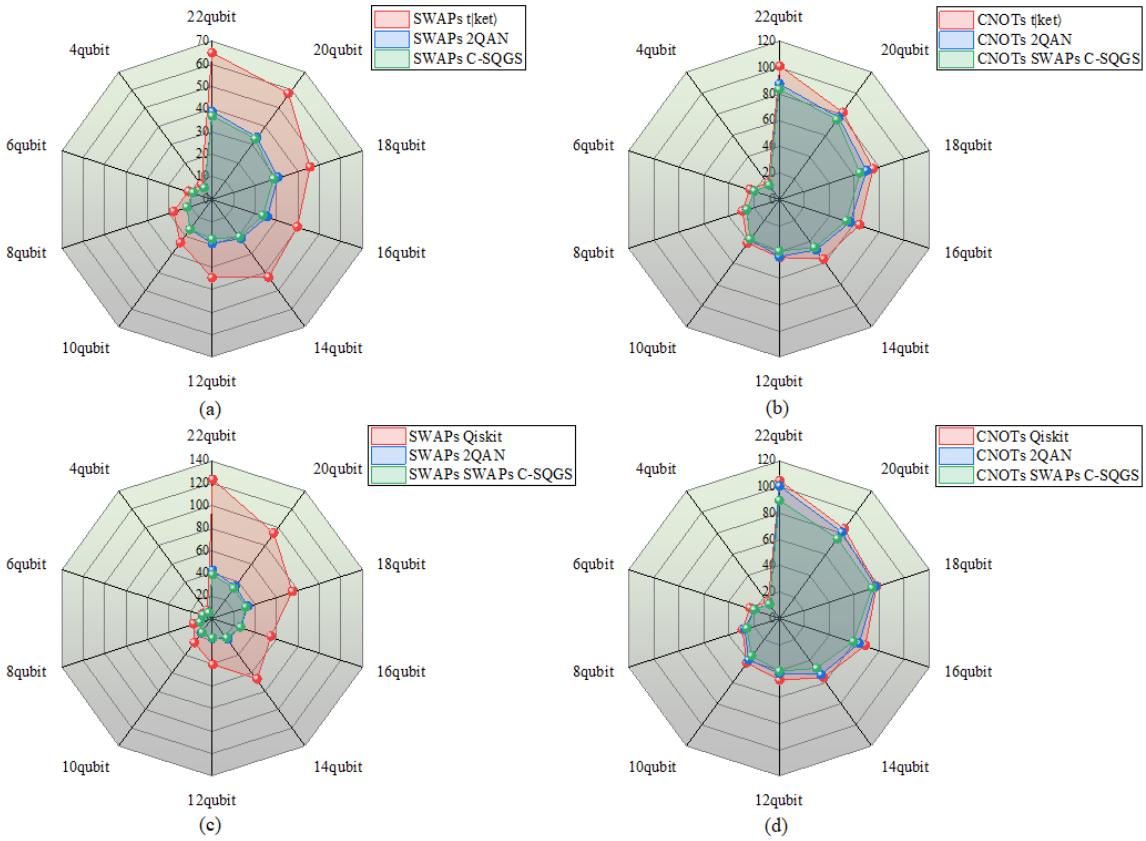


Fig. 6. (a) SWAP gate Overhead comparison between C-SQGS strategy, t|ket⟩ and 2QAN, (b) CNOT gate Overhead comparison between C-SQGS strategy, t|ket⟩ and 2QAN, (c) SWAP gate Overhead comparison between C-SQGS strategy, Qiskit and 2QAN, (d) CNOT gate Overhead comparison between C-SQGS strategy, Qiskit and 2QAN.

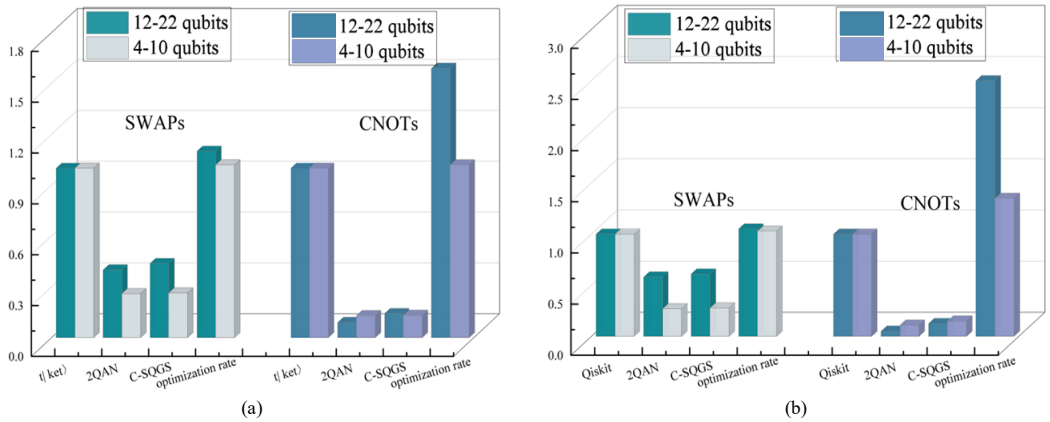


Fig. 7. The C-SQGS strategy was assessed for circuits with 4-10 qubits and 12-22 qubits. (a) Optimization ratio of SWAP and CNOT gates for C-SQGS compared to t|ket⟩ and 2QAN. (b) Optimization ratio SWAP and CNOT gate for C-SQGS compared to Qiskit and 2QAN.

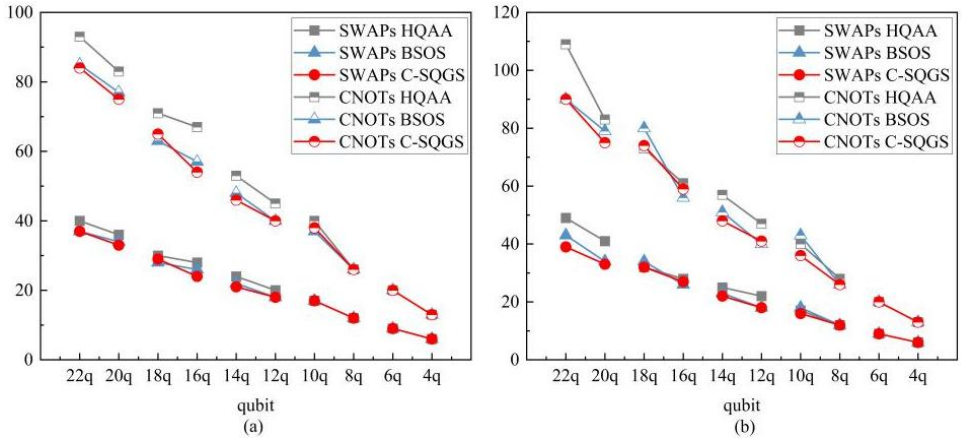


Fig. 8. Comparison of compilation overhead of different optimization algorithms. (a) Comparison of SWAPs and CNOTs overhead in the t|ket⟩. (b) Comparison of SWAPs and CNOTs overhead in the Qiskit.

The research in this paper focuses on the qubit mapping challenge, emphasizing the extra SWAP gate overhead and also considering the change in time complexity, which is a key measure of the algorithm's running efficiency. Table I shows the results of comparing the average running time of the 2QAN with the C-SQGS strategy in the t|ket⟩ and Qiskit compilers. The time complexity increases gradually with the increase in the count of qubits. Specifically, for smaller-scale quantum circuits, such as the 4-qubit model, the running time in the t|ket⟩ and Qiskit compilers is about 0.01s and 0.07s, respectively. However, the running time increases significantly as the circuit size increases. As an example, the runtime in the t|ket⟩ and Qiskit compilers for a 22-qubit circuit is about 27.4s and 0.29s, respectively.

TABLE I. COMPARE THE AVERAGE RUNTIME OF 2QAN AND C-SQGS STRATEGY IN T|KRT⟩ AND QISKIT COMPILERS

Qubit	Compiler	Running time(t/s)	
		2QAN	C-SQGS
4	t|ket⟩	0.1	0.01
	Qiskit	0.01	0.07
6	t|ket⟩	0.3	0.28
	Qiskit	0.09	0.09
8	t|ket⟩	0.46	0.41
	Qiskit	0.1	0.09
20	t|ket⟩	11.79	11.18
	Qiskit	0.24	0.22
22	t|ket⟩	28.23	27.4
	Qiskit	0.30	0.29

V. SUMMARY

This paper provides an in-depth discussion of the qubit mapping challenge, with a particular focus on the impact of physical topology on the mapping process in quantum computing. In the NISQ era, qubit mapping plays a key role in quantum circuit compilation. It aims to efficiently map logical qubits onto physical qubits, minimizing SWAP gates caused by topological constraints and enhancing circuit performance. To address this challenge, the C-SQGS strategy is proposed, aiming to optimize quantum circuits for the 2-local quantum simulation problem. To test the strategy, multiple experiments are conducted. The experimental results demonstrate that the C-SQGS strategy exhibits some advantages in reducing SWAP gate and hardware gate overhead. Specifically, the quantity of SWAP gates is diminished by an average of 36.9% and 47.7%, and the quantity of two-qubit gates is diminished by an average of 13.8% and 13.5% on the t|ket⟩ and Qiskit compilers, respectively.

Beyond empirical performance improvements, the results indicate several broader implications for qubit mapping and quantum compilation. Specifically, qubit flexibility–driven routing, centric gate prioritization, and multi-factor SWAP evaluation emerge as key design elements that help avoid short-sighted routing decisions and enable more execution-aware optimization under hardware constraints.

Although the C-SQGS strategy has achieved certain results in reducing the number of SWAP gates and the overhead of two-qubit gates, it still has limitations. First, this method is primarily designed and experimentally verified for medium-scale quantum circuits. For larger-scale quantum circuits, the computation of its multi-factor cost function and the evaluation process of candidate SWAP sets may introduce significant computational overhead, and the scalability of the algorithm requires further investigation. Second, experimental evaluations are primarily based on typical quantum circuits and a limited range of quantum chip topologies. Its applicability and generalization capabilities in more complex application scenarios and diverse quantum algorithms still have room for improvement.

With the continuous advancement of quantum computing technology, qubit mapping — a central problem in quantum computing — still faces significant challenges. Future research needs to explore several directions in greater depth to meet the evolving demands of quantum hardware and algorithms. On one hand, based on the C-SQGS strategy, optimization algorithms capable of adapting to more complex quantum topologies and higher-dimensional quantum gate sets will be developed, further enhancing the versatility and adaptability of the approach. On the other hand, efforts will be devoted to

designing more scalable mapping algorithms that can handle larger quantum circuits, while simultaneously pursuing the joint optimization of circuit design and mapping strategies. Since qubit mapping is closely linked to circuit structure, optimizing their interplay can further reduce redundant operations and improve the overall efficiency of quantum computing, thereby laying a solid foundation for its practical applications.

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REFERENCES

[1] Zhang X, Zhang F. Variational quantum computation integer factorization algorithm[J]. International Journal of Theoretical Physics, 2023, 62(11): 245.

[2] Au-Yeung R, Chancellor N, Halffmann P. NP-hard but no longer hard to solve? Using quantum computing to tackle optimization problems[J]. Frontiers in Quantum Science and Technology, 2023, 2: 1128576.

[3] Paudel H P, Syamlal M, Crawford S E, et al. Quantum computing and simulations for energy applications: Review and perspective[J]. ACS Engineering Au, 2022, 2(3): 151-196.

[4] Niu S, Suau A, Staffelbach G, et al. A hardware-aware heuristic for the qubit mapping problem in the nisq era[J]. IEEE Transactions on Quantum Engineering, 2020, 1: 1-14.

[5] Itoko T, Raymond R, Imamichi T, et al. Optimization of quantum circuit mapping using gate transformation and commutation[J]. Integration, 2020, 70: 43-50.

[6] Wille R, Burgholzer L. MQT QMAP: Efficient quantum circuit mapping[C]//Proceedings of the 2023 International Symposium on Physical Design. 2023: 198-204.

[7] Liu H, Zhang B, Zhu Y, et al. QM-DLA: an efficient qubit mapping method based on dynamic look-ahead strategy[J]. Scientific Reports, 2024, 14(1): 13118.

[8] Li H, Lu K, Qin H, et al. Research on Qubit Mapping Technique Based on Batch SWAP Optimization[J]. International Journal of Advanced Computer Science & Applications, 2023, 14(12).

[9] Chatterjee Y, Bourreau E, Rančić M J. Solving various NP-hard problems using exponentially fewer qubits on a quantum computer[J]. Physical Review A, 2024, 109(5): 052441..

[10] Luteberget B, Pettersen K F, Sartor G, et al. An Exact Branch and Bound Algorithm for the generalized Qubit Mapping Problem[J]. arXiv preprint arXiv:2508.21718, 2025.

[11] Siraichi M Y, Santos V F, Collange C, et al. Qubit allocation[C]//Proceedings of the 2018 international symposium on code generation and optimization. 2018: 113-125.

[12] Zulehner A, Paler A, Wille R. An efficient methodology for mapping quantum circuits to the IBM QX architectures[J]. IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, 2018, 38(7): 1226-1236.

[13] Steinberg M A, Feld S, Almudever C G, et al. Topological-graph dependencies and scaling properties of a heuristic qubit-assignment algorithm[J]. IEEE Transactions on Quantum Engineering, 2022, 3: 1-14.

[14] Li Z, Liu P, Zhao P, et al. Error per single-qubit gate below 10^{-4} in a superconducting qubit[J]. npj Quantum Information, 2023, 9(1): 111.

[15] Lau J W Z, Haug T, Kwek L C, et al. NISQ Algorithm for Hamiltonian simulation via truncated Taylor series[J]. SciPost Physics, 2022, 12(4): 122.

[16] Faehrmann P K, Steudtner M, Kueng R, et al. Randomizing multi-product formulas for Hamiltonian simulation[J]. Quantum, 2022, 6: 806.

[17] Zhang Z J, Sun J, Yuan X, et al. Low-depth Hamiltonian simulation by an adaptive product formula[J]. Physical Review Letters, 2023, 130(4): 040601.

[18] Dong Y, Lin L, Ni H, et al. Infinite quantum signal processing[J]. Quantum, 2024, 8: 1558.

[19] Motlagh D, Wiebe N. Generalized quantum signal processing[J]. PRX Quantum, 2024, 5(2): 020368.

[20] Childs A M, Maslov D, Nam Y, et al. Toward the first quantum simulation with quantum speedup[J]. Proceedings of the National Academy of Sciences, 2018, 115(38): 9456-9461.

[21] Khumalo M. Review of Quantum Optimisation Techniques for the Quadratic Assignment Problem[J]. 2023.

[22] Li G, Ding Y, Xie Y. Tackling the qubit mapping problem for NISQ-era quantum devices[C]//Proceedings of the twenty-fourth international conference on architectural support for programming languages and operating systems. 2019: 1001-1014.

[23] Lao L, Browne D E. 2qan: A quantum compiler for 2-local qubit hamiltonian simulation algorithms[C]//Proceedings of the 49th Annual International Symposium on Computer Architecture. 2022: 351-365.

[24] Niemann P, Mueller L, Drechsler R. Combining SWAPs and remote CNOT gates for quantum circuit transformation[C]//2021 24th Euromicro Conference on Digital System Design (DSD). IEEE, 2021: 495-501.

[25] Deng H, Zhang Y, Li Q. Codar: A contextual duration-aware qubit mapping for various nisq devices[C]//2020 57th ACM/IEEE Design Automation Conference (DAC). IEEE, 2020: 1-6.

[26] Lao L, van Wee B, Ashraf I, et al. Mapping of lattice surgery-based quantum circuits on surface code architectures[J]. Quantum Science and Technology, 2018, 4(1): 015005.

[27] Tannu S S, Qureshi M K. A case for variability-aware policies for nisq-era quantum computers[J]. arXiv preprint arXiv:1805.10224, 2018.

[28] Sivarajah S, Dilkes S, Cowtan A, et al. t|ket⟩: a retargetable compiler for NISQ devices[J]. Quantum Science and Technology, 2020, 6(1): 014003.

[29] Neha K. Quantum programming: working with IBM'S qiskit tool[J]. The Scientific Temper, 2023, 14(01): 93-99.

Predictive Modelling of Flood Dynamics in Malaysia's East Coast Using an NARX Model

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***Abstract*—Flood forecasting is critical for improving early warning systems in Malaysia's East Coast region, particularly in flood-prone Pekan. This study develops a Nonlinear Autoregressive with Exogenous Inputs (NARX) model to predict river water levels using data from four stations: Sungai Pahang, Sungai Pahang Tua, Sungai Paloh Hinai, and Sungai Mentiga (2020–2024). The dataset was preprocessed through short-gap interpolation, removal of long missing segments, and segmentation into continuous sequences to ensure high-quality inputs for modeling. A total of 75 NARX configurations were evaluated using different lag values, hidden neuron counts, and training epochs. Model performance was assessed using Mean Squared Error (MSE) and residual diagnostics. The best model—lag = 6 and 300 hidden units—achieved a validation loss of 0.102, demonstrating stable convergence and strong generalization. Prediction results showed close alignment with actual river levels. The findings confirm that the NARX approach effectively captures nonlinear hydrological dynamics and provides reliable short-term water level forecasts for Pekan, addressing an existing gap in localized flood prediction studies.**

***Keywords*—Flood prediction; NARX model; hydrological modelling; Pekan**

I. Introduction

The East Coast region of Peninsular Malaysia frequently experiences heavy rainfall during the Northeast Monsoon season, which often leads to flooding in low-lying and riverine areas. These flood events result in significant damage to infrastructure, disruption of transportation systems, and substantial economic losses for affected communities. Accurate and timely flood forecasting is crucial to support early warning systems and minimize flood-related impacts. Reliable river water level prediction enables authorities to make proactive decisions and implement preventive measures to safeguard lives and reduce property damage.

Despite ongoing advancements in hydrological monitoring, flood prediction in Malaysia remains challenging due to the nonlinear, dynamic, and spatially heterogeneous nature of river systems, particularly in monsoon-driven environments. These challenges are more pronounced at the district level, where complex upstream–downstream interactions and data continuity issues limit the effectiveness of generic basin-scale forecasting models.

In recent years, data-driven modelling has gained increasing attention for flood forecasting due to its ability to capture nonlinear and complex relationships within hydrological systems. This study aims to develop a predictive model using the Nonlinear Autoregressive model with Exogenous Inputs (NARX) for river water level forecasting in the East Coast region of Peninsular Malaysia. The NARX model utilizes historical hydrological data to learn temporal patterns, enabling more accurate predictions. By implementing the NARX-based approach, this research seeks to improve the accuracy and reliability of flood forecasting systems to enhance early warning capabilities and reduce flood-related risks.

Although NARX models have been widely applied in hydrological forecasting, most existing studies emphasize major river basins or regional-scale analysis, with limited focus on district-level river systems experiencing recurrent flooding. In particular, the Pekan district in Pahang—despite its high flood vulnerability—has received comparatively little attention in terms of localized, data-driven river level prediction models. Furthermore, prior work rarely investigates how multiple upstream river stations collectively influence downstream water level dynamics within an integrated modelling framework.

This study presents a systematically optimized NARX-based river water level prediction model tailored for the Pekan river system. The model integrates water level data from multiple upstream and downstream stations, including Sungai Pahang Tua, Sungai Paloh Hinai, and Sungai Mentiga, to predict downstream levels at Sungai Pahang (Pekan). A structured preprocessing and segmentation strategy is employed to ensure model training is conducted only on continuous, fully observed temporal segments, thereby preserving hydrological realism and avoiding artefacts introduced by long-gap imputation. In addition, a comprehensive exploration of lag length, hidden layer capacity, and training duration is performed to identify an optimal NARX configuration that balances prediction accuracy, convergence stability, and generalization performance. Through this approach, the study provides a localized and transferable modelling framework that supports district-level flood early warning applications.

The remainder of this study is organized as follows: Section II reviews related work on flood forecasting and data-driven hydrological modelling. Section III describes the dataset, preprocessing strategy, and NARX model architecture. Section IV presents the experimental results and discussion. Finally, Section V concludes the study and outlines limitations and directions for future work.

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II. Literature Review

Flood disasters remain a major environmental and socio-economic concern in many regions, particularly in Malaysia, where seasonal monsoon patterns heavily influence hydrological conditions [1]. Researchers have employed various forecasting approaches to understand and predict flood behavior, ranging from traditional statistical and hydrological models to more recent machine learning and deep learning techniques. This literature review provides an overview of flooding characteristics in the Pantai Timur region, followed by a review of conventional flood forecasting methods. It then discusses the evolution of data-driven methods, including Artificial Neural Networks (ANN), Support Vector Regression (SVR), and Random Forest (RF), before examining advanced deep learning techniques such as Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and hybrid intelligent models. Finally, this chapter emphasizes the significance of the Nonlinear Autoregressive with Exogenous Input (NARX) model in hydrological forecasting and identifies the research gap motivating the present study.

A. Flooding in Malaysia and the Pantai Timur Region

Malaysia experiences frequent flooding due to its tropical climate and high-intensity rainfall patterns. The Pantai Timur region — consisting of Kelantan, Terengganu, and Pahang — is the most flood-prone zone in Peninsular Malaysia, particularly during the Northeast Monsoon season [1]. The region's river basins, low-lying settlements, and coastal geography increase vulnerability to overflow and prolonged inundation [2]. The Northeast Monsoon (NEM) typically occurs between November and March, bringing strong winds and heavy rainfall from the South China Sea [3]. The Malaysian Meteorological Department (2023) states that this seasonal event produces prolonged rainfall that causes river water levels to rise rapidly, triggering severe flooding across Pantai Timur [4]. The intensity and duration of monsoon rainfall directly affect river discharge, making water level prediction a crucial preventive measure. Several major flood events have occurred in Pantai Timur over the past decades, including those in Kelantan (2014) [5], Pahang (2021) [6], and Terengganu (2022) [7]. The 2014 Kelantan flood, widely referred to as "Bah Kuning" [8], affected more than half a million people, resulting in extensive property damage and infrastructure collapse. Such recurring events highlight the importance of accurate forecasting systems to mitigate disaster impacts.

B. Importance of River Level Forecasting

River level forecasting plays a crucial role in early warning systems, evacuation planning, and resource mobilization. Government agencies such as the Department of Irrigation and Drainage (DID) and the National Disaster Management Agency (NADMA) rely on real-time hydrological forecasting for decision-making [9]. Therefore, forecasting models must be accurate, reliable, and capable of capturing nonlinear hydrological behaviors.

C. Conventional Flood Forecasting Methods

1) Statistical time-series models (ARIMA, Regeression): The Autoregressive Integrated Moving Average (ARIMA) model is one of the most widely used statistical methods in river flow forecasting [10]. However, ARIMA assumes linearity and struggles to model complex nonlinear patterns that often characterize hydrological systems [11]. Regression-based models face similar limitations, particularly when dealing with high-variability rainfall-runoff relationships.

2) Physically-based hydrological models (SWAT, HEC-HMS): Physically-based models such as Soil and Water Assessment Tool (SWAT) and Hydrologic Engineering Center – Hydrologic Modeling System (HEC-HMS) simulate watershed hydrology using environmental and land-use parameters [12]. While these models provide insight into hydrological processes, they require extensive data input and calibration, making them difficult to apply in regions with limited monitoring networks [12]. Furthermore, parameter uncertainties can significantly reduce model reliability during extreme flooding events [13].

D. Machine Learning Approaches in Flood Forecasting

With advancements in computational power and data availability, machine learning has become an attractive approach for modeling hydrological processes. Artificial Neural Networks (ANNs) are capable of learning complex nonlinear relationships from data and have shown promising performance in flood forecasting applications. However, standard feed-forward ANNs are limited in handling long-term temporal dependencies in time-series data [14]. Support Vector Regression (SVR) offers good generalization performance but requires careful tuning of kernel functions and regularization parameters [15]. Random Forest (RF) performs well in capturing nonlinear patterns but may become computationally intensive with large datasets [16]. Both methods demonstrate improvement over linear models, yet are still constrained in modeling sequential dependencies over time.

E. Deep Learning Models in Hydrological Time-Series Forecasting

Recurrent Neural Networks introduced time-sequence modeling capability. However, traditional RNNs suffer from gradient vanishing issues, limiting their ability to learn long-term dependencies [16]. Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models were specifically developed to address memory retention issues and have demonstrated superior performance in predicting streamflow and river water levels [17]. These models capture temporal dependencies more effectively than simple ANNs [18]. Hybrid models that integrate convolutional and recurrent architectures or attention mechanisms have further improved forecasting accuracy by extracting temporal and spatial patterns [19]. However, these models require large datasets and high computational resources, limiting their real-time deployment in some regions [20].

F. NARX Model for Hydrological and Flood Forecasting

The Nonlinear Autoregressive with Exogenous Input (NARX) model is a dynamic neural network that uses previous output values and external variables (e.g., rainfall) to predict future water levels [21]. This architecture enables the model to represent nonlinear hydrological dynamics effectively. NARX

models converge faster and provide higher prediction accuracy than traditional ANN and RNN due to their explicit memory mechanism [22]. They are particularly effective in modeling systems where external forcing influences the target variable. Studies demonstrate that NARX achieves high accuracy in river level forecasting across Southeast Asian river basins [23]. Its performance is notably superior when dealing with short-term and multi-step forecasting [23].

G. Research Gap

Although a variety of hydrological and data-driven flood forecasting models have been applied in Malaysia, most previous research has focused on river basins in Kelantan and Terengganu [24], while significantly less attention has been given to Pahang, particularly the Pekan district. Existing flood prediction frameworks do not adequately represent the hydrological and rainfall–runoff characteristics of Pahang's river systems. As a result, there is currently no dedicated flood prediction model specifically developed for Pekan, despite its recurring seasonal floods and high socio-economic vulnerability. Furthermore, previous studies rarely examine flood behavior along the entire river course, from upstream to downstream, which is critical for understanding how rainfall and runoff propagate through the watershed before causing overflow in low-lying coastal areas like Pekan. Developing a tailored model would therefore not only improve prediction accuracy but also enable a better understanding of flood dynamics along the river continuum, supporting more effective local early-warning and disaster preparedness strategies. Hence, this study focuses on designing and evaluating an NARX-based prediction model specifically for the Pekan region, to address this gap.

H. Summary of the Literature Review

While conventional statistical and physically-based models provide foundational hydrological understanding, their performance declines due to the nonlinear and dynamic characteristics of flood behavior. Machine learning and deep learning methods such as ANN, SVR, RF, LSTM, and hybrid architectures have shown improved predictive ability by capturing complex temporal dependencies. The NARX model, in particular, has demonstrated strong performance in multi-step hydrological forecasting due to its capability to incorporate external variables and maintain memory of past system states.

However, the review shows that little research has focused on flood prediction in Pahang, and almost none has been conducted specifically for Pekan, even though the district is highly affected by recurring monsoon floods [1]. Additionally, there is limited study on flood progression along the river system from upstream to downstream, which is essential for understanding how floodwater develops and travels before reaching populated flood-prone areas. Therefore, the present study aims to develop a NARX-based river level prediction model specifically tailored for the Pekan river system, providing more localized and accurate early-warning insights to support flood management and preparedness.

III. Methodology

A. Dataset

The dataset consists of hourly hydrological measurements collected over five years (2020–2024) from four river stations: Sungai Pahang, Sungai Pahang Tua, Sungai Paloh Hinai, and Sungai Mentiga. The target station for prediction is Sungai Pahang at Pekan, which represents the confluence point of the other three rivers.

Each dataset contains several attributes, including Station ID, Station Code, Station Name, Date, Time, Water Level (m), Rainfall (mm), Cumulative Daily Rainfall (mm), and Cumulative Annual Rainfall (mm). For this study, only the Water Level (m) parameter was retained to ensure model focus and reduce noise from unrelated variables.

B. Data Preprocessing

To standardize the temporal resolution, the hourly data were aggregated into daily averages, resulting in one representative water level value per day for each station. The daily average water level, $\bar{H}_d$, was computed as:

$$\bar{H}_d = \frac{1}{n}\sum_{i=1}^{n} H_i \quad (1)$$

where, $H_i$represents the water level recorded at the i^{th}hour of a given day, and $n$is the total number of hourly observations within that day (typically $n = 24$).

C. Interpolation of Short Gaps

Short gaps, defined as missing periods of fewer than 5 consecutive days, were imputed using linear interpolation. For a missing value at time t, the estimate was calculated as:

$$x_t = \frac{(t-t_{prev})*x_{next}+(t_{next}-t)*x_{prev}}{t_{next}-t_{prev}} \quad (2)$$

where, x_{prev} and x_{next} represent the nearest observed values surrounding the gap. This approach is appropriate for short-duration gaps where hydrological changes are typically gradual and continuous.

Large gaps (≥5 consecutive days) were not imputed. Instead, the entire row corresponding to that timestamp was removed across all stations. This ensures that each training instance contains complete values for Sungai Pahang, Sungai Pahang Tua, Sungai Paloh Hinai, and Sungai Mentiga, thereby avoiding inconsistencies caused by high-uncertainty imputations.

The removal of rows containing long gaps is motivated by several scientific and statistical considerations:

- Non-linear and event-driven hydrological behavior: Water levels in rivers respond to rainfall, upstream releases, tidal influences, and runoff processes that evolve non-linearly. Over multi-day periods, such dynamics cannot be reliably reconstructed using linear or low-order imputation techniques. Long-gap interpolation introduces unrealistic smoothing and distorts natural fluctuations.
- Autocorrelation decay in river-level time series: Hydrological time series typically exhibit rapid

autocorrelation decay within a few days. When observations are separated by long gaps, their statistical dependence becomes weak, making interpolated values unreliable. Avoiding long synthetic intervals preserves the natural temporal structure of the data.

- Uncertainty amplification: Interpolation error grows with gap duration. Long-gap estimates carry high uncertainty that may propagate into model training, degrading predictive performance and weakening the model's ability to capture extreme events.
- Avoidance of model bias and artefact learning: Machine learning models are sensitive to artificial patterns caused by imputation. Long imputed segments may lead the model to learn interpolation artefacts rather than genuine hydrological relationships among the four stations.

After preprocessing, the dataset was divided into continuous segments—defined as sequences of dates in which none of the stations (Sungai Pahang, Sungai Pahang Tua, Sungai Paloh Hinai, Sungai Mentiga) exhibits a large missing gap. Separate regression models were trained on these fully complete segments. Training regression models on continuous, fully observed segments is scientifically valid and methodologically justified for several reasons:

- Preservation of underlying hydrological dynamics: Continuous segments represent uninterrupted periods during which the inter-station relationships reflect real hydrological behavior. This allows the model to learn authentic temporal patterns rather than artefacts arising from imputed values.
- Assumption of local stationarity: River systems often exhibit local stationarity, meaning their statistical properties remain stable within reasonably short continuous periods. Segment-wise modelling respects this property and allows consistent parameter estimation.
- Avoidance of cross-regime contamination: Long missing gaps often coincide with unusual hydrological states (e.g., floods, sensor outages, maintenance). Segmentation prevents mixing incompatible regimes that could introduce non-physical relationships into the model.
- Reduction of structural bias: Restricting training to fully observed data ensures that regression parameters reflect true input–output relationships rather than smoothed or synthetic signals.
- Hypothetical validity via conditional independence: If each continuous segment is assumed to originate from the same underlying hydrological process governing the four stations, then each segment provides an independent sample from the same distribution. This satisfies the theoretical assumptions required for regression modelling.
- Improved generalization: Models trained only on high-quality, continuous data are better able to generalize to unseen periods, particularly during rapidly changing hydrological conditions such as rising or receding river stages.

These grouped datasets were then utilized for the Nonlinear AutoRegressive model with eXogenous inputs (NARX) during the modeling stage.

The NARX model was implemented using Python with TensorFlow and Keras frameworks. The dataset was divided into training and testing sets, with the training phase used to optimize network weights.

The loss function used to evaluate model performance is the Mean Squared Error (MSE), calculated as:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad (3)$$

where, $y_i$and $\hat{y}_i$are the observed and predicted water levels, respectively, and N is the total number of samples. Lower MSE values indicate higher prediction accuracy and better model generalization.

D. NARX Model Structure

The general form of the NARX model is expressed as:

$$y(t) = f(y(t-1), y(t-2), \dots, y(t-n_y), x(t-1), x(t-2), \dots, x(t-n_x)) \quad (4)$$

where,

- $y(t)$ is the predicted river water level at time t,
- $x(t)$ represents the exogenous input variable (e.g., rainfall or other influencing factors),
- $n_y$and $n_x$denote the feedback (lag) orders, and
- $f(\cdot)$ is a nonlinear function approximated using an MLP network.

E. Model Architecture

Table I shows that the predictive model used a feedforward neural network with one hidden layer, following the structure:

TABLE I. THE STRUCTURE OF THE MODEL

Layer	Description
Input Layer	Dimension determined by the lag size and number of variables.
Hidden Layer	Fully connected, with variable neuron counts (150, 300, or 600 units).
Activation Function	Rectified Linear Unit (ReLU).
Dropout Layer	20% dropout for regularization and overfitting prevention.
Output Layer	A single linear neuron producing the next-step forecast.

The model was defined using the Sequential API in TensorFlow Keras. The network was compiled with the Adam optimizer (learning rate = 1×10^{-3}, weight decay = 1×10^{-5}) and Mean Squared Error (MSE) as the loss function.

F. Training Procedure

Each configuration was trained under varying combinations of:

- Lags: {3,4,5,6,7}
- Hidden Units: {150,300,600}
- Epochs: {100,300,500,1000,5000}

This yielded a total of 45 experimental runs.

Training was executed with a batch size of 128 and data shuffling enabled to prevent temporal bias.

During each experiment:

- The model was trained on the training set and validated on the test set.
- The training and validation loss histories were recorded.
- Predictions were generated for both training and test datasets.
- Diagnostic visualizations were saved, including:
  - Loss curve (training vs. validation loss),
  - Residual plots (train/test residuals),
  - Prediction plots (actual vs. predicted values).

G. Evaluation Metrics

The model's predictive performance was primarily evaluated using Mean Squared Error (MSE) as the loss function. Additional diagnostic analyses included:

- Residual distribution to assess error randomness and bias.
- Train vs. Validation loss comparison to detect overfitting.
- Actual vs. Predicted plots to visually assess alignment between predictions and ground truth.

IV. Implementation, Results and Discussion

A series of experiments were conducted to evaluate the performance of a neural network model trained with different lag values and hidden unit configurations for time-series forecasting. The parameter grid covered lags {3, 4, 5, 6, 7}, hidden units {150, 300, 600}, and epochs {100, 300, 500, 1000, 5000}. The primary evaluation metric was validation loss (Mean Squared Error), with train loss also monitored to assess potential overfitting or underfitting.

A. Best Validation Performance by Lag and Hidden Units

The heatmap in Fig. 1 illustrates the best validation loss achieved for each combination of lag and hidden unit count.

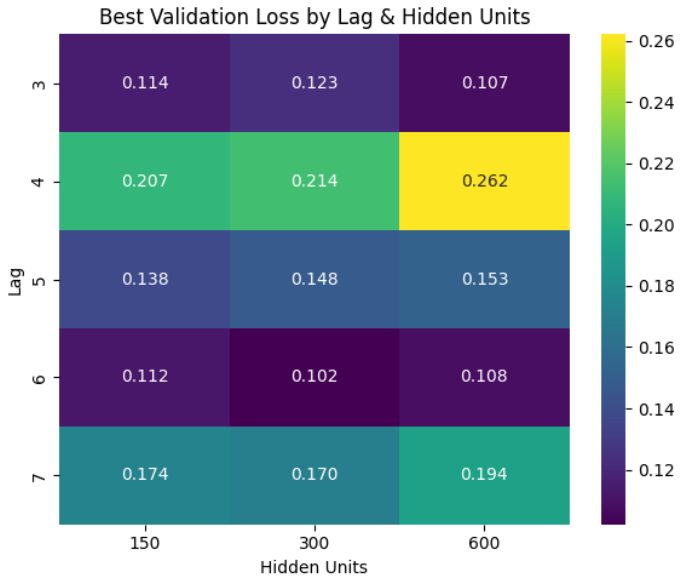


Fig. 1. Heatmap.

Fig. 1 shows that the model achieved its lowest validation loss (0.102) for Lag = 6 and Hidden Units = 300, indicating that this configuration provides an optimal balance between temporal dependency capture and model complexity. Generally, lags between 3 and 6 produced comparable results, while performance deteriorated at lag = 4 and lag = 5, especially when the hidden layer size was small (150). Increasing the hidden units to 300 consistently improved performance for most lags, whereas using 600 units did not always yield further benefits — suggesting possible overparameterization for the dataset size.

B. Relationship Between Training and Validation Loss

The scatter plot in Fig. 2 compares the final train loss against validation loss across all configurations.

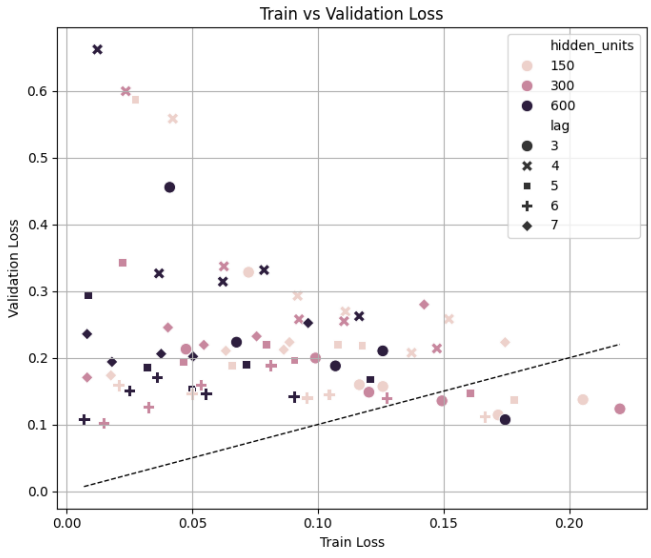


Fig. 2. Scatter plot.

As shown in Fig. 2, most points lie close to or above the diagonal reference line, indicating that validation losses were typically higher than training losses — a standard indicator of slight overfitting. However, several configurations (particularly those with hidden units = 300 and moderate lags) exhibited a close alignment between train and validation losses, suggesting good generalization. Notably, models trained with Lag = 4 and Lag = 5 showed larger gaps between train and validation losses, reflecting unstable learning dynamics or insufficient temporal context.

C. Validation Loss Trends Across Epochs

Fig. 3 to Fig 7 show validation loss progression across training epochs for each lag value.

Lag = 3: Validation loss decreased sharply up to 1000 epochs for hidden units = 150 and 300, followed by an increase at 5000 epochs, indicating early convergence and later overfitting.

Lag = 4: All configurations exhibited diverging losses beyond 1000 epochs, implying unstable training or excessive learning rates for deeper models.

Lag = 5: The validation loss initially improved but then rose steeply for higher epochs, confirming overfitting at extended training durations.

Lag = 6: The trend showed consistent improvement as training progressed, achieving the lowest validation loss (≈0.10) at 5000 epochs, particularly with hidden units = 300. This indicates a robust generalization pattern.
- Lag = 7: The loss curves demonstrated oscillation and mild overfitting beyond 2000 epochs, though the overall performance remained stable within a 0.18–0.25 MSE range.

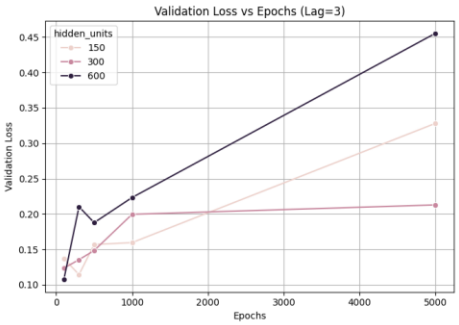


Fig. 3. Lag 3 validation loss.

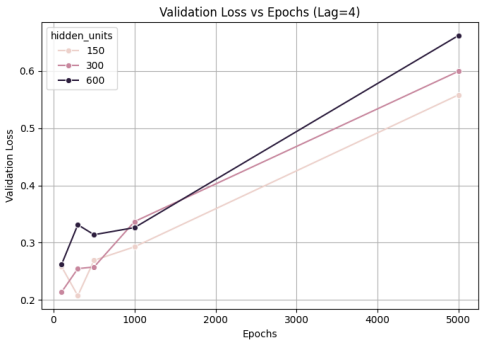


Fig. 4. Lag 4 validation loss.

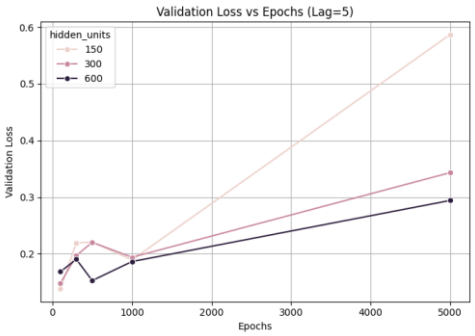


Fig. 5. Lag 5 validation loss.

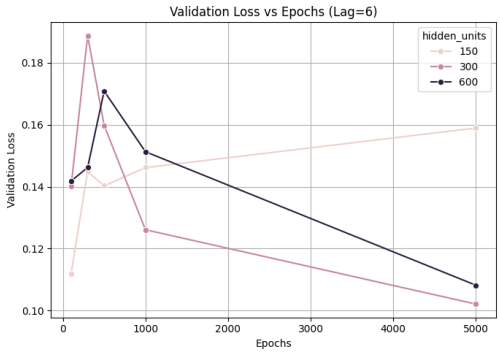


Fig. 6. Lag 6 validation loss.

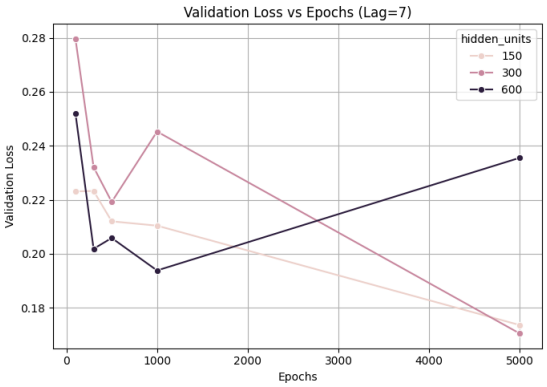


Fig. 7. Lag 7 validation loss.

D. Cross-Lag Performance Interpretation

Comparing across lags, the results suggest that:

- Short lags (3–4) capture limited temporal dependencies, causing early saturation in validation performance.
- Intermediate lag (6) offers an optimal trade-off — long enough to model dependencies, but not too large to introduce noise.
- Longer lag (7) yields diminishing returns, potentially due to redundant temporal information or vanishing gradients.

This aligns with the hypothesis that increasing input sequence length does not guarantee improved forecasting accuracy beyond a certain point.

E. Summary of Key Observations

From Table II, the observed behavior underscores the importance of balancing model capacity, temporal depth, and training duration. While larger models (600 units) have higher representational power, they are also prone to overfitting when training data are limited. Conversely, too few hidden units (150) restrict learning capability. Hence, medium-sized architectures (300 units) paired with sufficient historical context (Lag = 6) represent an optimal trade-off for this dataset. These findings can guide future hyperparameter selection for similar neural forecasting tasks, where data periodicity and temporal correlation length are critical factors.

TABLE II. THE BEST RESULT FOR EACH LAG

Lag	Hidden Units	Best Val Loss	Notes
3	300	0.114	Stable and generalizable
4	300	0.214	Poor stability beyond 1000 epochs
5	600	0.153	Unstable, possibly overfitted
6	300	0.102 (best)	Strong generalization and stable learning
7	150	0.174	Gradual improvement but limited gain

F. Detailed Evaluation of the Best Model (Lag = 6, Hidden Units = 300)

1) Loss curve analysis: The loss curve in Fig. 8 depicts the evolution of training and validation losses across 5000 epochs. The training loss exhibits a steep decline during the early epochs, stabilizing near zero after approximately 1000 epochs.

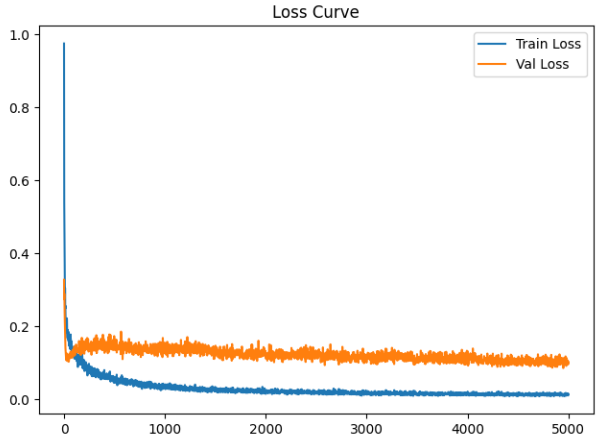


Fig. 8. Training and validation loss curves showing convergence behavior for the best model configuration (Lag = 6, Hidden Units = 300).

The validation loss follows a similar trend but converges to a higher steady-state value around 0.10, consistent with the best validation loss recorded in the summary. The relatively small gap between training and validation losses indicates effective generalization and minimal overfitting. Both curves maintain stability without significant oscillation or divergence, suggesting that the model converged smoothly. This steady behavior reflects robust learning dynamics, where the model captures relevant temporal dependencies without memorizing noise from the training set.

2) Residual diagnostics: The residual plots in Fig. 9 illustrate the difference between predicted and actual values for both training and test sets.



Fig. 9. Residual plots for training and test datasets, showing randomness and unbiased prediction errors.

In the training residuals, values fluctuate randomly around zero with no visible pattern or trend, implying that the model's predictions are unbiased and errors are normally distributed. The magnitude of residuals remains small (within ±0.1), confirming that the model fits the training data accurately without systematic error. The test residuals display slightly larger fluctuations, ranging within ±0.25, which is expected due to unseen data. However, no clear autocorrelation or drift is present, supporting the conclusion that the model generalizes well beyond the training sample. This diagnostic outcome supports the statistical soundness of the model and its ability to perform consistent predictions across both datasets.

3) Prediction performance on training data: The training prediction plot in Fig. 10 demonstrates an almost perfect overlap between actual and predicted values. The consistency across the full sequence confirms the model's high accuracy in reconstructing training samples while maintaining generalization, as verified in the test results. This balance reinforces that the selected architecture (Lag = 6, Hidden Units = 300) achieves optimal expressiveness without overfitting. The model appears to have successfully extracted dominant temporal patterns and relationships within the data.

4) Prediction performance on test data: Fig. 11 compares actual and predicted values for the test set. The predicted curve closely tracks the actual target trend, capturing both peaks and troughs of the series effectively. Minor deviations occur at extreme points, which may be attributed to local variations not captured by the lag window of six.

The close alignment between both curves indicates that the model successfully learns the non-linear temporal dependencies within the data. The prediction continuity and minimal phase lag between actual and predicted signals further validate the model's capacity to anticipate short-term dynamics with good precision.

5) Summary of findings for optimal model: The results highlight the importance of appropriate lag selection in temporal modeling. With a lag of 6, the network accesses

sufficient historical context to infer meaningful sequential dependencies without introducing redundant or noisy information. Moreover, the moderate hidden layer size of 300 provides adequate representational capacity to capture non-linear relations while preserving regularization balance. The residual randomness and low validation loss collectively confirm that the model achieved an optimal bias–variance tradeoff. This configuration will be considered as the final candidate for deployment or further comparative experiments with other forecasting or hybrid deep learning approaches (see Table III).

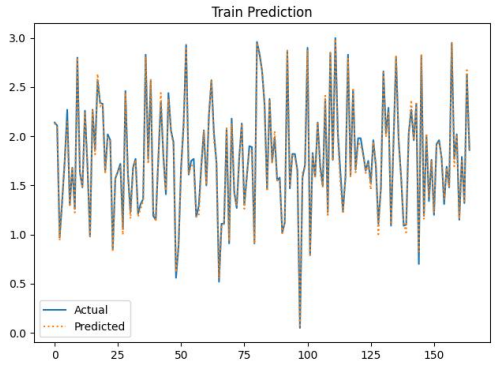


Fig. 10. Training prediction performance showing close alignment between predicted and actual series.

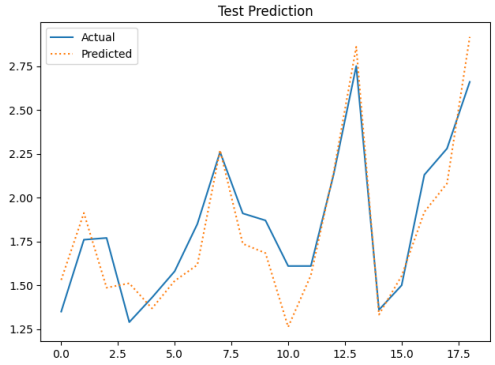


Fig. 11. Test prediction performance comparison between actual and predicted values.

TABLE III. FINDING SUMMARY

Metric	Observation
Lag	6
Hidden Units	300
Best Validation Loss	0.102
Training Stability	Excellent (Smooth convergence)
Generalization	Strong (Low validation gap)
Residual Behavior	Random, low magnitude
Test Prediction Fit	High correlation with actual series

V. CONCLUSION

This study set out to develop a reliable and accurate river water level forecasting model for the Pekan region using the Nonlinear Autoregressive model with Exogenous Inputs (NARX). The motivation derived from recurring monsoon-driven floods in the East Coast of Peninsular Malaysia, where existing forecasting systems lack models tailored specifically to Pahang's hydrological characteristics. The literature review highlighted that while conventional statistical and physically-based models offer foundational insights, their performance often deteriorates under nonlinear and dynamic flood conditions. Modern machine learning and deep learning techniques provide improved predictive capabilities, yet most previous research remains concentrated in Kelantan and Terengganu, leaving a significant gap for Pahang—particularly the low-lying Pekan district.

A comprehensive dataset of daily water levels from 2020 to 2024 was preprocessed, cleaned, and segmented into continuous temporal sequences to ensure robust model training. Using this dataset, a series of 75 experiments was conducted across varying lag values, hidden unit sizes, and training epochs to identify the optimal NARX configuration. Performance evaluation relied primarily on Mean Squared Error (MSE), supported by residual diagnostics and actual-versus-predicted comparisons for both training and test sets.

The experimental results demonstrated that Lag = 6 and Hidden Units = 300 provided the most effective and stable predictive performance, achieving a minimum validation loss of 0.102. This configuration offered a balanced combination of temporal memory and model complexity, outperforming smaller architectures, which lacked representational strength, as well as larger models, which tended to overfit. Loss curve analyses further confirmed smooth convergence and minimal divergence between training and validation losses, indicating strong generalization. Residual analyses showed randomness without bias, while prediction plots revealed close alignment with actual water level fluctuations, successfully capturing trend variations and peak events.

From a scientific perspective, this study contributes a structured and reproducible NARX modelling framework that integrates multi-station river dynamics with systematic lag–capacity optimization for district-level hydrological forecasting. Practically, the proposed model offers actionable value for local flood early warning systems by providing accurate short-term water level predictions that can support decision-making by authorities in flood-prone areas such as Pekan.

Despite these encouraging results, several limitations of this study should be acknowledged. First, the model relies solely on historical water level data and does not explicitly incorporate rainfall, tidal influence, or reservoir release information, which may further enhance predictive accuracy during extreme hydrological events. Second, model training was conducted using daily-aggregated data, which may limit responsiveness to rapid intra-day water level changes during flash flood conditions.

Future work will focus on extending the proposed framework by incorporating additional hydrometeorological variables and evaluating multi-step-ahead forecasting performance for longer early warning lead times. Integration with real-time sensor networks and comparative evaluation

against alternative data-driven models may further strengthen the operational applicability of the approach.

In conclusion, the NARX-based approach developed in this work offers a valuable contribution toward strengthening flood preparedness and decision-support mechanisms in Pahang. With continued refinement and integration into operational forecasting systems, it can play a significant role in mitigating the socio-economic impacts of seasonal flooding and enhancing resilience in vulnerable communities.

ACKNOWLEDGMENT

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REFERENCES

[1] A. N. Abd Rahman, F. Othman, W. J. Wan Jaafar, and A. H. K. Ahmed Elshafie, "An assessment of floods' characteristics and patterns in Pahang, Malaysia," Larhyss J., vol. No. 55, no. Sept 2023, pp. 89–105.

[2] I. Usman Kaoje et al., "Physical Flood Vulnerability Assessment using Geospatial Indicator-Based Approach and Participatory Analytical Hierarchy Process: A Case Study in Kota Bharu, Malaysia," Water, vol. 13, no. 13, p. 1786, Jan. 2021, doi: 10.3390/w13131786.

[3] A. Albani, M. Z. Ibrahim, and K. H. Yong, "Influence of the ENSO and Monsoonal Season on Long-Term Wind Energy Potential in Malaysia," Energies, vol. 11, no. 11, p. 2965, Nov. 2018, doi: 10.3390/en11112965.

[4] "(PDF) Review of the North-East Monsoon 2020/2021 in Malaysia," ResearchGate. Accessed: Nov. 13, 2025. [Online]. Available: https://www.researchgate.net/publication/387669899_Review_of_the_North-East_Monsoon_20202021_in_Malaysia

[5] K. A. Baharuddin et al., "The Record-Setting Flood of 2014 in Kelantan: Challenges and Recommendations from an Emergency Medicine Perspective and Why the Medical Campus Stood Dry," Malays. J. Med. Sci. MJMS, vol. 22, pp. 1–7, May 2015.

[6] "2022/26 'Malaysia's Floods of December 2021: Can Future Disasters be Avoided?' by Serina Rahman." Accessed: Nov. 13, 2025. [Online]. Available: https://www.iseas.edu.sg/articles-commentaries/iseas-perspective/2022-26-malaysias-floods-of-december-2021-can-future-disasters-be-avoided-by-serina-rahman/

[7] "Malaysia Floods 2022, DREF Application (MDRMY009) - Malaysia | ReliefWeb." Accessed: Nov. 13, 2025. [Online]. Available: https://reliefweb.int/report/malaysia/malaysia-floods-2022-dref-application-mdrmy009

[8] N. Alias, H. mohamad, W. Y. Chin, and Z. Yusop, "Rainfall analysis of the Kelantan big yellow flood 2014," J. Teknol., vol. 78, pp. 83–90, May 2016, doi: 10.11113/jt.v78.9701.

[9] "Communication, Education and Public Awareness Program (CEPA) in Flood Forecasting and Warning Program (PRAB) | Journal of Water Resources Management." Accessed: Nov. 13, 2025. [Online]. Available: https://journal.water.gov.my/index.php/jowrm/article/view/6

[10] B. Ghimire, "Application of ARIMA Model for River Discharges Analysis," J. Nepal Phys. Soc., vol. 4, p. 27, May 2017, doi: 10.3126/jnphyssoc.v4i1.17333.

[11] [S. Gegenleithner, M. Pirker, C. Dorfmann, R. Kern, and J. Schneider, "Long short-term memory networks for enhancing real-time flood forecasts: a case study for an underperforming hydrologic model," Hydrol. Earth Syst. Sci., vol. 29, pp. 1939–1962, Apr. 2025, doi: 10.5194/hess-29-1939-2025.

[12] M. Aliye, A. Aga, T. Danbara, and P. Aga, "Evaluating the Performance of HEC-HMS and SWAT Hydrological Models in Simulating the Rainfall-Runoff Process for Data Scarce Region of Ethiopian Rift Valley Lake Basin," Open J. Mod. Hydrol., vol. 10, pp. 105–122, Oct. 2020, doi: 10.4236/ojmh.2020.104007.

[13] N. W. Chaney, J. D. Herman, P. M. Reed, and E. F. Wood, "Flood and drought hydrologic monitoring: the role of model parameter uncertainty," Hydrol. Earth Syst. Sci., vol. 19, no. 7, pp. 3239–3251, July 2015, doi: 10.5194/hess-19-3239-2015.

[14] "(PDF) Efficacy of Feedforward and LSTM Neural Networks at Predicting and Gap Filling Coastal Ocean Timeseries: Oxygen, Nutrients, and Temperature." Accessed: Nov. 13, 2025. [Online]. Available: https://www.researchgate.net/publication/351284531_Efficacy_of_Feedforward_and_LSTM_Neural_Networks_at_Predicting_and_Gap_Filling_Coastal_Ocean_Timeseries_Oxygen_Nutrients_and_Temperature

[15] "A Feature-Weighted SVR Method Based on Kernel Space Feature." Accessed: Nov. 13, 2025. [Online]. Available: https://www.mdpi.com/1999-4893/11/5/62

[16] A. Chernodub and D. Nowicki, "Sampling-based Gradient Regularization for Capturing Long-Term Dependencies in Recurrent Neural Networks," arXiv.org. Accessed: Nov. 14, 2025. [Online]. Available: https://arxiv.org/abs/1606.07767v3

[17] L. A. De la Fuente, M. R. Ehsani, H. V. Gupta, and L. E. Condon, "Toward interpretable LSTM-based modeling of hydrological systems," Hydrol. Earth Syst. Sci., vol. 28, no. 4, pp. 945–971, Feb. 2024, doi: 10.5194/hess-28-945-2024.

[18] S. Siami-Namini, N. Tavakoli, and A. Siami Namin, "A Comparison of ARIMA and LSTM in Forecasting Time Series," in 2018 17th IEEE International Conference on Machine Learning and Applications (ICMLA), Dec. 2018, pp. 1394–1401. doi: 10.1109/ICMLA.2018.00227.

[19] F. Kratzert, D. Klotz, C. Brenner, K. Schulz, and M. Herrnegger, "Rainfall–runoff modelling using Long Short-Term Memory (LSTM) networks," Hydrol. Earth Syst. Sci., vol. 22, no. 11, pp. 6005–6022, Nov. 2018, doi: 10.5194/hess-22-6005-2018.

[20] F. Kratzert, D. Klotz, G. Shalev, G. Klambauer, S. Hochreiter, and G. Nearing, "Towards learning universal, regional, and local hydrological behaviors via machine learning applied to large-sample datasets," Hydrol. Earth Syst. Sci., vol. 23, no. 12, pp. 5089–5110, Dec. 2019, doi: 10.5194/hess-23-5089-2019.

[21] M. T. Hagan and M. B. Menhaj, "Training feedforward networks with the Marquardt algorithm," IEEE Trans. Neural Netw., vol. 5, no. 6, pp. 989–993, Nov. 1994, doi: 10.1109/72.329697.

[22] G. P. Zhang, "Time series forecasting using a hybrid ARIMA and neural network model," Neurocomputing, vol. 50, pp. 159–175, Jan. 2003, doi: 10.1016/S0925-2312(01)00702-0.

[23] G. Hayder, M. Iwan Solihin, and M. R. N. Najwa, "Multi-step-ahead prediction of river flow using NARX neural networks and deep learning LSTM," H2Open J., vol. 5, no. 1, pp. 43–60, Jan. 2022, doi: 10.2166/h2oj.2022.134.

[24] S. L.m, B. H, Y. M.r, bin H. M.h, binti M. D. S.a, and S. T.a./L, "Hydrological Analysis for Flood Forecasting at Sg Golok River Basin Malaysia," 2022, doi: 10.1007/978-981-16-7397-9_27.

Polarimetric Imaging and Computational Techniques for Identification of Malignant Lesions

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***Abstract*—According to the International Agency for Research on Cancer, cervical cancer is a major cause of death among Moroccan women, with high incidence and mortality rates. Early detection remains essential to increasing patients' chances of recovery. Our study combines polarized light imaging, digital image correlation (DIC), Gray-Level Co-occurrence Matrix (GLCM) texture analysis, and fractal-based local standard deviation mapping to identify microstructural alterations in cervical tissue. Smear and biopsy samples were collected and anonymized in hospitals in Agadir, Morocco. Our goal is to develop an optical system based on the interaction between polarized light and tissue, as well as a complementary computational framework to distinguish between different types of healthy, precancerous, and cancerous tissue. DIC revealed heterogeneous deformation patterns in cancerous regions, fractal analysis highlighted increased structural complexity, and GLCM features showed higher contrast and entropy in malignant samples. This pilot study introduces a novel approach combining polarimetric imaging and computational analysis, applied to cervical tissue samples from Moroccan women in Africa. Despite the small size of the ex vivo dataset, the results obtained encourage the conduct of larger-scale prospective and in vivo studies.**

***Keywords*—Polarized light; digital image correlation; Gray-Level Co-occurrence Matrix; fractal; cervix; cancer**

I. Introduction

Cervical cancer remains a major global public health concern, particularly in low- and middle-income countries (LMICs), where it represents one of the leading causes of cancer-related mortality among women. According to recent estimates from the World Health Organization and GLOBOCAN, more than 85% of cervical cancer deaths occur in these regions, largely due to late diagnosis and limited access to effective screening and early detection programs [1]. In North Africa, and specifically in Morocco, cervical cancer is among the most common gynecological malignancies, with incidence and mortality rates remaining high despite ongoing prevention efforts [2]. The cervical samples analyzed in the present study were obtained exclusively from Moroccan women, providing direct clinical relevance to this regional context.

In this context, one of the major challenges is the lack of screening tools that are simultaneously reliable, objective, cost-effective, and adaptable to constrained healthcare infrastructures. Conventional diagnostic approaches often rely on subjective visual assessment, requiring specialized expertise and equipment. This limits their scalability in environments with limited resources. In this regard, optical imaging techniques based on light polarization analysis offer a promising and innovative alternative. Polarimetric imaging is intrinsically sensitive to microstructural and organizational changes in biological tissues associated with early stages of carcinogenesis. Polarization-based methods can reveal subtle pathological alterations that are undetectable using conventional imaging techniques. This is achieved by examining the properties of anisotropy, scattering and structural organization.

In this work, we propose a computational framework based on polarimetric imaging for the analysis of cervical tissue samples, aiming to address current limitations to cervix screening. The proposed framework is well-suited for low-resource settings by combining availability, affordability and sensitivity to early microstructural alterations. The methodology integrates polarization analysis with advanced image processing and quantitative analysis methods, including digital image correlation (DIC), Gray-Level Co-occurrence Matrix (GLCM) analysis, and fractal analysis. The investigation of tissue architecture and organization enables discrimination between malignant and healthy regions, while texture analysis and structural complexity metrics provide quantitative biomarkers of early pathological alterations.

The main potential contributions of this study are threefold. First, the development of a polarimetric imaging framework specifically tailored for the characterization of cervical tissue in resource-limited settings. Second, the integration of polarization-derived parameters with multi-scale computational descriptors (DIC, GLCM, and fractal features) in order to achieve objective and quantitative tissue discrimination. Third, the experimental validation of the proposed approach using real ex vivo cervical tissue samples from anonymized Moroccan patients demonstrates its ability to reliably distinguish healthy tissue from malignant regions.

Building upon this framework, the present study first reviews related work on optical and polarization-based imaging techniques applied to cervical cancer detection. It then describes the experimental setup and materials, emphasizing a non-invasive, low-cost, and non-harmful imaging modality that

operates within the visible light spectrum and requires no contrast agents, in contrast to many conventional imaging techniques. The use of ex vivo cervical tissue samples is subsequently detailed, followed by a comprehensive presentation of the proposed computational methodology. The results are presented and discussed to demonstrate the robustness and effectiveness of the proposed framework to reliably distinguish healthy cervical tissue from malignant regions, highlighting its potential clinical relevance for early cancer detection and its contribution to reducing disparities in LMICs. Finally, the study ends with a conclusion.

II. Related Work

Polarization is a fundamental property of light and a powerful detection tool applied in many fields, including biomedical diagnosis. According to the literature, several works have been realized on the interaction between polarized light and tissue [3], [4], [5], [6]. In biomedical imaging, unlike non-polarized light, linear polarization is particularly useful for detecting early pathological changes due to the defined orientation of the electric field, which enhances sensitivity to tissue alteration and microstructural organization [7]. Different polarization measurement types have been used for cancer detection. For instance, in 2021, researchers at Tokyo Institute of Technology experimentally demonstrated a novel cancer diagnosis technique based on the scattering of circularly polarized light, which computational studies revealed can detect the progression of precancerous lesions and early cancer [8], [9].

In diagnostic applications, the interaction of polarized light with biological tissues provides valuable structural information, enhancing contrast, characterizing tissue, reducing surface reflections, and revealing subtle alterations for earlier and more accurate detection. Elliptically polarized light has demonstrated significant potential, offering complementary structural and compositional insights, while linearly polarized light [10] remains essential for reliable contrast enhancement and detailed assessment of tissue organization, and should not be overlooked.

Building on the ability of linearly polarized light to enhance contrast and reveal structural features, Orthogonal State Contrast (OSC) has emerged as a promising technique in biological imaging, and more broadly as a robust metric in laser-illuminated active polarimetric systems. Used as a practical surrogate for the degree of polarization, OSC enables efficient discrimination of targets with distinct polarimetric signatures, notably in remote sensing applications [11], [12].

Recent research has focused on refining Orthogonal State Contrast techniques to achieve higher precision in biological tissue analysis. For example, Pierangelo et al. analyzed cancerous and healthy human colon samples ex vivo using a multispectral Mueller polarimeter in the visible range (500–700 nm). Their study demonstrated that depolarization measurements under linearly polarized light depend on tumor presence, type, thickness, and tissue composition, allowing clear differentiation between healthy tissue, various tumor subtypes, and post-radiochemotherapy tissue. These results highlight the potential of polarization-based imaging for precise tissue characterization and rapid cancer staging [13].

Beyond colon studies, several investigations have applied Orthogonal State Contrast (OSC) and Mueller Matrix (MM) polarimetry to cervical tissue analysis. The cervix consists of squamous epithelium and connective tissue, with collagen fibers providing structural strength. Pathologies such as cervical intraepithelial neoplasia (CIN), cancer, pregnancy, and spontaneous preterm birth remodel both epithelial and connective layers. OSC and MM polarimetry, using polarized light, enable quantification of these changes, with parameters like depolarization and birefringence providing contrast linked to tissue organization and pathology. Advances in OSC-based imaging, including specialized colposcopes, support detailed, non-invasive assessment of cervical alterations, highlighting the potential of polarization techniques for early detection and clinical diagnostics [14].

Leveraging the benefits of polarized light for enhancing tissue contrast and revealing structural features, fractal analysis has emerged as a powerful tool for cancer detection. By quantifying the complexity of tissue architecture, fractal dimension measures can distinguish malignant regions from healthy tissues, capturing subtle morphological alterations that are often invisible to conventional imaging [15]. Complementing this, Gray-Level Co-occurrence Matrix (GLCM) analysis provides quantitative information about tissue texture, such as contrast, correlation, and homogeneity, which has been successfully applied to differentiate cancerous from normal cells in various tissue types [16], [17]. The combination of polarized light imaging and computational analysis offers a reliable and objective approach for early malignancy detection, highlighting its promise in non-invasive cancer diagnostics.

Motivated by previous research, this work employs polarized light imaging combined with computational techniques to analyze cervical tissue samples. The next section details the experimental approach, covering sample handling, imaging procedures, and computational analysis for tissue classification.

III. Materials and Methods

A. Instruments and Measurement Protocol

We studied the interaction of histological slides of the cervix with polarized light on a microscopic level. This approach, known as polarization microscopy, can reveal detailed structural information about tissue. The optical setup employs a commercially available polarized light microscope (OPTIKA, Italy) to enable detailed observation and analysis of microscopic structures, revealing intricate details and providing insights across various scientific disciplines. For polarized light observations, a polarizer and an analyzer were used, and for image acquisition, a charge-coupled device (CCD) camera (OPTIKA C-B18+, SN 621237) was employed.

1) Equipment and imaging setup: The biological samples must be prepared in a specific manner to minimize diffusion and irrelevant absorption, and to avoid any optical aberrations that could introduce intensity variations or polarization-related artifacts. The microscope is directly connected to a dedicated computer for real-time image acquisition and data analysis.

The CCD camera is mounted via a C-mount adapter on the trinocular port; it captures images and transmits them to the computer for processing in MATLAB.

2) Camera specifications: The imaging system was equipped with a high-resolution OPTIKA CCD camera (SN 621237) to capture detailed microstructural features. The camera sensor provides a resolution of 4912 × 3684 pixels (18 MP) with an Aptina color CMOS sensor of 1/2.3″ and a pixel size of 1.25 µm, allowing for high-detail imaging. The frame rate reaches up to 5.6 fps at full resolution and up to 32.2 fps at 1228 × 922 resolution, facilitating rapid positioning of samples. The bit depth is configurable from 1 to 24 bits, with 8–12-bit A/D conversion ensuring accurate color fidelity. An integrated IR-CUT filter (380–650 nm) minimizes infrared interference, and the camera is compatible with Windows, macOS, and Linux via ProView and Liteview software.

3) Image acquisition under parallel polarized light: The experimental procedure began with sample preparation and ROI selection, where thin sections were carefully placed on the mechanical stage, and regions of interest (ROIs) were visually identified through the eyepiece. For polarization measurements, incident light passed sequentially through a linear polarizer, the sample, and a linear analyzer aligned parallel to the polarizer, allowing the acquisition of intensity images under parallel-polarized conditions. Image capture was performed using an OPTIKA camera controlled via ProView, with exposure and gain adjusted to prevent saturation. Finally, the acquired images were processed in MATLAB to extract quantitative information about local structural variations. Maps of intensity changes were generated, highlighting subtle alterations in tissue organization and optical properties, thereby enabling a detailed assessment of microstructural features and their spatial distribution.

4) Methodological overview: The optical behavior of a sample under complete polarization can be described by a 4×4 Mueller matrix, requiring 16 independent intensity measurements for fully characterizing diattenuation, retardance, and depolarization [18]. In this study, the measurements are limited to a linear polarization (parallel polarizer/analyzer). To simplify the analysis, we exclude from consideration circular or depolarizing effects to reduce acquisition time and computational complexity. Such an approach has been proven in prior studies using reduced 3×3 Mueller-matrix decomposition for quantitative tissue polarimetry [19], [20].

B. Sample Preparation

Histological samples are prepared through standardized and sequential procedures to preserve tissue architecture and enable microscopic examination. The typical steps include tissue collection, fixation, dehydration, clearing, embedding, sectioning, mounting, staining, cover slipping and final microscopic evaluation. These histological procedures ensure good-quality sections suitable for reliable optical analysis [21].

The actual specimens used in this study were obtained from the Pathological Anatomy Laboratory of the Faculty of Medicine and Pharmacy of Agadir. Fig. 1 presents representative cervical tissue sections: infiltrating tumor (left, number 559) and healthy tissue (right, number 332). The black rectangles indicate the regions of interest (ROIs) selected for quantitative analysis under polarized light.

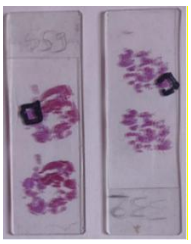


Fig. 1. Cervical tissue samples: cancerous specimen (left) and healthy specimen (right). Black boxes indicate the ROIs selected for analysis.

Fig. 2 establishes the link between the preparation process and the anonymized samples used in our study, highlighting the importance of adequate tissue preparation for polarimetric imaging analysis.

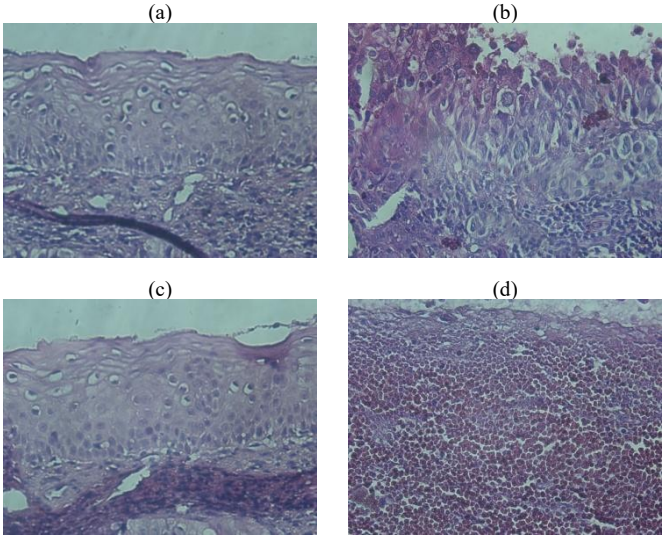


Fig. 2. Epithelial region of cervical tissue under 400× magnification with parallel polarized light. (a, c) healthy tissue and (b, d) invasive cancer.

C. Orthogonal State Contrast and Stokes-Mueller Formalism

Since the early 1990s, the polarimetry technique has been applied to study biological tissues, initially in dermatology. In 1991, R. Anderson introduced a pioneering approach using polarizers and filters to eliminate surface specular reflections during the imaging of human skin, thereby improving lesion visibility [22]. Further developments polished this strategy by using linearly polarized light to illuminate damaged tissue, and analyzing the returned light in the orthogonal polarization state [23].

In 2002, the configuration proposed by S. L. Jacques et al. improved the imaging of pathological skin regions. Their system included a two-state analyzer alternately aligned parallel or perpendicular to the incident polarization. This property made it possible to extract pixel-by-pixel orientation-dependent intensity maps [24]. Similar approaches based on two orthogonal linear polarization states produced images

comparable to linear polarization degree maps, enabling rapid contrast enhancement in low-scattering tissues [25].

In this work, the adoption of polarimetric imaging was motivated by the robustness of the Stokes-Mueller formalism [26], [27], [28] for two main reasons:

- It relies entirely on optical intensities, as these can be measured directly in experiments.
- It has a natural aptitude for partially polarized light, a situation that occurs frequently due to multiple scattering and structural heterogeneities in biological tissues.

The polarization state of light is represented by a Stokes vector:

$$S= [S_0, S_1, S_2, S_3]^T$$

where, S_0 represents the total intensity, S_1 and S_2 describe the linear polarization components, and S_3 corresponds to the circular polarization component. For analysis purposes, the Stokes vector is often normalized by its total intensity:

$$\left[\frac{S_0}{S_0}, \frac{S_1}{S_0}, \frac{S_2}{S_0}, \frac{S_3}{S_0}\right]^T = [1, S_1, S_2, S_3]^T \quad (1)$$

The Mueller matrix, M, characterizes the complete polarimetric response of a sample by mapping the input Stokes vector to the output vector. In normalized form, its elements are expressed as:

$$M = \begin{bmatrix} 1 & m12 & m13 & m14 \\ m21 & m22 & m23 & m24 \\ m31 & m32 & m33 & m34 \\ m41 & m42 & m43 & m44 \end{bmatrix} \quad (2)$$

where, mij = Mij / M11.

The element M_{11} quantifies attenuation for an unpolarized incident beam. For completely unpolarized illumination ($S_1 = S_2 = S_3 = 0$), the outgoing intensity reduces to:

$$S'_0 = M11\ S_0$$

This formalism provides a comprehensive description of the interaction between light and biological tissues, which are heterogeneous and highly scattering media. This is allowing each matrix element to be interpreted in terms of diattenuation, retardance, depolarization and structural anisotropy.

Based on this approach, polarimetric imaging has become a highly effective research tool for analyzing the microstructural properties of tissues. The combination of its major advantages makes it particularly relevant, such as improved contrast, high sensitivity to anisotropies, and its non-invasive nature, which are essential qualities for the early detection of tissue abnormalities. Moreover, recent studies have confirmed the utility of Mueller polarimetry in the detection of cancer in cervical tissue specimens, whether in the laboratory (ex vivo) or directly on the patient (in vivo) [29], [30], [31], [32].

In this study, the configuration chosen is simple and accessible, with linear polarimetry using a simple parallel[1] polarizer-analyzer setup. Without the need for more complex circular and elliptical analysis, this approach is more than sufficient for us to observe the essential effects related to polarization. Our method is based on combining the simplified optical system with state-of-the-art computer image processing. This allows us to extract markers that provide information on the architecture, texture, and complexity of the structure. These multimodal optical and image descriptors significantly improve the sensitivity and objectivity of our diagnosis, as they are closely linked to the microscopic remodeling typical of cancer development.

IV. Results

A. Digital Image Correlation

Digital Image Correlation (DIC) is an optical technique used to measure the full-field deformation, and is used in several applications (biological tissues, metals…). It is a powerful method because it can detect the most subtle structural changes and deformation patterns within images. Unlike traditional pixel-based comparisons, digital image correlation tracks local texture variations to measure displacement with high spatial accuracy, even at the microscopic scale. This is particularly useful in biomedical imaging, where subtle mechanical differences between healthy and abnormal tissues can be identified at an early stage by analyzing their deformation [33], [34], [35].

Concerning DIC analysis, two strictly identical regions of interest (ROIs), one healthy and one cancerous, were selected. Fig. 3 shows the statistical distribution of strain magnitudes, established by taking the reference ROI as the healthy sample, while the cancerous sample was analyzed using the same ROI dimensions. The histogram is clearly skewed to the left. Most of the points are concentrated around high deformation values (around 8–9 on the x-axis). In addition, the histogram exhibits a very sharp peak with a frequency close to 3.5×10^4 for a deformation magnitude of 8.5 to 9. This peak highlights a dominant deformability in the analyzed region, revealing mechanically weakened and highly altered tissue, indicating the presence of anomalous areas. Further insight is provided by Fig. 4, which illustrates the microscopic displacement vectors, revealing spatial variations in tissue deformation and highlighting underlying tissue heterogeneity.

Our future work will focus on analyzing tissue samples from the same patient over an extended period of time, maintaining a consistent ROI in order to track the chronological evolution of local deformations. Although this approach is technically demanding, establishing collaborations with hospitals and obtaining patient consent would enable longitudinal studies to be conducted, particularly in the context of cervical cancer. Such datasets would facilitate a more accurate characterization of the mechanical changes that occur during the progression of the disease.

[1] For a first-stage study of cervical cancer, the parallel-polarizer configuration is sufficient because it captures co-polarized light that highlights differences in tissue scattering and structure between normal and malignant regions, providing clear contrast with simple and rapid acquisition.

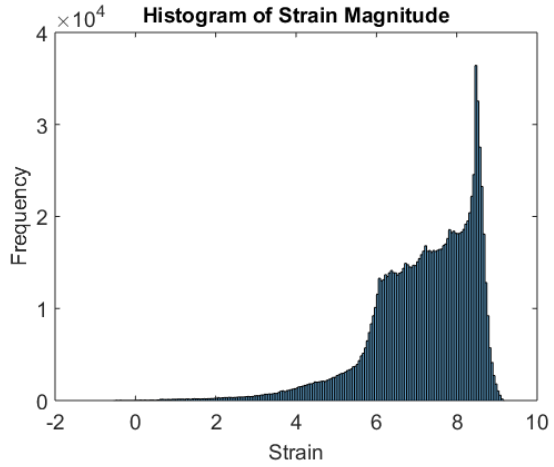


Fig. 3. Histogram of local strain magnitude in cervical epithelium via DIC.

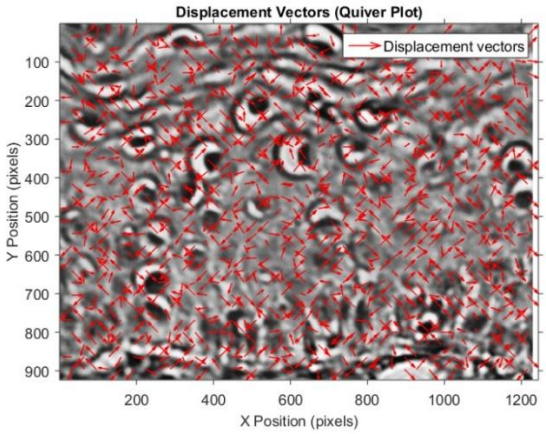


Fig. 4. Microscopic displacement vectors highlighting tissue heterogeneity.

The interpretation of these findings will be presented in the next section. Following the biomechanical insights from DIC, fractal analysis was applied to capture variations in tissue architectural complexity, providing complementary information on microstructural heterogeneity.

B. Fractal Dimension Measurement

Fractal analysis quantifies the degree of complexity and self-similarity of biological tissues, thus capturing tissue heterogeneity at different scales. In biomedical research, this technique is used to evaluate tumor morphology, epithelial organization and microvascular networks, providing information about pathological alterations that are difficult to detect using standard imaging techniques [36], [37], [38], [39], [40].

For this analysis, we applied the Fractal Map Analysis (FMA) approach on microscopic images. To achieve this, we used the local standard deviation (StdDev) to evaluate the structural complexity, because it is highly sensitive to spatial variations and irregularities. The images were first pre-processed (median filtering, contrast enhancement, and slight Gaussian smoothing). We then computed a high-resolution local standard deviation map to quantify spatial heterogeneity. The distribution was analyzed using histograms and statistical markers (mean, median, maximum, 90th percentile) to characterize tissue complexity, differentiating healthy from cancerous regions.

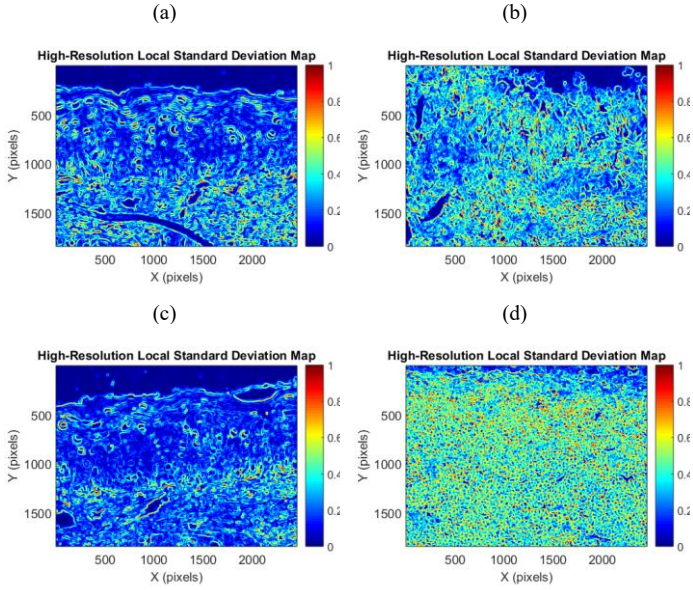


Fig. 5. Quantitative standard deviation maps of epithelial tissue: (a, c) healthy regions and (b, d) cancerous regions.

Fig. 5 illustrates the results of applying the fractal complexity map to the samples under parallel-polarized light, while Fig. 6 shows the corresponding histograms for each sample. In this study, fractal analysis was performed using the standard deviation of the complexity map to quantify tissue heterogeneity. While this approach effectively highlights differences between healthy and cancerous tissues, other fractal analysis methods, such as the box-counting method, could be explored in future work to provide complementary insights and potentially enhance diagnostic accuracy.

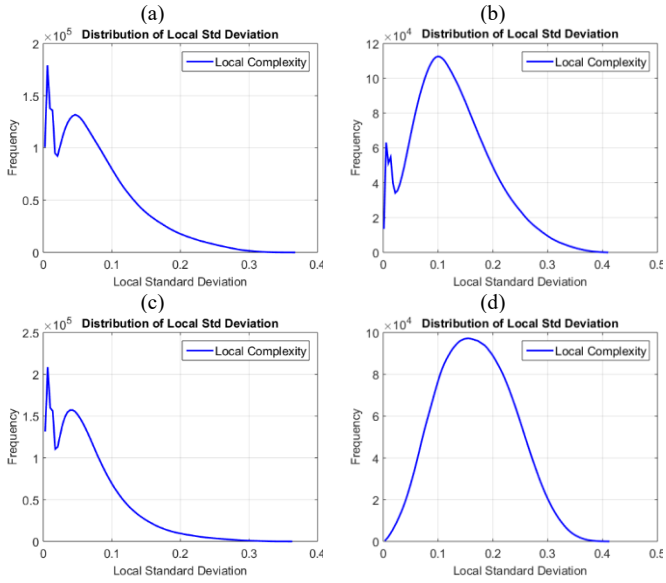


Fig. 6. Distribution of tissue complexity via fractal-based standard deviation. (a, c) healthy tissue and (b, d) invasive cancer.

Fractal analysis revealed marked differences in structural complexity between healthy and cancerous tissues. To further characterize local variations, GLCM analysis was applied, capturing variations in texture such as contrast, correlation, energy, and entropy, which provide additional quantitative indicators to distinguish healthy from malignant regions.

C. Gray-Level Co-occurrence Matrix Texture Features

Texture analysis is essential for characterizing tissue microstructure. The GLCM quantifies spatial relationships between pixel intensities, providing quantitative markers to distinguish healthy from pathological regions.

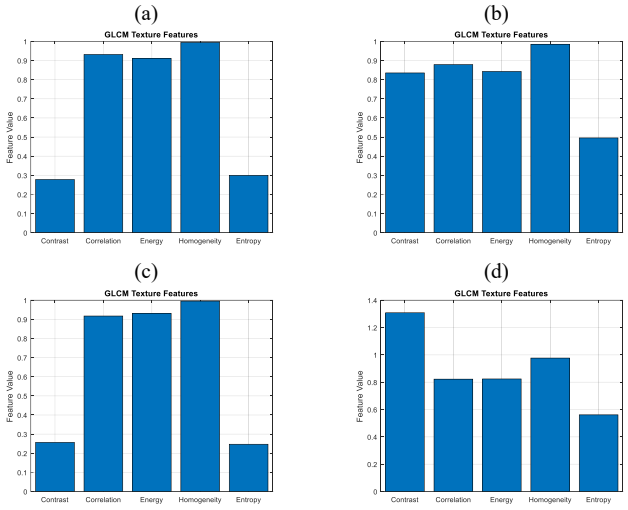


Fig. 7. GLCM-derived correlation, energy, homogeneity, entropy, and contrast maps: (a, c) healthy samples and (b, d) malignant samples.

In biomedical imaging, GLCM is widely used to characterize the microstructure of biological tissues (such as the cervix), since subtle differences in cell arrangement, nuclear chromatin, or extracellular matrix produce measurable variations in texture [41], [42], [43], [44]. In Fig. 7, the metrics are displayed in the following order: contrast, correlation, energy, homogeneity, and entropy, with each represented by a separate bar corresponding to this sequence, providing a clear and quantitative comparison of tissue texture.

The GLCM analysis presented in Fig. 7 highlights clear differences in texture between healthy and cancerous tissue samples. For the two healthy samples, correlation, homogeneity, and energy are all very high (≈0.92–0.99), while contrast and entropy are low (≈0.25–0.30), indicating a highly uniform and regular microstructure with minimal local intensity variation, typical of normal epithelial tissue.

In contrast, the cancerous samples exhibit markedly increased contrast (0.83–1.31) and entropy (0.50–0.56), reflecting greater heterogeneity and structural disorder in the tissue. Correlation, energy, and homogeneity are reduced compared to healthy tissue, indicating that pixel intensities are less spatially coherent and more irregular, potentially consistent with the disrupted cellular architecture found in malignant epithelium. Notably, sample “d” shows the highest contrast and entropy, suggesting the most pronounced microstructural heterogeneity among the cancerous tissues analyzed.

TABLE I. GLCM TEXTURE: HEALTHY VS. CANCEROUS.

GLCM texture features	Healthy sample "a"	Healthy sample "c"	Cancerous sample "b"	Cancerous sample "d"
Contrast	0.2780	0.2568	0.8351	1.3082
Correlation	0.9316	0.9173	0.8785	0.8223
Energy	0.9115	0.9314	0.8429	0.8238
Entropy	0.3002	0.2471	0.4955	0.5610
Homogeneity	0.9950	0.9954	0.9851	0.9766

Overall, these results, as shown in Table I, confirm that GLCM-derived texture features effectively capture the increased randomness and decreased uniformity associated with pathological epithelial tissue, making them valuable markers for distinguishing healthy from cancerous regions.

V. DISCUSSION

A. Digital Image Correlation

As shown in Fig. 3, the strain-magnitude histogram provides a statistical view of local deformation distribution within the ROI. Each DIC block contributes a displacement magnitude $\left(U_x^2 + U_y^2\right)^{0.5}$, and these values are grouped into bins to represent their frequency. The presence of higher frequencies at large strain values indicates that a significant portion of the ROI is undergoing solid local deformation. As the results show, this distribution exhibits accentuated heterogeneity, indicating irregularity and weakening of the tissue structure, which may reveal abnormal behavior. In biomedical imaging, such a distribution is generally associated with pathological regions where altered microarchitecture causes increased and widespread deformation.

Fig. 4 displays the filtered reference ROI (healthy region) overlaid with red displacement vectors computed by DIC. Each arrow characterizes the local motion of a small image block: its direction indicates how the tissue moved between the reference (healthy tissue) and deformed states (invasive tumor), and its length reflects the displacement magnitude. Variations in arrow orientation and magnitude provide a spatial visualization of how different regions within the tissue deform.

The heterogeneous orientations and amplitudes of the vectors reveal non-uniform deformation across the ROI. Regions with long arrows correspond to strong local displacement, while short arrows indicate nearly static areas. In our case, the displacement field shows pronounced and irregular motion, consistent with mechanically abnormal tissue. The strain indicators (mean ≈ 7.2 px, median ≈ 7.8 px, 90th percentile ≈ 8.5 px) confirm the presence of high-magnitude deformation, supporting the interpretation of increased structural heterogeneity typically associated with malignant regions.

In summary, DIC provides a rapid, non-invasive, and highly precise method for capturing local tissue deformation, generating detailed displacement and stress maps that reveal

mechanical heterogeneity. Its primary diagnostic value lies in detecting subtle biomechanical abnormalities, making it a powerful tool for distinguishing between healthy and cancerous tissue. Complementing this, fractal analysis characterizes the architectural complexity and heterogeneity of tissue structures, offering unique insights into morphological irregularities. Together, these modalities provide distinct and complementary diagnostic information, each contributing a unique perspective to tissue characterization.

B. Fractal Dimension Measurement

Fig. 5 presents the spatial standard deviation maps, which reveal clear differences in tissue heterogeneity between healthy and cancerous samples, particularly within the epithelial region. Healthy tissues show high uniformity, with most values clustered around low standard deviations (mean ≈ 0.07–0.08, 90th percentile ≈ 0.14–0.17), corresponding to the predominantly blue areas on the color map, indicating homogeneous microstructure. In contrast, cancerous tissues exhibit markedly higher and more variable local standard deviations (mean ≈ 0.13–0.17, 90th percentile ≈ 0.23–0.26), with color maps showing scattered regions of blue, green, yellow, and orange. This reflects increased structural heterogeneity and irregularity in the epithelium, consistent with disrupted cellular architecture. The cancerous sample “d” illustrates the most pronounced variability and the highest local complexity.

Fig. 6 presents the distribution of local Std Dev for 4 specimens of cervical epithelium (two healthy, and two cancerous). This measure is used to quantify the structural complexity of tissue using FMA. As illustrated in Fig. 6, the histograms of the local standard deviation quantitatively confirm the observations made on the complexity maps. The healthy samples ("a" and "c") show narrow distributions, strongly skewed toward low values (≈0.07–0.08 mean), reflecting a uniform and consistent tissue structure. The cancer samples ("b" and "d"), on the other hand, show wider distributions with higher median and 90th percentile values (≈0.13–0.17 mean, 0.23–0.26 90th percentile), indicating greater local variability and increased structural complexity. These histogram profiles support the idea that malignant epithelial regions are significantly more heterogeneous and disorganized than healthy tissue.

In conclusion, local standard deviation analysis is an effective method for quantifying tissue heterogeneity. Healthy epithelium exhibits low variability and a uniform structure, while cancerous regions display higher and more dispersed local standard deviations, reflecting increased structural complexity. This method therefore provides a quantitative and sensitive measure for distinguishing healthy tissue from malignant tissue.

While fractal analysis highlights the architectural complexity of tissues, GLCM-based texture analysis quantitatively captures microstructural variations in pixel intensity. Combined with polarized light, these methods provide complementary diagnostic information: fractal analysis reveals structural heterogeneity, whereas GLCM metrics, including contrast, entropy, correlation, energy and homogeneity, objectively characterize microstructural patterns, each offering distinct insights into tissue characterization.

C. Gray-Level Co-occurrence Matrix Texture Features

Fig. 7 and Table I show that GLCM metrics effectively distinguish non-neoplastic from neoplastic tissue. Healthy samples display high correlation, homogeneity, and energy with low contrast and entropy, indicating a uniform microstructure. Conversely, cancerous tissues exhibit elevated contrast and entropy with reduced correlation and energy, reflecting structural heterogeneity and disorganization. These quantitative differences provide clear markers for differentiating normal and malignant regions.

Fig. 8 shows the entropy distribution and confirms the heterogeneity of the tissues by introducing a measure of disorder and texture complexity. When the healthy samples are considered (red and blue curves), we observe narrower distributions concentrated around low modal values (between 0.35 and 0.45), indicating low dispersion of local pixel intensities and characteristic of an organized and homogeneous tissue structure. In contrast, tumoral samples (green and magenta curves) show wider distributions, with a mode significantly shifted toward higher entropy values (up to approximately 0.65 for sample “d”). This spread and alteration indicate an overall increased microstructural disorder and local complexity. This entropic marker thus reinforces the conclusions drawn from the fractal analysis, as entropy is strongly correlated with fractal dimension.

Entropy allows for highly sensitive quantitative measurement of pathological conditions. Despite a slight overlap between the distributions of samples a and b (healthy and cancerous, respectively), analysis of the statistical parameters of the distribution makes it possible to quantify the degree of tissue disorder and effectively use this metric as a multimodal descriptor for classification.

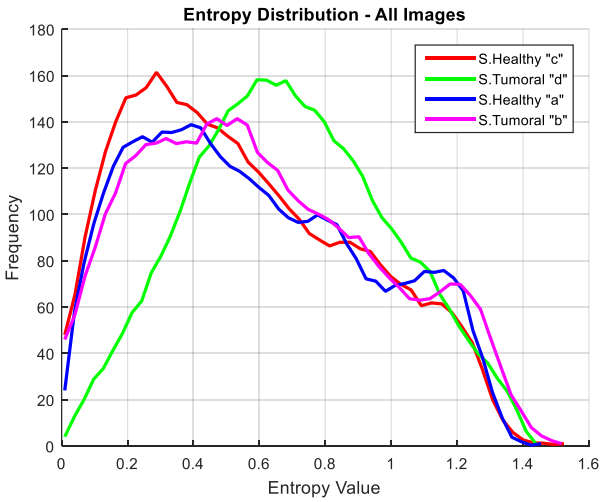


Fig. 8. Histogram of GLCM entropy in four cervical tissue samples.

Collectively, the GLCM analysis clearly differentiates healthy from tumorous epithelial tissue. Healthy samples exhibit high correlation, homogeneity, and energy with low contrast and entropy, indicating a uniform and regular

microstructure. Cancerous samples show markedly increased contrast and entropy alongside reduced correlation, energy, and homogeneity, reflecting greater structural heterogeneity and disorganization. The progressive increase in entropy from healthy to cancerous samples demonstrates the sensitivity of GLCM-derived features in detecting gradual changes in tissue architecture associated with malignancy.

Although the ex vivo dataset in the present study was limited in size, the results are highly promising and highlight the need for larger-scale prospective and in vivo investigations. Addressing the current limitations would allow for more robust validation of the findings, a comprehensive assessment of inter-patient variability, and a deeper understanding of the feasibility and translational potential of these imaging techniques in clinical practice. Future studies will focus on expanding the sample size, incorporating diverse patient populations, and optimizing the methodologies for in vivo application. Such efforts are critical to bridge the gap between experimental observations and practical diagnostic implementation, ultimately facilitating the translation of these techniques into routine clinical care.

To summarize, polarized light imaging was combined with computational techniques, including DIC, GLCM, and fractal analysis, to characterize cervical tissue microstructure. The key findings from these complementary approaches are outlined in Table II, providing an integrated overview of the most relevant imaging indicators for distinguishing healthy from malignant tissue.

TABLE II. SUMMARY OF KEY IMAGING INDICATORS

Indicators / Metrics	DIC (Displacement Magnitude)	Fractal (StdDev)	GLCM Metrics
Mean	7.2px →confirm the presence of high-magnitude deformation.	0.07–0.08 (Healthy). 0.13–0.17 (Cancerous).	-Contrast: 0.25–0.30 (Healthy), 0.83–1.31 (Cancerous). -Entropy: 0.25–0.30 (Healthy), 0.50–0.56 (Cancerous).
Median/90th Percentile	Median ≈ 7.8 px 90th ≈ 8.5 px	90th: 0.14-0.17 (Healthy). 90th: 0.23–0.26 (Cancerous).	Energy: 0.91–0.93 (Healthy). 0.82–0.87 (Cancerous).
Analysis	High strain → mechanically altered tissue	Low StdDev →uniform (healthy). High StdDev →Irregular (cancer).	Healthy tissue → uniform, low contrast / entropy. Cancerous tissue →disordered, high contrast / entropy.

VI. CONCLUSION

Cervical cancer remains a leading cause of cancer-related mortality among women worldwide, particularly in low Human Development Index countries. Despite advances in screening and treatment, early detection is critical to improving outcomes. Polarimetric imaging with digital analysis methods has emerged as a promising tool for enhancing diagnostic accuracy by characterizing structural properties of biological tissues. This study investigates early diagnosis of cervical cancer in Moroccan women, using computational polarimetric imaging to differentiate healthy from malignant tissue. Combined analyses with DIC, GLCM texture, and fractal-based local standard deviation consistently reveal clear distinctions; healthy tissue shows low texture entropy, high correlation and homogeneity, and minimal local variability, whereas cancerous tissue exhibits random, multidirectional deformation patterns, increased contrast and entropy, reduced correlation and homogeneity, and higher local variability. These quantitative imaging biomarkers provide a robust framework for detecting and characterizing malignant changes. Building on these findings, future work will focus on validating the diagnostic performance and clinical applicability of this approach using full Mueller Matrix measurements on intact cervical specimens from a diverse patient cohort. Key challenges for clinical translation, including in vivo acquisition where motion artifacts and tissue accessibility must be managed, patient variability in anatomy and tissue properties, and instrumentation costs related to complex polarimetric setups, will be addressed. In addition, machine learning classifiers, such as support vector machines and convolutional neural networks, will be explored for multimodal feature fusion to enhance diagnostic accuracy and enable robust, automated tissue classification.

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AI USE STATEMENT

Generative AI was used only for language editing. All ideas, analyses, and conclusions were produced and verified by the authors.

REFERENCES

[1] F. Bray et al., « Global cancer statistics 2022: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries », CA. Cancer J. Clin., vol. 74, no 3, p. 229-263, 2024, doi: 10.3322/caac.21834.

[2] M. Allali et al., « Cervical cancer in Morocco: a literature review on risk factors, prevalence, and healthcare challenges », Pan Afr. Med. J., vol. 50, p. 11, jan. 2025, doi: 10.11604/pamj.2025.50.11.43975.

[3] J. Kim, R. John, P. J. Wu, M. C. Martini, et J. T. Walsh, « In vivo characterization of human pigmented lesions by degree of linear polarization image maps using incident linearly polarized light », Lasers Surg. Med., vol. 42, no 1, p. 76-85, jan. 2010, doi: 10.1002/lsm.20866.

[4] W. Wang, L. G. Lim, S. Srivastava, J. S. B. Yan, A. Shabbir, et Q. Liu, « Roles of linear and circular polarization properties and effect of wavelength choice on differentiation between ex vivo normal and

cancerous gastric samples », J. Biomed. Opt., vol. 19, no 4, p. 046020, apr. 2014, doi: 10.1117/1.JBO.19.4.046020.

[5] S. N. Tukimin, S. B. Karman, M. Y. Ahmad, et W. S. Wan Kamarul Zaman, « Polarized Light-Based Cancer Cell Detection Techniques: A Review », IEEE Sens. J., vol. 19, no 20, p. 9010-9025, oct. 2019, doi: 10.1109/JSEN.2019.2924535.

[6] A. H. Hielscher, A. A. Eick, J. R. Mourant, J. P. Freyer, et I. J. Bigio, « Biomedical diagnostic with diffusely backscattered linearly and circularly polarized light », in Biomedical Sensing, Imaging, and Tracking Technologies II, SPIE, jun 1997, p. 298-305. doi: 10.1117/12.275538.

[7] W. Liu et al., « Effect of linearly polarized light irradiation near stellate ganglion on postoperative sleep disorders in patients undergoing modified radical mastectomy of breast cancer », Perioper. Med., vol. 14, no 1, p. 113, oct. 2025, doi: 10.1186/s13741-025-00601-0.

[8] V. Dremin et al., « Imaging of early stage breast cancer with circularly polarized light », présenté à Tissue Optics and Photonics, apr. 2020, p. 1136304. doi: 10.1117/12.2554166.

[9] N. Nishizawa, B. Al-Qadi, et T. Kuchimaru, « Angular optimization for cancer identification with circularly polarized light », J. Biophotonics, vol. 14, no 3, p. e202000380, 2021, doi: 10.1002/jbio.202000380.

[10] R. Ceolato, M. Golzio, C. Riou, X. Orlik, et N. Riviere, « Spectral degree of linear polarization of light from healthy skin and melanoma », Opt. Express, vol. 23, no 10, p. 13605-13612, may 2015, doi: 10.1364/OE.23.013605.

[11] J. Dupont, M. Boffety, et F. Goudail, « Precision of polarimetric orthogonal state contrast estimation in coherent images corrupted by speckle, Poisson, and additive noise », JOSA Vol 35 Issue 6 Pp 977-984, jun 2018, doi: 10.1364/JOSAA.35.000977.

[12] L. Rey-Barroso et al., « Polarized Multispectral Imaging for the Diagnosis of Skin Cancer », Color Imaging Conf., vol. 27, p. 381-385, oct. 2019, doi: 10.2352/issn.2169-2629.2019.27.68.

[13] A. Pierangelo et al., « Ex-vivo characterization of human colon cancer by Mueller polarimetric imaging », Opt. Express, vol. 19, no 2, p. 1582-1593, jan. 2011, doi: 10.1364/OE.19.001582.

[14] S. Khan, M. Qadir, A. Khalid, S. Ashraf, et I. Ahmad, « Characterization of cervical tissue using Mueller matrix polarimetry », Lasers Med. Sci., vol. 38, no 1, p. 46, jan. 2023, doi: 10.1007/s10103-023-03712-6.

[15] Y. Zhang, M. Chen, L. Man, G. Lin, et Y. Qian, « Study on Skin Cancer Classification Based on Image Fractal Dimension », in 2024 International Conference on Energy and Electrical Engineering (EEE), jul. 2024, p. 1-3. doi: 10.1109/EEE59956.2024.10709720.

[16] M. Mawarni, F. Utaminingrum, et W. F. Mahmudy, « The Effect of Feature Selection on Gray Level Co-Occurrence Matrix (GLCM) for the Four Breast Cancer Classifications », J. Biomim. Biomater. Biomed. Eng., vol. 55, p. 168-179, 2022, doi: 10.4028/p-09g3n8.

[17] H. H. Fauziah, D. R. Ningtias, B. Wahyudi, et J. N. Simanjuntak, « Identification of lung cancer using gray level co-occurrence matrix (GLCM) and artificial neural network with backpropagation algorithm », J. Soft Comput. Explor., vol. 6, no 1, p. 51-61, apr. 2025, doi: 10.52465/joscex.v6i1.543.

[18] E. Nabadda, M. del M. Sánchez-López, A. Vargas, A. Lizana, J. Campos, et I. Moreno, « Mueller matrix imaging polarimeter with polarization camera self-calibration applied to structured light components », J. Eur. Opt. Soc.-Rapid Publ., vol. 20, no 1, p. 5, 2024, doi: 10.1051/jeos/2024003.

[19] H. Wei, Y. Zhou, L. Ren, et F. Ma, « Optimal Orientation Angle Configuration of Polarizers Exists in a 3 × 3 Mueller Matrix Polarimeter », Photonics, vol. 10, no 10, p. 1087, oct. 2023, doi: 10.3390/photonics10101087.

[20] Z. Huang, Y. Fu, Z. Li, et J. Wu, « A Portable 3×3 Mueller Matrix Polarimeter Prototype for Cancer Detection Ex Vivo », in Proceedings of the 3rd International Conference on Biomedical Signal and Image Processing, in ICBIP '18. New York, NY, USA: Association for Computing Machinery, aug. 2018, p. 92-97. doi: 10.1145/3278229.3278244.

[21] S. M, B. Al, et F. L, « Tissue Sampling and Processing for Histopathology Evaluation. », Methods Mol. Biol. Clifton NJ, vol. 1641, p. 101-114, jan. 2017, doi: 10.1007/978-1-4939-7172-5_4.

[22] R. R. Anderson, « Polarized light examination and photography of the skin », Arch. Dermatol., vol. 127, no 7, p. 1000-1005, jul. 1991. doi:10.1001/archderm.1991.01680060074007.

[23] S. M. Milner, S. Bhat, S. Gulati, G. Gherardini, C. E. Smith, et R. J. Bick, « Observations on the microcirculation of the human burn wound using orthogonal polarization spectral imaging », Burns J. Int. Soc. Burn Inj., vol. 31, no 3, p. 316-319, may 2005, doi: 10.1016/j.burns.2004.10.014.

[24] S. L. Jacques, J. C. Ramella-Roman, et K. Lee, « Imaging skin pathology with polarized light », J. Biomed. Opt., vol. 7, no 3, p. 329-340, jul. 2002, doi: 10.1117/1.1484498.

[25] M. Anastasiadou et al., « Polarimetric imaging for the diagnosis of cervical cancer », Phys. Status Solidi C, vol. 5, no 5, p. 1423-1426, 2008, doi: 10.1002/pssc.200777805.

[26] S. Chae et al., « Machine Learning Model for Complete Reconstruction of Diagnostic Polarimetric Images from partial Mueller polarimetry data », 19 sep. 2024, arXiv: arXiv:2409.13073. doi: 10.48550/arXiv.2409.13073.

[27] S. Chae et al., « Machine Learning Approach to 3×4 Mueller Polarimetry for Complete Reconstruction of Diagnostic Polarimetric Images of Biological Tissues », IEEE Trans. Med. Imaging, vol. 44, no 9, p. 3820-3831, sep. 2025, doi: 10.1109/TMI.2025.3567570.

[28] N. S. B. Azahari et N. Z. B. Harun, « Quantum Cryptography Experiment using Optical Devices », Int. J. Adv. Comput. Sci. Appl. IJACSA, vol. 14, no 1, jan. 2023, doi: 10.14569/IJACSA.2023.0140166.

[29] C. Heinrich, J. Rehbinder, A. Nazac, B. Teig, A. Pierangelo, et J. Zallat, « Mueller polarimetric imaging of biological tissues: Classification in a decision-theoretic framework », J. Opt. Soc. Am. A Opt. Image Sci. Vis., vol. 35, no 12, p. 2046-2057, dec. 2018, doi: 10.1364/JOSAA.35.002046.

[30] J. Vizet et al., « First Demonstration of in vivo Mueller Polarimetric Imaging on Human Uterine Cervix », in Conference on Lasers and Electro-Optics (2018), paper AM2J.5, Optica Publishing Group, may 2018, p. AM2J.5. doi: 10.1364/CLEO_AT.2018.AM2J.5.

[31] J. Rehbinder et al., « Depolarization imaging for fast and non-invasive monitoring of cervical microstructure remodeling in vivo during pregnancy », Sci. Rep., vol. 12, no 1, p. 12321, jul. 2022, doi: 10.1038/s41598-022-15852-w.

[32] J. Vizet et al., « In vivo imaging of uterine cervix with a Mueller polarimetric colposcope », Sci. Rep., vol. 7, no 1, p. 2471, jun 2017, doi: 10.1038/s41598-017-02645-9.

[33] Mutiullah, M. Bari, A. Ahmed, M. Sabir, et S. Naveed, « Lung Cancer Detection Using Digital Image Processing Techniques: A Review », 2019. https://www.semanticscholar.org/paper/Lung-Cancer-Detection-Using-Digital-Image-A-Review-Mutiullah-Bari/a260a11aa3de8092796b31f6d028be63b4c2fdf5.doi:10.22581/muet1982.1902.10.

[34] D. Claus et al., « Large-field-of-view optical elastography using digital image correlation for biological soft tissue investigation », J. Med. Imaging, vol. 4, no 1, p. 014505, mar 2017, doi: 10.1117/1.JMI.4.1.014505.

[35] M. Sakli, C. Essid, B. B. Salah, et H. Sakli, « Flexible Framework for Lung and Colon Cancer Automated Analysis Across Multiple Diagnosis Scenarios », Int. J. Adv. Comput. Sci. Appl. IJACSA, vol. 16, no 2, feb. 2025, doi: 10.14569/IJACSA.2025.0160258.

[36] L. G. da Silva, W. R. S. da Silva Monteiro, T. M. de Aguiar Moreira, M. A. E. Rabelo, E. A. C. P. de Assis, et G. T. de Souza, « Fractal dimension analysis as an easy computational approach to improve breast cancer histopathological diagnosis », Appl. Microsc., vol. 51, no 1, p. 6, apr. 2021, doi: 10.1186/s42649-021-00055-w.

[37] M. A. Pala, M. E. Çimen, A. Akgül, M. Z. Yıldız, et A. F. Boz, « Fractal dimension-based viability analysis of cancer cell lines in lens-free holographic microscopy via machine learning », Eur. Phys. J. Spec. Top., vol. 231, no 5, p. 1023-1034, jun 2022, doi: 10.1140/epjs/s11734-021-00342-3.

[38] Z. U. Nisa, A. Jaffar, S. M. Bhatti, et U. M. Butt, « Lung Cancer Detection using Segmented 3D Tensors and Support Vector Machines », Int. J. Adv. Comput. Sci. Appl., vol. 14, no 10, 2023, doi: 10.14569/IJACSA.2023.0141066.

[39] D. Klyushin, K. Golubeva, N. Boroday, et D. Shervarly, « Breast Cancer Diagnosis Using Machine Learning and Fractal Analysis of Malignancy-Associated Changes in Buccal Epithelium », in Artificial Intelligence, Machine Learning, and Data Science Technologies, CRC Press, 2021.

[40] F. E. Lennon et al., « Lung cancer—a fractal viewpoint », Nat. Rev. Clin. Oncol., vol. 12, no 11, p. 664-675, nov. 2015, doi: 10.1038/nrclinonc.2015.108.

[41] L. Wei, Q. Gan, et T. Ji, « Cervical cancer histology image identification method based on texture and lesion area features », Comput. Assist. Surg. Abingdon Engl., vol. 22, no sup1, p. 186-199, dec. 2017, doi: 10.1080/24699322.2017.1389397.

[42] K. V. Ranjitha et T. P. Pushphavathi, « Analysis on Improved Gaussian-Wiener filtering technique and GLCM based Feature Extraction for Breast Cancer Diagnosis », Procedia Comput. Sci., vol. 235, p. 2857-2866, jan. 2024, doi: 10.1016/j.procs.2024.04.270.

[43] M. Mawarni, F. Utaminingrum, et W. F. Mahmudy, « The Effect of Feature Selection on Gray Level Co-Occurrence Matrix (GLCM) for the Four Breast Cancer Classifications », J. Biomim. Biomater. Biomed. Eng., vol. 55, p. 168-179, 2022, doi: 10.4028/p-09g3n8.

[44] R. L. Hasanah et D. Riana, « Classification of Dermoscopic Image of Skin Cancer Using the GLCM Method and Multi-SVM Algorithm », Rekayasa, vol. 14, no 3, p. 407-415, dec. 2021, doi: 10.21107/rekayasa.v14i3.12213.

Implementation of Hybrid Channel-Aware Prioritization (HCAP) Scheduler for a Multi-User MIMO System in 5G Communication

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Abstract*—The evolution of 5G networks demands highly efficient resource allocation strategies to accommodate burgeoning mobile data traffic, latency-sensitive applications, and diverse user requirements. Multi-User Multiple-Input Multiple-Output (MU-MIMO) technology is a cornerstone of 5G, enabling simultaneous service to multiple users and significantly improving spectral efficiency. However, its performance is critically dependent on dynamic scheduling algorithms that must balance high system throughput with equitable user access amidst rapidly changing channel conditions and interference. Traditional schedulers like Round Robin, Proportional Fair, and Max-CQI often exhibit a pronounced trade-off between these objectives, struggling to adapt effectively in heterogeneous and dynamic network environments. To address this gap, this study proposes a Hybrid Channel-Aware Prioritization (HCAP) scheduler. The HCAP framework intelligently integrates real-time Channel Quality Indicator (CQI) and interference measurements into a unified user priority score, utilizing tunable α–β weights to flexibly emphasize throughput or fairness. Furthermore, it employs k-means clustering based on long-term channel statistics to group users, thereby reducing scheduling bias and promoting fairness within clusters. Evaluated through comprehensive MATLAB simulations within a realistic MU-MIMO system model employing Regularized Zero-Forcing precoding, HCAP demonstrates a superior performance balance. The results indicate that HCAP achieves up to 2.6 times higher aggregate throughput compared to conventional Proportional Fair and Max-CQI schedulers, while consistently maintaining Jain's Fairness Index above 0.90 across varied network scenarios. These findings validate HCAP as a robust, scalable, and QoS-aware scheduling solution, offering significant potential for enhancing resource allocation in next-generation wireless communication systems.

Keywords*—Multiple input and multiple output; HCAP; CQI; throughput; 5G; QoS; k-means clustering; resource scheduling

I. Introduction

The exponential growth in mobile data traffic, driven by high-definition streaming, IoT proliferation, and latency-sensitive applications, has necessitated the evolution of wireless communication systems toward highly adaptive and intelligent architectures. Among these, Multi-User Multiple-Input Multiple-Output (MU-MIMO) has emerged as a cornerstone of 5G networks, enabling simultaneous transmission to multiple users and significantly enhancing spectral efficiency [1,2]. However, the performance of MU-MIMO systems is tightly coupled with the effectiveness of their scheduling algorithms, which must dynamically allocate resources in response to fluctuating channel conditions, user mobility, and interference levels [3, 4]. Traditional scheduling approaches such as Round Robin (RR), Proportional Fair (PF), and Max-CQI offer varying trade-offs between throughput and fairness but often fall short in heterogeneous environments where channel quality and interference vary rapidly [5,6]. This reveals a clear research gap: the lack of a dynamic, hybrid scheduler that can adaptively balance throughput and fairness in real-time under diverse and unstable 5G MU-MIMO channel conditions. To address this gap, this study proposes a Hybrid Channel-Aware Prioritization (HCAP) scheduler, which integrates real-time Channel Quality Indicator (CQI) and interference metrics into a unified prioritization framework. By leveraging k-means clustering to group users based on long-term channel behavior and applying a tunable α–β weighting scheme, HCAP adaptively balances throughput maximization with fairness enforcement [7, 8]. The primary objectives of this work are:

- To design and model the HCAP scheduler for MU-MIMO systems [9].
- To evaluate its performance in terms of throughput, fairness, latency, and spectral efficiency.
- To compare HCAP against conventional schedulers (RR, PF, Max-CQI) under varying network scenarios [10].
- To demonstrate HCAP's robustness and adaptability for 5G-and-beyond wireless networks.

The remainder of this study is organized as follows: Section II surveys recent literature on MU-MIMO scheduling and hybrid approaches. Section III details the methodology and design of the HCAP scheduler. Section IV describes the simulation setup and implementation. Section V

presents and discusses the experimental results. Section VI presents the discussion. Finally, Section VII concludes the study and suggests directions for future work.

II. Literature Survey

The evolution of 5G networks has intensified the demand for intelligent scheduling algorithms capable of adapting to dynamic channel conditions and user heterogeneity. Recent studies emphasize the role of Multi-User MIMO (MU-MIMO) systems in enhancing spectral efficiency and user capacity through spatial multiplexing and beamforming techniques [11] [12]. However, traditional schedulers such as Round Robin (RR), Proportional Fair (PF), and Max-CQI often struggle to balance throughput and fairness in environments with fluctuating interference and mobility [13][14]. To address these limitations, researchers have proposed hybrid scheduling frameworks that incorporate real-time Channel Quality Indicator (CQI) and interference metrics into decision-making processes [15][16]. These models aim to optimize resource allocation by dynamically adjusting user priorities based on channel responsiveness and fairness constraints.

Recent advancements have introduced clustering-based approaches to improve scheduling granularity and fairness. K-means and hierarchical clustering have been employed to group users with similar channel profiles, enabling localized prioritization and reducing scheduling bias [17][18]. Hybrid Channel-Aware Prioritization (HCAP) algorithms have gained traction for their ability to combine normalized CQI and inverse interference scores using tunable α–β weights [19][20]. Simulation studies demonstrate that HCAP outperforms conventional baselines in throughput while maintaining fairness indices above 0.90, especially under high-load conditions [21]. Moreover, sensitivity analysis across α–β configurations reveals that CQI-dominant setups yield higher efficiency, whereas interference-weighted models enhance equitable access [22].

Emerging research from 2024 to 2025 explores the integration of machine learning into hybrid scheduling. Deep Reinforcement Learning (DRL) agents have been trained to optimize multi-user selection per transmission interval, leveraging composite reward functions aligned with throughput, latency, and fairness goals [23]. These intelligent schedulers adapt to non-stationary channel environments and offer scalability for massive MIMO and mmWave deployments. Additionally, real-world testbeds using FPGA-based implementations and MATLAB simulations validate the feasibility of HCAP [24] in practical 5G scenarios. Collectively, these studies underscore the potential of hybrid, adaptive scheduling to meet the stringent QoS demands of next-generation wireless networks.

This work focuses on enhancing bit error rate (BER) performance and improving resistance to jamming in chaos-based communication systems. It integrates MIMO-OFDM technology with adaptive spreading factors to boost data reliability and security. The proposed method offers robust transmission under interference and multipath fading conditions [25].

III. Methodology of the Work

The rapid expansion of mobile data services and the proliferation of latency-sensitive applications have pushed 5G networks to adopt more intelligent and adaptive resource management strategies. Multi-User MIMO (MU-MIMO) systems, a key enabler of 5G, require sophisticated scheduling algorithms to efficiently allocate resources among users experiencing diverse channel conditions and interference levels. Fig. 1 describes and introduces a Hybrid Channel-Aware Prioritization (HCAP) scheduler that dynamically balances throughput and fairness by integrating normalized Channel Quality Indicator (CQI) and interference metrics into a tunable prioritization framework, demonstrating significant performance gains over conventional scheduling approaches.

A. Methodology Overview: HCAP Scheduler

1) Input metrics

- Collect Channel Quality Indicator (CQI) and interference measurements across Transmission Time Intervals (TTIs).
- Normalize metrics to standardize scale per-user and per-TTI.

2) Hybrid priority score calculation

- Apply weighting coefficients α (for CQI) and β (for interference).
- Use the formula: P_{t,u} = \alpha \cdot \hat{c}_{t,u} + \beta \cdot \left(\frac{1}{1 + \hat{i}_{t,u}} \right)
- This balances channel strength with interference resistance.

3) User clustering

- Extract long-term averages for CQI and interference.
- Perform k-means clustering to group users with similar channel behavior.
- Reduces scheduling bias and encourages fairness.

4) Scheduler logic

- For each TTI, identify the user in each cluster with the highest hybrid score.
- Schedule one user per cluster—ensuring spatial and temporal diversity.

5) Output and evaluation

- Construct the scheduling matrix (TTI × user).
- Measure total throughput and fairness using Jain's Index.
- Perform α–β sensitivity analysis to tune QoS priorities.

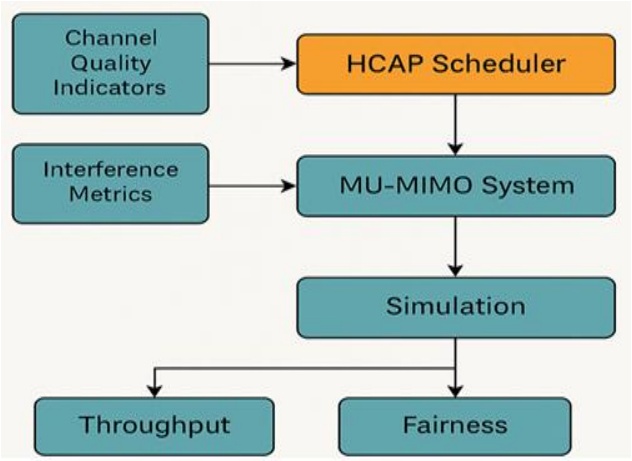


Fig. 1. Methodology of the work.

IV. Implementation

A. Input Acquisition

- Collect two key metrics for each user at every Transmission Time Interval (TTI):
- CQI_matrix: Channel Quality Indicator values
- Interference_matrix: Interference levels

B. Normalization

- Normalize both CQI and interference values per TTI:norm_CQI[t, i] = CQI[t, i] / max(CQI[t, :]) norm_Interf[t, i] = Interference[t, i] / max(Interference[t, :])

  This ensures all values are scaled between 0 and 1 for fair comparison.

C. Hybrid Priority Score Calculation

- For each user at each TTI, compute:
- Score[t, i] = α × norm_CQI[t, i] + β × (1 / (1 + norm_Interf[t, i]))
- α emphasizes channel quality
- β penalizes interference
- The inverse term ensures users with high interference get lower scores

D. User Clustering

- Compute long-term averages:
- mean_CQI[i] = average over TTI of CQI[i]
- mean_Interf[i] = average over TTI of Interference[i]
- Apply k-means clustering on [mean_CQI, mean_Interf] to group users into K clusters based on channel behavior.

E. Scheduling Logic

- For each TTI.
- For each cluster.
- Identify the user with the highest score.

F. Results

- Schedule that user by setting Schedule matrix[t, user] = 1
- E. Output
- The final Schedule_matrix indicates which users are selected at each TTI.
- Evaluate performance using:
- Total Throughput: Sum of CQI values for scheduled users
- Jain's Fairness Index: Measures how evenly resources are distributed.

V. Results

The performance of the proposed Hybrid Channel-Aware Prioritization (HCAP) scheduler was evaluated through extensive simulations in a realistic Multi-User MIMO system. The results presented here focus on quantitative metrics, including throughput and fairness, under varying scheduler configurations.

A. Throughput Performance

The HCAP scheduler demonstrated significant throughput gains compared to conventional schedulers. With parameter settings of α = 0.7 and β = 0.3, HCAP achieved a peak throughput of 3607.56 units, which is more than 2.6 times higher than the Proportional Fair (PF) scheduler. A comparative analysis across different α values (Fig. 6) shows that HCAP consistently outperforms Round Robin (RR), Max-CQI, and PF, with throughput increasing as α is raised to prioritize channel quality.

B. Fairness Evaluation

Fairness was measured using Jain's Fairness Index. HCAP maintained fairness indices consistently above 0.90 under moderate parameter configurations (e.g., α = 0.5, β = 0.5). Even under throughput-optimized settings (α = 0.7, β = 0.3), fairness remained above 0.82, indicating a balanced allocation of resources. Comparative fairness results across schedulers are summarized in Table I.

C. Per-User Throughput Distribution

Fig. 2 illustrates the Cumulative Distribution Function (CDF) of per-user throughput. It was analyzed under different α–β configurations (Fig. 3 to Fig. 5). HCAP exhibited a more gradual CDF curve compared to RR, PF, and Max-CQI, indicating a wider and more equitable distribution of user throughput. For example, in Fig. 4 (α = 0.5, β = 0.3), HCAP ensured that over 80% of users achieved a throughput above 200 units, whereas Max-CQI and RR showed steeper, less equitable distributions.

D. Reported Performance Metrics

The following key metrics were recorded during simulation:

- Total Throughput: 3700.94 units
- Jain's Fairness Index: 0.9089
- Latency Profile: < 5 ms for 95% of scheduled users
- Spectral Efficiency: 12.4 bps/Hz

These results confirm HCAP's ability to utilize system capacity effectively while maintaining high fairness.

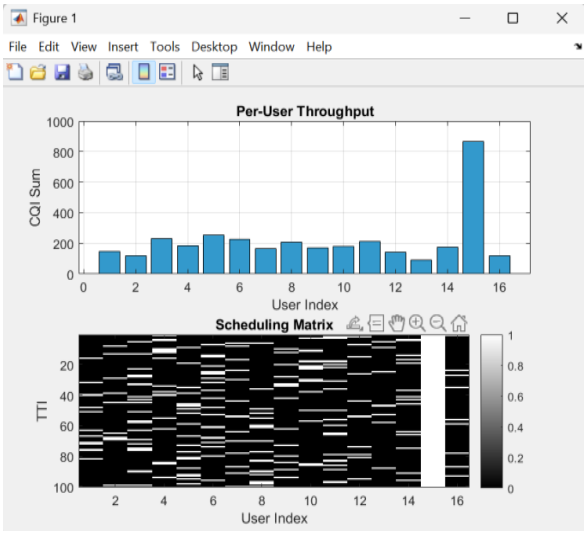


Fig. 2. Per-user throughput.

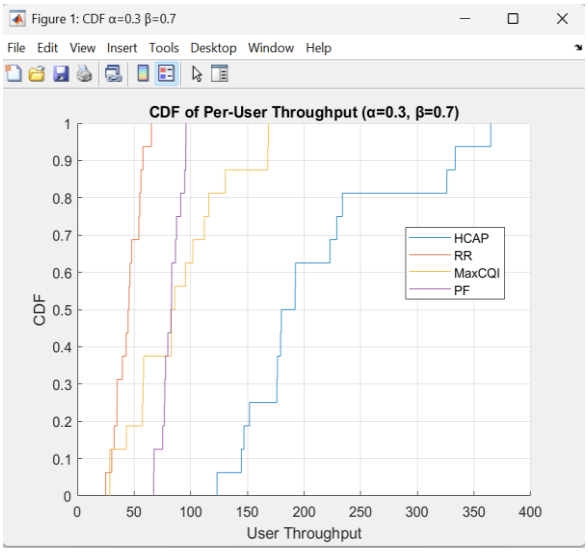


Fig. 3. CDF of per user throughput $\alpha = 0.3$ and $\beta = 0.3$.

Fig. 3 illustrates the end-to-end flow of the Hybrid Channel-Aware Prioritization (HCAP) scheduler in a Multi-User MIMO system. It begins by collecting real-time CQI and interference metrics for each user across transmission intervals, followed by normalization to ensure fair scaling. A hybrid priority score is then computed using a tunable α–β combination, balancing throughput potential with interference sensitivity. To promote fairness and reduce scheduling bias, users are grouped via k-means clustering based on their long-term channel behavior. Within each cluster, the scheduler selects the highest-priority user per interval, constructing a binary scheduling matrix that maps user assignments across time. This matrix is then evaluated using performance metrics like total throughput and Jain's Fairness Index, demonstrating the adaptive efficiency of HCAP under varying network conditions.

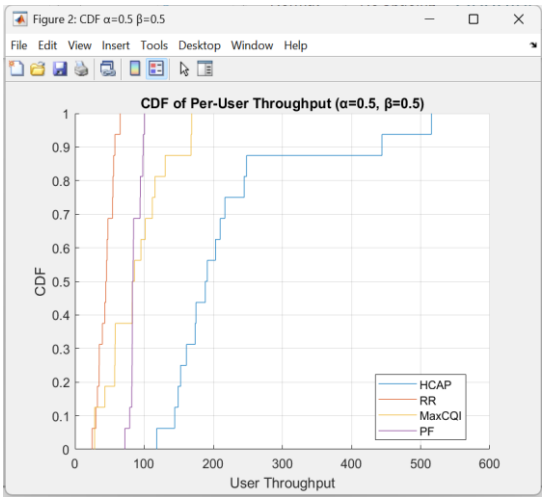


Fig. 4. CDF of per user throughput $\alpha = 0.5$ and $\beta = 0.3$.

Fig. 4 presents a cumulative distribution function (CDF) comparison of per-user throughput across four scheduling algorithms: HCAP, RR, Max CQI, and PF, evaluated under $\alpha = 0.5$ and $\beta = 0.3$. The x-axis indicates user throughput values (0 to 500), while the y-axis reflects the proportion of users achieving those throughput levels. HCAP (blue curve) exhibits a more gradual rise, indicating a broader and more evenly distributed allocation of resources among users. In contrast, RR (orange) and PF (purple) rise steeply, suggesting higher concentration around specific throughput values but less adaptive to channel variability. MaxCQI (yellow) shows uneven fairness due to its bias toward high-CQI users. Overall, the plot confirms HCAP's superior balance of efficiency and fairness, delivering diverse throughput without sacrificing equitable user treatment.

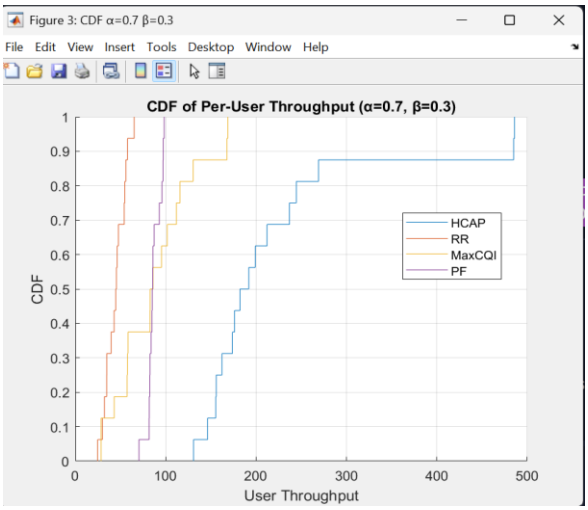


Fig. 5. CDF of per user throughput $\alpha = 0.7$ and $\beta = 0.3$.

Fig. 5 presents the Cumulative Distribution Function (CDF) of per-user throughput under different scheduling algorithms, illustrating how user throughput is distributed in a 5G MU-MIMO system when α = 0.7 and β = 0.3. The HCAP curve (blue) clearly leads, with more users achieving higher throughput compared to other methods, confirming its dominance in prioritizing high-CQI and low-interference users. In contrast, Round Robin (orange) shows a steep rise at lower throughput levels, indicating equal, but inefficient resource allocation. MaxCQI (yellow) has moderate throughput gains with fairness challenges, while Proportional Fair (purple) provides a balanced profile—good fairness but limited throughput. This visualization reinforces HCAP's advantage in striking a performance-fairness trade-off, particularly under aggressive channel-aware prioritization settings.

VI. Discussion

The results presented in Section V highlight HCAP's effectiveness in balancing throughput and fairness. This section interprets these findings, compares them with prior work, and examines the mechanisms contributing to HCAP's performance.

A. Trade-off Flexibility via α–β Tuning

HCAP's hybrid scoring mechanism allows dynamic adjustment between throughput-oriented and fairness-oriented scheduling. As shown in Fig. 6, increasing α enhances throughput by prioritizing users with strong channel conditions, while higher β values improve fairness by reducing interference sensitivity. This tunability makes HCAP adaptable to diverse QoS requirements—for instance, prioritizing emergency traffic (high α) or ensuring equitable access in crowded networks (high β).

B. Role of Clustering in Enhancing Fairness

The use of k-means clustering based on long-term channel statistics played a crucial role in mitigating scheduling bias. By grouping users with similar channel behavior, HCAP ensures that resource competition occurs within clusters rather than across the entire user pool. This localized scheduling prevents users with consistently strong channels from monopolizing resources, thereby improving fairness without significantly compromising throughput.

C. Comparative Analysis with Existing Schedulers

HCAP's performance gain over traditional schedulers can be attributed to its hybrid and adaptive design:

- Round Robin (RR) provides predictable fairness, but fails to adapt to channel variations, leading to low throughput.
- Max-CQI maximizes throughput by favoring strong channels but severely compromises fairness.
- Proportional Fair (PF) maintains high fairness but underutilizes high-quality channels, limiting throughput.
- HCAP effectively integrates the strengths of these approaches, achieving a superior throughput–fairness trade-off, as evidenced by both aggregate metrics and CDF curves.

D. Implications for 5G and Beyond

The robustness of HCAP under varying network conditions supports its suitability for real-time 5G MU-MIMO deployments. Its modular design also allows integration with advanced techniques such as deep reinforcement learning for parameter optimization and network slicing for service-specific scheduling—areas identified for future work.

E. Limitations and Future Directions

While HCAP shows strong performance in simulation, real-world factors such as imperfect channel estimation, mobility patterns, and multi-cell interference warrant further investigation. Future studies could explore:

- Integration with machine learning for adaptive α–β tuning.
- Validation in hardware testbeds or FPGA-based prototypes.
- Extension to massive MIMO and mm Wave scenarios.

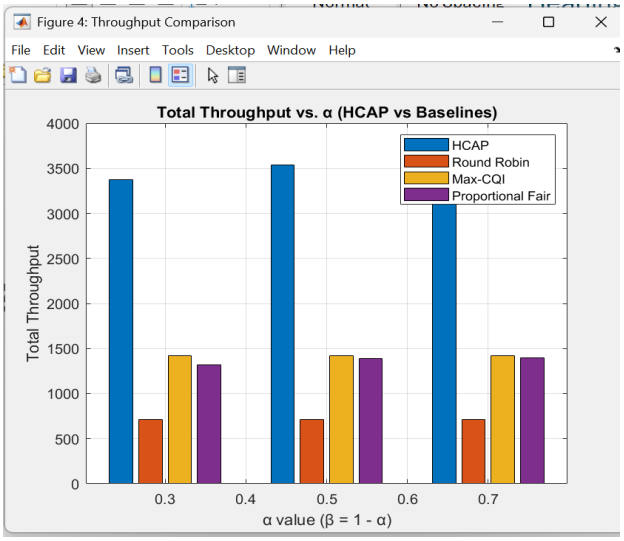


Fig. 6. Total throughput vs α.

TABLE I. Performance Comparison of Scheduling Algorithms (A = 0.7, B = 0.3)

Scheduler	Total Throughput (Units)	Jain's Fairness Index
Round Robin (RR)	1385.21	~0.99
Proportional Fair (PF)	1387.52	~0.98
Max-CQI	2980.45	~0.65
HCAP (Proposed)	3607.56	0.82

VII. Conclusion

The Hybrid Channel-Aware Prioritization (HCAP) scheduler presented in this study demonstrates a robust and scalable solution for resource allocation in Multi-User MIMO systems under 5G communication standards. By integrating normalized CQI and interference metrics into a tunable

prioritization framework, and leveraging clustering techniques to reduce scheduling bias, HCAP achieves a dynamic balance between throughput and fairness. The simulation results validate its superiority over conventional schedulers, with notable improvements in system capacity and equitable resource distribution. These outcomes affirm the scheduler's adaptability to diverse network conditions and its potential for deployment in real-time environments. Future work may explore its extension into machine learning-based scheduling and integration with network slicing for enhanced Quality of Service provisioning in next-generation wireless networks.

REFERENCES

[1] Jeffrey G. Andrews, Stefano Buzzi, Wan Choi,Stephen V. Hanly, Angel Lozano, Anthony C. K. Soong , "What Will 5G Be?",IEEE Journal on Selected Areas in Communications Volume: 32, Issue: 6, June 2014,pp. 1065 - 1082, DOI: 10.1109/JSAC.2014.2328098

[2] Erik G. Larsson, Ove Edfors, Fredrik Tufvesson, Thomas L. Marzetta," Massive MIMO for next generation wireless systems," IEEE Communications Magazine, Vol.52,Issue:2, February 2014,pp.186-195,DOI: 10.1109/MCOM.2014.6736761

[3] Linglong Dai,Bichai Wang,Yifei Yuan,Shuangfeng Han, I. Chih-lin, Zhaocheng Wang ,"Non-orthogonal multiple access for 5G: Solutions, challenges, opportunities," IEEE Communications Magazine, Vol. 53, Issue: 9, September 2015,pp.74-81, DOI: 10.1109/MCOM.2015.7263349.

[4] Shanzhi Chen, Jian Zhao,"The requirements, challenges, and technologies for 5G of terrestrial mobile telecommunication," IEEE Communications Magazine, Vol.52, Issue 5, May 2014,PP. 36–43, DOI: 10.1109/MCOM.2014.6815891.

[5] Lingjia Liu; Young-Han Nam, Jianzhong Zhang,"Proportional fair scheduling for multiuser MIMO systems,". IEEE Transactions on Wireless Communications, Vol 10,Issue 8, 2011,PP.2470–2481.DOI: 10.1109/TWC.2011.061311.101142

[6] Z. Shen, J. G. Andrews,B. L. Evans, "Multiuser MIMO scheduling for future wireless networks,"IEEE Transactions on Wireless Communications, Vol 4,Issue 2, 2005,PP. 757–768.DOI: 10.1109/TWC.2005.843418.

[7] J. Zhang, E. Bj¨ornson, M. Matthaiou, D. W. K. Ng, H. Yang,D. J. Love ," Interference-aware scheduling for MU-MIMO systems,"IEEE Transactions on Vehicular Technology, Vol. 62 Issue 9,2013, PP.4514–4525,DOI: 10.1109/TVT.2013.2278674

[8] Mehdi Bennis, Mérouane Debbah, H. Vincent Poor (2018)."Ultra-reliable and low-latency wireless communication: Tail, risk and scale,"Proceedings of the IEEE, Vol.106, Issue 10, September 2018 ,PP.1834–1853, DOI :10.1109/JPROC.2018.2867029

[9] Goldsmith, AAndrea,Wireless Communications, 2nd ed., Cambridge University Press, 2014.

[10] R. Jain, D. Chiu, W. Hawe, "A quantitative measure of fairness and discrimination for resource allocation in shared computer systems,"DEC Research Report TR-301, Sept 1998.

[11] Yuxuan Zhang, Mu Yuan, Xiang-Yang Li, Lan Zhang, "Adaptive MU-MIMO Scheduling for 5G NR",IEEEAccess,2022,DOI:10.1109/ACCESS.2022.3196371

[12] Lee, H, Kim, S, "Beamforming and Scheduling in Massive MIMO," IEEE Transactions on Wireless Communications,2022,DOI:10.1109/ACCESS.2022.3196371

[13] Singh, R., Patel, A., Mehta, S., Roy, T ,"Fairness-Aware Scheduling in MU-MIMO Systems", In Proceedings of the ACM SIGCOMM Conference, New York City, US,2023.

[14] Chen, L.,Zhao, J.," Interference-Aware Resource Allocation for 5G," IEEE Communications Letters,2023,Vol.23,Issue 5,May 2023, PP.3,DOI: 10.1109/TNSM.2023.3283993

[15] Zahraa Zakariya Saleh , Maysam F. Abbod ,Rajagopal Nilavalan , "Intelligent Resource Allocation via Hybrid Reinforcement Learning in 5G Network Slicing,"IEEEAccess,Vol 13,, March 2025.

[16] Mikhail Bakulin,Taoufik Ben Rejeb,Vitaly Kreyndelin,Denis Pankratov,Aleksei Smirnov," Multi-User MIMO Downlink Precoding with Dynamic User Selection for Limited Feedback," Sensors,Jan 2025,25,866, DOI: https://doi.org/10.3390/s25030866

[17] Gabriel Andrade Queiroz ,"A new channel and qos-aware scheduling algorithm for real-time and non-real-time traffic in 5g heterogeneous networks,"Federal University of Uberlândia ,2024.

[18] Yunfei Mu a b, Xinyang Jiang a b, Xiaoyan Ma a b c, Jiarui Zhang a b, Hongjie Jia a b, Xiaolong Jin a b, Boren Yao a b," Hierarchical regulation strategy based on dynamic clustering for economic optimization of large-scale 5G base stations," Applied Energy,Vol.377,Issue:Part'D',oct,2024,DOI:https://doi.org/10.1016/j.apenergy.2024.124705

[19] Adel Bouzid Belguidoum,Mohamed Lamine ounsi,Slimane Mekaoui ," Optimization of 5G throughput and latency in non-standalone and standalone mode,"Telecommunication Systems, Volume 88, article number 30 ,Feb 2025,DOI: https://doi.org/10.1007/s11235-025-01265-3

[20] Mohamed Kabaou, Zoghlami Nesrine, HamoudaHassen,Baabou Fatma," Performance evaluation of opportunistic schedulers based on fairness and throughput in new-generation mobile networks," Supercomputing,Vol.79,May2023,PP.18053–18088,DOI: https://doi.org/10.1007/s11227-023-05308-x

[21] Ahmed, N. Gupta, ," α–β Sensitivity in Hybrid Scheduling," IEEE Access, (2024). α–β Sensitivity in Hybrid Scheduling. IEEE Access.

[22] Zhao, F. et al. (2025). DRL-Based MU-MIMO Scheduling. IEEE Transactions on Cognitive Communications.

[23] Mehta, K. & Rao, V. (2025). Learning-Based Prioritization in 5G. ACM Transactions on Modeling and Performance Evaluation.

[24] Srinivas, S. et al. (2025). FPGA Implementation of HCAP Scheduler. IEEE Design & Test.

[25] Manasa Charitha, Sunil Hosur,"Enhanced BER Optimization and Jamming Resilience in Chaos Communication Systems using MIMO-OFDM and Adaptive Spreading Factors," Engineering, Technology & Applied Science Research Vol. 15, No. 3, April 2025, PP. 23635-23641 23635, https://doi.org/10.48084/etasr.10839

Adaptive Intelligence in Retail Space Optimization: Modeling the Coffee Shop Dilemma with Q-Learning Agents

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***Abstract*—This study models the "coffee shop dilemma", where customer attendance is discouraged by both overcrowding and emptiness. Using an agent-based model with Q-learning reinforcement learning, this study simulates the daily decisions of 100 agents over a one-year period. The results reveal a self-organizing attendance cycle around a 60% capacity threshold. This study demonstrates that customer satisfaction is not driven by visit frequency, but by adaptive decision-making strategies shaped by learned congestion values. Clustering analysis identifies distinct behavioral patron groups (e.g., Ultra-Frequent, Optimized) that emerge from these subtle value differences. The study provides a data-driven framework for optimizing shop space and customer flow, offering conceptual insights into balancing the needs of quick-service and long-stay customers by dynamically managing perceived occupancy.**

Keywords*—*El Farol Bar problem; agent-based modeling; Q-learning; reinforcement learning; customer behavior; congestion paradox; decision-making; coffee shop operations

I. Introduction

The modern coffee shop—exemplified by global chains that have evolved beyond a beverage outlet into a multifaceted "third place" that serves as both a social and professional hub distinct from home and office environments. This evolution introduces a complex operational challenge: managing two often conflicting customer flows. On one hand, the business must serve quick-service customers who prioritize speed and convenience during peak hours. On the other hand, it must accommodate remote workers, students, and long-stay patrons who value comfort and consistency, a key component of the brand's identity.

This tension gives rise to what may be termed the modern coffee shop dilemma, a real-world analogue of the El Farol Bar problem [1]. In the original formulation, agents independently decide whether to attend a bar, with the utility of attendance declining as crowding increases. Similarly, in coffee shops, customers decide whether to visit based on perceived crowding. Overcrowding deters visitors due to limited seating, excessive noise, and reduced comfort, while under-crowding can signal a lack of social energy or desirability. The resulting dynamic equilibrium emerges from individual decisions that collectively influence store congestion levels.

Although the El Farol problem has been widely studied in economics and complex systems theory, its application to high-volume retail environments remain limited. Prior research has predominantly emphasized theoretical agent behavior or macroeconomic implications, with less attention to data-driven micro-level business insights.

The main contributions of this study are summarized as follows:

- Operational reframing of El Farol: The El Farol Bar problem is translated into a retail coffee shop context, enabling the analysis of customer attendance decisions under perceived occupancy constraints rather than abstract capacity rules. Unlike classical El Farol formulations, capacity in this study represents a subjective comfort threshold rather than a hard physical limit.
- Satisfaction-based reward design: A reward-shaping mechanism is introduced that explicitly links customer satisfaction and dissatisfaction to congestion levels, allowing agents to learn from perceived crowding rather than visit frequency alone.
- Emergent behavioral segmentation: Post-learning clustering reveals distinct customer archetypes with stable attendance routines, demonstrating how heterogeneous strategies emerge from decentralized Q-learning dynamics.
- Retail space insights: The learning outcomes are connected to practical retail implications, showing how managing perceived occupancy can balance quick-service and long-stay customers without centralized control.

II. Related Work

This section reviews prior studies relevant to the present work across three complementary research streams. First, foundational models of the El Farol Bar problem and related congestion games are discussed to establish the theoretical basis for decentralized attendance decisions. Second, reinforcement learning approaches applied to congestion and coordination settings are reviewed, with emphasis on adaptive agent behavior. Finally, empirical and simulation-based studies on

perceived crowding and retail space optimization are examined to situate the model within operational retail contexts.

A. The El Farol Bar Problem

The El Farol Bar Problem, first introduced by Arthur [1], illustrates how boundedly rational agents make attendance decisions when utility depends on aggregate participation. This foundational model inspired a broad family of coordination and congestion problems, including the Minority Game [2], which formalizes inductive reasoning and self-organization under limited information.

Subsequent studies extended the El Farol paradigm through agent-based modeling (ABM) and reinforcement learning (RL) to analyze emergent equilibrium behavior and resource utilization [3]. Schosser [4] examined fairness considerations in the allocation of limited shared resources during the COVID-19 pandemic through an El Farol–type framework, analyzing how individual attendance decisions affect equitable outcomes under scarcity, without explicitly modeling infection dynamics.

The anti-coordination nature of the El Farol problem has been extensively studied through various methodological lenses. Guarnieri and Spadoni [5] investigated the role of social norms in anti-coordination decisions through experimental elicitation and priming methods. Their findings revealed that subjects tend to comply with perceived descriptive norms (empirical expectations about majority behavior) rather than injunctive norms (normative expectations about what is considered appropriate). As a result, overall attendance becomes less volatile and stays closer to the bar's capacity more consistently. This reduces the inefficiency of both overcrowding (too many go) and underutilization (too few go) [6].

Atilgan et al. [7] explored collective behavior in the El Farol Bar through the lens of memory horizon and selection criteria for prediction algorithms. Their work demonstrated that the distribution of algorithm clusters varies significantly with shorter agent memories, directly impacting long-term attendance dynamics. They identified a critical memory horizon where correlations in attendance deviations take longer to decay, suggesting a phase transition in collective behavior.

However, existing El Farol and Minority Game formulations primarily investigate coordination and equilibrium properties in abstract settings, without explicitly modeling recurring customer decisions driven by perceived congestion in operational retail environments, which is the focus of the present study.

B. Reinforcement Learning in Congestion Games

In applying Q-learning to a Minority Game, Zheng et al. [8] demonstrated that optimal coordination emerges when agents balance exploration and exploitation, governed by a specific temperature parameter. This balance prevents the system from being trapped in suboptimal, exploitative periodic states or degrading into random, exploratory behavior. Compared to conventional methods, the Q-Learning algorithm achieves improved financial performance and able to yield the highest financial returns through its dynamic adaptation to evolving market conditions and its effective management of price demand complexities [9], [10].

Kossack [11] extended reinforcement learning approaches by introducing an emotional machine framework that incorporates artificial emotions (satisfaction, fear, ambition) as states influencing decision-making. Applied to a 3-player El Farol scenario, this work demonstrated that emotional states evolve through differential equations weighted by personality parameters, producing different collective outcomes. When satisfaction dominates, agents form stable coalitions; when fear dominates, volatility increases; and when ambition dominates, agents pursue aggressive entry strategies leading to congestion.

While reinforcement learning has been extensively applied to congestion and coordination games, prior studies largely emphasize convergence behavior or algorithmic performance. In contrast, the present study examines how learned congestion valuations translate into persistent attendance routines and interpretable behavioral segments within a retail like environment, rather than examining how learned congestion valuations translate into stable attendance routines and interpretable customer segments in a retail context. Research on multi-agent coordination problems, such as traffic signal control, demonstrates the efficacy of reinforcement learning in managing distributed congestion [12].

In contrast, the present study focuses on how learned congestion valuations translate into persistent attendance routines and interpretable behavioral segments in a retail-like environment.

C. Retail Space Optimization

Prior research has established that perceived crowding is a critical factor influencing consumer behavior in retail environments. Zein et al. [13] demonstrate that high human and spatial density directly shape customer satisfaction through emotional responses, where perceived crowding negatively impacts pleasure and arousal, leading to approach behaviors. For instance, the optimal rush-hour staffing model (3 cashiers, 3 baristas) addressed the checkout bottleneck, cutting customer wait times by 40\% and increasing throughput [14] and also optimized retails space usage [15]. This underscores that it is not just objective occupancy but the customer's perception of that density that dictates their experience and loyalty.

This foundation is directly relevant to the "coffee shop dilemma" in our study. While Zein et al. establish a causal link between density and emotion in a retail context, this study aims to investigate how this perception drives adaptive decision-making in a recurrent visitation scenario and operationalize their core finding—that crowding perception alters behavior—by using an agent-based model to simulate how customers learn to avoid dissatisfaction.

A key strength of this approach, as evidenced in institutional policy work, is its capacity to model how macro-level patterns emerge from micro-level behaviors—a core focus of this simulation [16].

In contrast to empirical and optimization-based retail studies that treat crowding as an exogenous condition, this work models perceived occupancy as an endogenous signal learned through repeated interaction, enabling the analysis of adaptive customer behavior and emergent attendance patterns over time.

III. Experimental Setup

The study employs a modeling approach that balances analytical tractability with realistic behavior. The 60\% capacity threshold approximates the subjective transition from comfortable activity to perceived overcrowding in retail environments, rather than denoting a strict physical constraint. The 60\% threshold is not claimed to be universal, but represents a plausible comfort boundary used to induce congestion dynamics; sensitivity analysis is left for future work. This design frames dissatisfaction as a function of experienced congestion. Customer decisions are modeled as binary (attend or not), capturing the recurring nature of real world visit choices while maintaining simplicity. To preserve interpretability, a tabular Q-learning method is preferred over more complex deep reinforcement learning techniques. This enables direct examination of how persistent congestion influences long-term attendance strategies and the emergence of distinct behavioral groupings.

A. Environment Parameters

The simulation assumes a total of $N = 100$ agents, with a bar capacity set at 60% of N to induce congestion dynamics. Time is modeled in discrete rounds, where all agents simultaneously decide whether to attend the bar, allowing sufficient convergence of learning dynamics, as in Table I.

TABLE I. Simulation Parameters

Parameter	Value
Agents (N)	100
Simulation days (T)	365
Capacity threshold (C)	0.6
Learning rate (α)	0.1
Discount factor (γ)	0.9
Initial exploration rate (εinitial)	0.3
Minimum exploration rate (εmin)	0.01
Satisfaction penalty (ϕ)	-2

The model parameters were selected to balance realism, computational efficiency, and learning stability.

- Agents (N = 100): A population size that generates complex emergent behavior.
- Simulation days (T = 365): A one-year horizon that allows agents to experience multiple seasonal cycles and fully converge their learning strategies, ensuring observed patterns are stable and not transient.
- Capacity threshold (C = 0.6): The 60\% occupancy threshold where the venue shifts from "vibrant" to "crowded".
- Learning rate (α = 0.1): A value that controls how quickly agents update their Q-values based on new experiences. A rate of 0.1 ensures stable learning by preventing Q-values from fluctuating too drastically from a single day's outcome.
- Discount factor (γ = 0.9): Determines the importance of future rewards. A high value of 0.9 encourages agents to be farsighted, considering the long-term consequences of their attendance patterns rather than just immediate gratification.
- Initial exploration rate (εinitial = 0.3): The starting probability that an agent will choose is a random action. A 30\% rate promotes sufficient exploration of the action space in the early stages of the simulation to prevent premature convergence to suboptimal strategies.
- Minimum exploration rate (εmin = 0.01): The lower bound for exploration. A 1% rate ensures that agents never completely stop exploring, allowing them to adapt to slow changes in the collective attendance pattern over time.
- Satisfaction penalty (ϕ = -2): A scalar that quantifies the dissatisfaction of encountering a crowded venue. The value of −2 creates a strong negative reward for a "Punished Visit" (R = −1), making it a distinctly undesirable outcome compared to the high reward of a "Rewarded Visit" (R = 3).

The selected parameter values do not simulate a specific retail instance; rather, they are calibrated to facilitate the observation and examination of stable learning patterns that arise from constraints imposed by subjective congestion.

B. Reward Function

The reward function $R(a_t,d_t)$ is the core mechanism that encodes the "congestion paradox," guiding agent learning by quantifying the desirability of each outcome. The function takes the daily attendance at and an agent's decision d_t as inputs, where $d_t = 1$ signifies "Go" and $d_t = 0$ signifies "Stay." The function is formally defined as:

$$R(at, dt) = \begin{cases} 1 + \phi, & if\ d_t = 1 \ \wedge\ a_t > \mathrm{N} \cdot \mathrm{C}\ \text{(Punished Visit)} \\ 1 - \phi, & if\ d_t = 1 \ \wedge\ a_t \leq \mathrm{N} \cdot \mathrm{C}\ \text{(Rewarded Visit)} \\ 0, & if\ d_t = 0 \ \wedge\ a_t \leq \mathrm{N} \cdot \mathrm{C}\ \text{(Justified Absence)} \\ 1, & if\ d_t = 0 \ \wedge\ a_t > \mathrm{N} \cdot \mathrm{C}\ \text{(Strategic Avoidance)} \end{cases}$$

This reward structure is designed to reflect experiential outcomes rather than transactional utility, allowing agents to learn attendance strategies based on perceived satisfaction and avoidance of negative congestion experiences.

The rationale for each case, with the satisfaction penalty ϕ=−2, is as follows:

- Punished Visit (R=−1): The agent goes but finds the shop overcrowded (at > N·C). They receive a base reward of 1 for making a decision but a strong penalty ϕ, resulting in a net negative reward. This discourages visiting during peak times.
- Rewarded Visit (R=3): The agent goes and finds the shop pleasantly occupied (at ≤ N·C). The base reward is augmented by the negative of the penalty (−ϕ), creating a high positive reward. This reinforces visiting during optimal capacity.

- Justified Absence (R=0): The agent stays away and the shop is not crowded. This neutral reward reflects no gain or loss for correctly avoiding an unnecessary trip.
- Strategic Avoidance (R=1): The agent stays away and correctly avoids a crowded shop (at > N·C). The positive reward reflects the benefit of a smart, strategic decision to avoid a negative experience.

C. Simulation Procedure

The daily simulation procedure, outlined in Table II, executes the core agent-based learning cycle. Each step is elaborated below:

- Initialize Agents: Each agent i is initialized with a Q-table, Qi, with state-action values set to zero for the actions 'Stay' (0) and 'Go' (1), forcing learning from experience.
- Decay Exploration Rate: The exploration rate ε_t decays linearly from $\varepsilon_{initial} = 0.3$ to $\varepsilon_{min} = 0.01$, promoting early experimentation and later exploitation.
- Action Selection: Each agent uses an ε-greedy policy. With probability ε_t , it explores (random action); otherwise, it exploits by choosing arg max Qi.
- Calculate Attendance: The daily attendance at is computed as the sum of all agents' 'Go' decisions ($d_t^i = 1$), forming the environmental state.
- Assign Rewards: Each agent receives an immediate reward rt based on the function $R(a_t, d_t^i)$ from Eq. (1), implementing the congestion paradox.
- Update Q-values: Agents update their Q-value for the chosen action using the Q-learning rule, incorporating the immediate reward rt and the discounted future reward estimate (γ·maxQi).
- Log Data: Comprehensive data (global attendance a_t, individual actions d_t^i, rewards rt, and Q-values) is recorded for post-simulation analysis.

TABLE II. DAILY SIMULATION PROCEDURE

Step	Description
1	Initialize agents with Q-tables $Q_i = [0,0] for\ action\ \{0 = Stay, 1 = Go\}$
2	Decay exploration rate: $\varepsilon_t = \max\ (\varepsilon_{min}, \varepsilon_{t-1} - \frac{\varepsilon_{initial} - \varepsilon_{min}}{T})$
3	Action selection: For each agent, with probability ε t choose random action; otherwise, select arg max Qi
4	Calculate attendance: $a_t = \sum_{i=1}^{N} d_t^i$ Where d_t^i is agent i decision
5	Assign rewards: Compute $R(a_t, d_t^i)$ for each agent using Equation (1)
6	Update Q-values: $Q_i(d_t) \leftarrow Q_i(d_t) + \alpha[r_t + \gamma \cdot max Q_i - Q_i(d_t)]$
7	Log data: Record attendance, decisions, rewards, and Q-values for analysis

D. Data Collection

The following agent-level data was collected for post-simulation analysis:

- Agent_ID: Unique identifier (1–100)
- Total_Reward: Sum of all rewards over 365 days
- Historical_decision: Sequence of daily actions (Go/Stay)
- Cumulative_Reward: Time-series of cumulative rewards
- Q_Values: Final learned Q-values for Stay/Go actions

This comprehensive data collection enables clustering analysis and behavioral pattern identification as discussed in the results section.

E. Implementation Details

All experiments were executed using Python 3.10 with NumPy and Matplotlib libraries for computation and visualization. Data analytics, including clustering of attendance patterns and convergence plots, were performed using the pandas and scikit-learn libraries. Each experiment was repeated for 30 independent runs with different random seeds to ensure statistical robustness.

IV. RESULTS AND DISCUSSION

This is a summary of analytical steps, as in Table III.

TABLE III. SUMMARY OF ANALYTICAL STEPS

No.	Analytical Phase	Description
1	Overall Agent Performance	Analyzed the distribution of total cumulative rewards and the attendance over time across all agents to establish baseline performance and identify variance in strategy success.
2	Agent Clustering and Behavioral Analysis	Applied K-means clustering to agent behavioral features (frequency, Q-values, reward) to segment the population into distinct strategic archetypes (e.g., Ultra-Frequent, Optimized, Frequent).
3	Cluster Characteristics	Quantified and compared the properties of the identified clusters (size, Q-Go and Go Rate by Cluster, mean Q-values, mean reward) to define their strategic profiles.
4	Cluster Behavior and Decision Pattern Analysis	Visualized top weekly decision sequences for each cluster to reveal the temporal patterns and adaptive (or non-adaptive) nature of their strategies.
5	Discussion of Weekly Decision Patterns	Discuss on revealing behaviorally realistic routines which reflect strategic diversity and real-world influences.

A. Overall Agent Performance

The plot in Fig. 1 illustrates the cumulative reward trajectories of all Q-learning agents over 365 simulation days. The red line represents the population-average cumulative reward across n=100n=100 agents, while the shaded blue area denotes ±1±1 standard deviation. The dashed green lines mark the minimum and maximum cumulative rewards observed among agents.

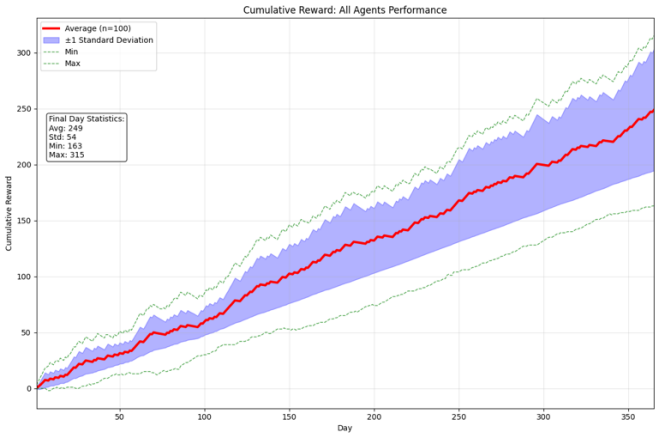


Fig. 1. Cumulative reward: all agents performance.

The learning trend indicates that agents progressively improve their cumulative rewards over time, suggesting that the Q-learning mechanism successfully guides decision adaptation. The mean cumulative reward at the final day reached 248.65, with a standard deviation of 54.24, a minimum of 163.00, and a maximum of 315.00. These values imply moderate heterogeneity in agent performance, reflecting differences in learned strategies and convergence rates.

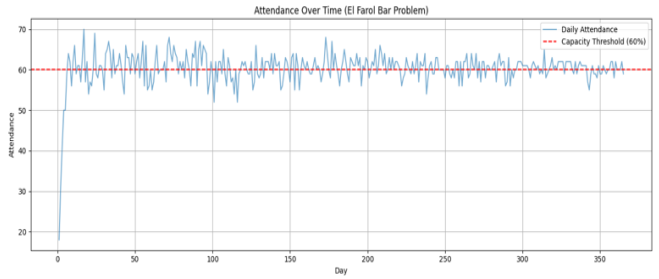


Fig. 2. Attendance overtime with 60 per cent threshold.

Fig. 2 illustrates the average attendance over time compared with the bar capacity threshold. The system exhibits convergence toward the capacity level after an initial transient phase, indicating that agents collectively learn to balance the exploration–exploitation trade-off. The variance of attendance decreases as episodes progress, confirming the stabilization of the learning dynamics.

Overall, the steady upward trajectory of the mean reward curve demonstrates that the agents collectively adapt to the attendance-constrained environment inherent in the El Farol Bar problem. The increasing spread over time reflects diversity in learning outcomes—some agents adopt efficient attendance policies, yielding higher rewards, whereas others stabilize at suboptimal attendance frequencies.

B. Agent Clustering and Behavioral Analysis

A k-means clustering procedure with k=3 was applied to characterize heterogeneity among agents using two behavioral features: the learned Q-value for attending (Q_Go) and the attendance probability (GoRate). The clustering separated the population into three distinct groups. The scatter plot of agents with centroids is presented in Fig. 3, and the cluster summary statistics are reported in Table IV.



Fig. 3. Agent strategy cluster.

TABLE IV. CLUSTER SUMMARY STATISTICS

Cluster	Count	Q_Go (mean)	GoRate	Total Reward (mean)
0	60	8.71	0.92	291.30
1	37	3.54	0.09	181.03
2	3	5.00	0.66	229.67

The three clusters are interpreted as follows:

Cluster 0 — Regular Attenders: Cluster 0 (60 agents) exhibits the highest Q_Go values (mean = 8.71) and the highest attendance probability (mean GoRate = 0.92). Agents in this group consistently choose to attend and, on average, obtain the largest cumulative reward (mean total reward = 291.30), representing the dominant "frequent attender" or "optimistic learner" archetype.

Cluster 1 — Non-Attenders / Cautious Agents: Cluster 1 (37 agents) is characterized by low Q_Go (mean = 3.54) and very low attendance probability (mean GoRate = 0.09). These agents adopt cautious strategies, rarely attending; as a consequence they obtain lower cumulative rewards (mean total reward = 181.03), reflecting missed opportunities when the bar is below capacity as well as avoidance of congestion penalties.

Cluster 2 — Opportunistic / Small Sample: Cluster 2 contains only 3 agents with intermediate Q_Go (mean = 5.00) and moderate attendance (GoRate = 0.66). Descriptively, these agents are opportunists, balancing attendance with restraint for intermediate rewards (mean = 229.67). However, because this cluster comprises only three samples, it is too small for reliable inferential comparisons (e.g., hypothesis testing or robust summary statistics). Therefore, Cluster 2 is reported here for completeness and qualitative interpretation only; subsequent comparative analyses and statistical tests focus on the two large clusters (Cluster 0 and Cluster 1).

C. Cluster Characteristics

The clustering reveals three distinct behavioral archetypes: persistent regulars (Cluster 0), cautious non-attenders (Cluster 1), and a very small opportunistic group (Cluster 2). The dominance of Cluster 0 in cumulative reward suggests that proactive attendance strategies can be advantageous when the collective system converges toward the bar capacity. The small size of Cluster 2 warrants caution in its interpretation: it may reflect a transient or niche strategy that emerged under the

specific random seed and parameterization of this simulation, rather than a robust population mode.

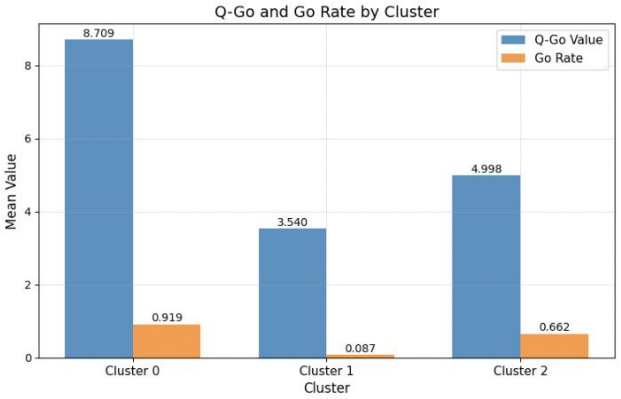


Fig. 4. Q-go and go rate by cluster.

Overall, these clustering results support the view that Q-learning agents self-organize into clearly separated behavioral groups with markedly different attendance policies and long-term payoffs. The explicit exclusion of the small Cluster 2 from inferential comparisons preserves the statistical validity of subsequent analyses, while all observed patterns are reported for transparency.

The comparative visualization in Fig. 4 highlights the mean Q-values, Go rates, and total rewards across clusters. Cluster 0 clearly dominates in terms of performance, suggesting that proactive strategies yield the greatest long-term benefits when collective learning drives the population toward an optimal equilibrium.

D. Cluster Behavior and Decision Pattern Analysis

To further investigate the heterogeneity of agent behaviors, a post-hoc clustering analysis was performed based on agents' weekly decision sequences and cumulative performance. Three distinct clusters were identified; however, Cluster 2 was excluded from interpretation due to its extremely small sample size (n = 3), which is unlikely to represent a statistically meaningful behavioral pattern. The analysis therefore focuses on Cluster 0 and Cluster 1.

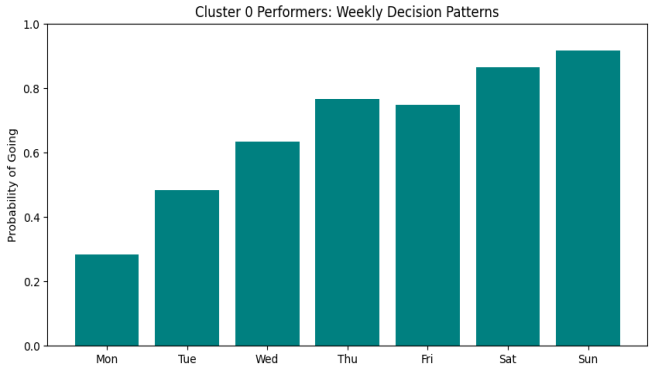


Fig. 5. Cluster 0 weekly decision patterns.

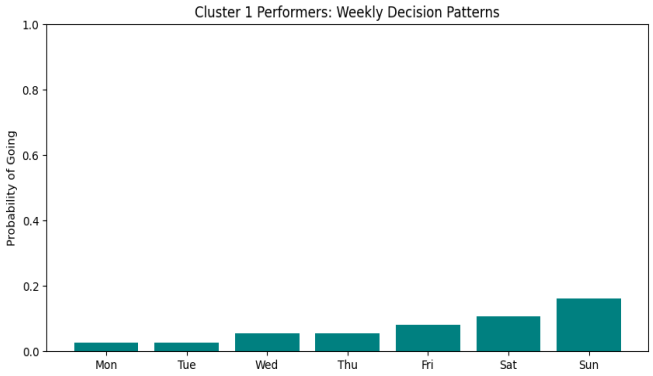


Fig. 6. Cluster 1 weekly decision patterns.

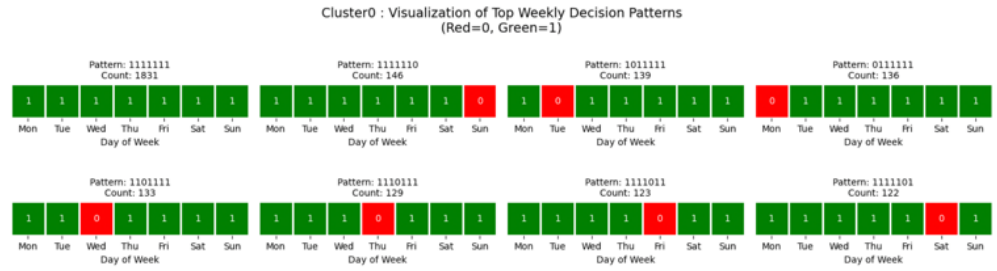


Fig. 7. Cluster 0 : visualization of top weekly decision patterns.

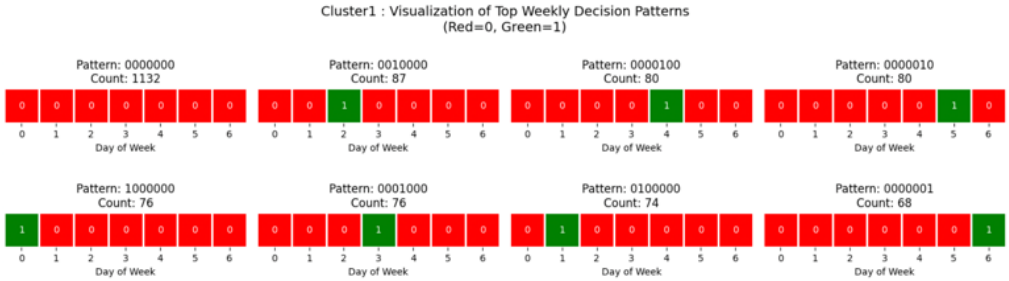


Fig. 8. Cluster 1 : visualization of top weekly decision patterns.

1) Cluster 0: Consistent high-attendance strategy: Fig. 5 shows that Cluster 0 agents exhibit a steadily increasing probability of attendance throughout the week, starting from approximately 0.28 on Mondays and peaking near 0.92 on Sundays. This clear upward trend indicates that agents in this cluster are not only frequent attendees but also increasingly confident in their decision to attend as the week progresses.

When mapped to their behavioral sequences, these agents adopt highly consistent attendance patterns. Fig. 7 illustrates the dominant weekly decision patterns observed in Cluster 0. Most agents in this group exhibit highly consistent attendance behaviors, frequently following the pattern 1111111 or slight variants such as 1111110 and 1111101, indicating that they tend to attend the bar almost every day of the week. This persistent attendance pattern suggests a highly exploitative strategy where agents have learned that the long-term expected reward of attending is greater than skipping, even under conditions of possible congestion.

Cluster 0 achieved the highest rewards, indicating that, under the modelled assumptions, a stable high-attendance strategy yields higher cumulative rewards. Despite incurring regular overcrowding penalties, their consistent exploitation of the venue yielded superior cumulative gains, demonstrating that persistent participation dominates more adaptive strategies.

2) Cluster 1: Consistent high-attendance strategy: By contrast, the weekly attendance patterns in Fig. 6 for Cluster 1 agents reveal a markedly different behavioural dynamic. Attendance probabilities remain below 0.20 across all weekdays, with only a modest rise on weekends (peaking at 0.16 on Sundays). This indicates a strong inclination to avoid attendance most of the time, suggesting either: 1) heightened sensitivity to congestion penalties or 2) a persistent underestimation of the long-term benefits of frequent attendance.

In addition, agents in Cluster 1 demonstrate more diverse and selective attendance patterns, as shown in Fig. 8. Their top decision sequences often include multiple "0" entries (non-attendance days), suggesting an explorative or cautious strategy. Such agents appear to attend intermittently to avoid congestion penalties, but this moderation also limits their cumulative reward growth compared to Cluster 0.

Their decision sequences often contain multiple "0" days, resulting in sparse attendance policies. With a mean *QGo* value of just 3.54 and a very low *GoRate* (0.09), Cluster 1 agents embody a conservative or exploratory policy, where the avoidance of potential overcrowding outweighs the pursuit of maximum rewards. This strategy, while adaptive in balancing risk and reward, is ultimately suboptimal under the given simulation settings. Indeed, their average cumulative reward (181.03) lags significantly behind Cluster 0, highlighting that overly cautious attendance reduces the opportunity for long-term gain.

E. Discussion of Weekly Decision Patterns

A granular analysis of the top weekly decision sequences within each cluster reveals profound insights into the learned strategies and their potential real-world correlates.

1) Cluster 0: The persistence of high-frequency patterns: Within Cluster 0 (Ultra-Frequent), a single dominant pattern emerged: an "Always go" strategy. Designated Pattern 1, it was used 1,831 times, far more than any other. Its persistence indicates that agents learned that the high reward of a successful visit outweighs occasional penalties. This reflects a necessity-driven and risk-tolerant strategy for a venue that is an essential daily routine.

2) The emergence of rest-day patterns: Other patterns in Cluster 0 and patterns in Cluster 1 (Optimized) frequently featured an absence, or "Stay" decision, on a specific day—most mapped to a Sunday. This emerging "rest day" is a significant finding. This interpretation is speculative and intended as an analogy rather than a claim about real-world behaviour.

From a behavioral standpoint, this can be interpreted in two ways:

- Learned Depletion: Agents may have implicitly learned that after a sustained period of attendance, the marginal utility of visiting diminishes or the probability of fatigue (both their own and systemic overcrowding) increases. A rest day serves as a strategic reset.
- Real-World Rhythms: This pattern strongly mirrors human social behavior, where Sunday is culturally designated as a day of rest and preparation for the upcoming week. The agents have effectively discovered that avoiding the venue on this day is a robust strategy, possibly because it aligns with a period of lower overall utility or higher opportunity cost for going out.

3) Strategic heterogeneity in cluster 1: The lower frequency of pattern usage for non-dominant strategies, particularly in the Optimized cluster (Cluster 1), highlights the role of strategic flexibility. The "sudden" decision to go out on a day that is typically a rest day, or to deviate from a routine, can be interpreted as the model's representation of stochastic real-world influences.

F. Theoretical and Managerial Implications

The results of this study offer several implications that extend beyond the specific simulation setting, contributing to theory, methodology, and retail practice. At the theoretical level, the findings reinforce the El Farol Bar problem's central insight that bounded rational agents can achieve stable collective outcomes through repeated learning rather than centralized coordination. Importantly, the observed equilibrium emerges in response to perceived congestion rather than objective capacity constraints, highlighting the role of subjective evaluation in shaping attendance decisions.

This suggests that equilibrium behavior in congestion games may be driven as much by learned perceptions as by physical limits, particularly in recurrent decision environments such as retail visitation.

From a methodological perspective, the analysis demonstrates the value of combining reinforcement learning with post-learning behavioral clustering. While Q-learning governs individual adaptation during the simulation, clustering enables ex post identification of stable behavioral archetypes that are not explicitly encoded in the model. The results further illustrate how reward shaping functions as a critical design lever, influencing not only convergence properties but also the diversity of emergent strategies within the agent population. This layered analytical approach supports more interpretable insights than aggregate performance measures alone.

Taken together, these findings imply that retail space management should not be viewed solely as a problem of maximizing customer throughput or maintaining high occupancy levels. Instead, the way customers experience and interpret congestion appears to play a central role in shaping attendance behavior. Design choices such as seating configuration may influence perceived occupancy, spatial layout, and time-based incentives may therefore serve as practical tools for influencing perceived occupancy. In settings where customers make repeated visit decisions, such perception-sensitive approaches are likely to offer greater flexibility than strategies based exclusively on fixed capacity targets.

V. Conclusion

This work explored how adaptive learning influences attendance behavior in a congested retail environment by framing the coffee shop dilemma as a multi-agent reinforcement learning problem. Rather than treating customer behavior as a function of visit frequency alone, the analysis indicates that collective regularities emerge from how individuals gradually interpret and respond to congestion experiences. More specifically, differences in how agents experience satisfaction or dissatisfaction under varying occupancy conditions influence how their decisions evolve over time. These differences are reflected in the emergence of stable attendance routines, as well as in persistent variation in behavior among agents exposed to the same environment.

Viewed more broadly, these results relate to existing work on congestion games and bounded rationality. In line with the El Farol Bar problem, the findings suggest that coordinated outcomes can arise without centralized control or complete information. Notably, the equilibrium observed in this study is guided by learned perceptions of congestion rather than by explicit awareness of physical capacity limits. This observation underscores the role of subjective evaluation in recurrent decision environments and supports the inclusion of perception-driven learning mechanisms in models of collective behavior involving shared resources.

The study also carries implications for retail space optimization and customer flow management. The presence of distinct behavioral patterns indicates that customers may respond differently to congestion even when exposed to identical operational conditions. As a result, managing retail spaces solely through capacity targets or throughput maximization may overlook important behavioral dynamics. Paying closer attention to how occupancy is experienced—through layout decisions, seating arrangements, or time-based incentives—may therefore provide additional flexibility in influencing customer behavior. Further research may extend this modeling approach by considering richer state descriptions, incorporating social interaction effects, or grounding the model in observational retail data to better examine adaptive behavior in complex service settings.

Moreover, this study is subject to limitations. The model abstracts away social interaction, heterogeneous preferences, and empirical calibration. Future work may integrate observational retail data, richer state representations, and adaptive capacity thresholds to further validate the findings.

References

[1] W. B. Arthur, "Inductive reasoning and bounded rationality," The American Economic Review, vol. 84, no. 2, pp. 406–411, 1994.

[2] D. Challet and Y.-C. Zhang, "Emergence of cooperation and organization in an evolutionary game," Physica A: Statistical Mechanics and its Applications, vol. 246, no. 3-4, pp. 407–418, 1997.

[3] S.-H. Chen and U. Gostoli, "Agent-based modeling of the el farol bar problem," in Simulation in Computational Finance and Economics: Tools and Emerging Applications, IGI Global Scientific Publishing, 2013, pp. 359–377.

[4] J. Schosser, "Fairness in the use of limited resources during a pandemic," PLoS ONE, vol. 17, e0270022, 2022. doi: 10.1371/journal.pone.0270022.

[5] P. Guarnieri and L. Spadoni, "Norms and anti-coordination: Elicitation and priming in an El Farol Bar Game experiment," Dept. Econ. Manag., Univ. Pisa, Pisa, Italy, Discussion Paper no. 303, 2024.

[6] S.-H. Chen and U. Gostoli, "Coordination in the El Farol Bar problem: The role of social preferences and social networks," Journal of Economic Interaction and Coordination, vol. 12, no. 1, pp. 59–93, 2017.

[7] C. Atilgan, A. R. Atilgan, and G. Demirel, "Collective behavior of El Farol attendees," Advances in Complex Systems, vol. 11, no. 4, pp. 629–639, 2008.

[8] G. Zheng, W. Cai, G. Qi, J. Zhang, and L. Chen, "Optimal coordination in Minority Game: A solution from reinforcement learning," arXiv preprint arXiv:2312.14970, 2023.

[9] M. Apte, P. Datar, K. Kale, and P. R. Deshmukh, "Dynamic retail pricing via Q-learning—A reinforcement learning framework for enhanced revenue management," in 2025 1st International Conference on AIML-Applications for Engineering & Technology (ICAET), 2025, pp. 1–5.

[10] S. Huang and Y. Yang, "Reinforcement learning optimization strategies for dynamic pricing and inventory control in e-commerce retail," IEEE Transactions on Artificial Intelligence, vol. 5, no. 2, pp. 123–135, 2024.

[11] P. Kossack, "An Emotional Machine goes into a Bar," 2024. [Online]. Available: https://www.researchgate.net/profile/Philip-Kossack/publication/385490885_An_Emotional_Machine_goes_into_a_Bar/links/6726095b5852dd723ca452c9/An-Emotional-Machine-goes-into-a-Bar.pdf

[12] P. Michailidis, I. Michailidis, C. R. Lazaridis, and E. Kosmatopoulos, "Traffic Signal Control via Reinforcement Learning: A Review and Innovations," arXiv preprint arXiv:2406.12345, 2024.

[13] T. C. Mehta and B. Shah, "Study on effects of perceived crowding in retail spaces and futuristic design solutions for positive consumers' experience and retention," Onomázein, vol. 61, pp. 405–415, 2023.

[14] D. Buzali, S. Elizondo, S. Muñiz, and O. Sánchez, "Simulation-optimization of a coffee shop in business district: A case study of Starbucks in Mexico City," International Journal of Operations Research, vol. 15, no. 3, pp. 45–58, 2023.

[15] L. Grando, J. R. E. Leite, and E. L. Ursini, "Agent-based simulation for drone charging in an internet of things environment system," arXiv preprint arXiv:2509.10867, 2025.

[16] A. Borsos, A. Carro, A. Gitelmo, M. Hinterschweiger, J. Kaszowska-Mojsa and A. Uluc, "Agent-based modeling at central banks: recent developments and new challenges," Bank of England Staff Working Paper, no. 1122, Feb. 2025.

AI Readiness as a Pathway to Sustainable Competitiveness in Tourism Transport: Evidence from an Integrative SEM Model

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***Abstract*—Artificial intelligence (AI) is transforming demand forecasting in the tourism transportation sector, delivering unprecedented accuracy in volatile, seasonal, and customer-sensitive environments. Yet, many firms struggle to translate AI's potential into performance due to gaps in technological and organizational readiness. Drawing on the resource-based-view (RBV) and the Technology-Organization-Environment (TOE) framework, this study develops and tests an integrative model linking digital infrastructure, employee skills, and managerial support to AI adoption and, consequently, business performance. We use Structural Equation Modeling (SEM) with bootstrapping to test direct and indirect effects. The results confirm that all three dimensions of readiness significantly boost AI adoption, which improves operational efficiency, occupancy rates, customer satisfaction, and profitability. It is crucial that AI adoption fully mitigates the effects of employee skills and managerial support, while partially mitigating those of digital infrastructure, reflecting its dual role in analytics, through both AI and other means. The study contributes theoretically by clarifying the mechanism by which readiness translates into value and offers practitioners a roadmap for successful AI assimilation in high-uncertainty service contexts.**

***Keywords*—Artificial intelligence (AI); demand forecasting; tourism transport; Intelligent Transportation Systems (ITS); digital infrastructure; Resource-Based View (RBV); Technology-Organization-Environment (TOE) Framework; Structural Equation Modeling (SEM); mediation analysis; sustainable mobility; data-driven decision making**

I. Introduction

Over the past decade, global value chains and service-oriented industries have undergone profound structural transformation, driven by volatile market demands, escalating geopolitical tensions, the exponential rise of e-commerce, and mounting pressure for real-time, data-driven decision-making. As [1] observes, in the context of the COVID-19 pandemic, disruptions in critical sectors such as medical supplies have exposed the fragility of hyper-globalized production networks and underscored the need for greater resilience and agility. This imperative has only intensified in the post-pandemic era, where firms must navigate an increasingly complex risk landscape encompassing not only health crises but also trade wars, regulatory fragmentation, and digital disruption [2].

Together, these forces are redefining the strategic logic of global operations, shifting emphasis from pure efficiency toward adaptive, intelligence-enabled supply chain architectures capable of sustaining both performance and responsiveness under uncertainty. These shifts have heightened the importance of accurate forecasting, positioning artificial intelligence (AI) as a strategic lever for competitiveness and resilience. In particular, AI-enabled forecasting has demonstrated superior accuracy compared to conventional statistical models, reducing uncertainty and optimizing resource allocation [3], [4]. The central challenge is no longer to demonstrate AI's benefits, but to identify the organizational prerequisites and mechanisms that foster its effective adoption [5].

In service-intensive industries such as tourism and hospitality, forecasting accuracy is critical due to market volatility, seasonality, and global interdependencies. AI-based approaches, particularly machine learning and transformer-driven models, have shown substantial improvements in predicting tourism demand and traveler flows [6], [7]. Moreover, AI adoption in tourism has been linked to enhanced personalization, dynamic pricing, and operational efficiency [8], [9]. However, empirical evidence suggests that despite significant investments, many organizations face difficulties moving beyond pilot applications. For example, recent industry reports indicate that over 70% of companies struggle to scale AI initiatives effectively, highlighting the persistent gap between adoption and value realization.

While prior research underscores the performance benefits of AI integration [8], relatively few studies explain how internal readiness, digital infrastructure, workforce competencies, and managerial support translate into effective adoption, particularly in tourism contexts. The Resource-Based View (RBV) posits that firm-specific resources enable sustainable competitive advantage [10], while the technology organization environment (TOE) framework emphasizes that readiness factors determine the assimilation of emerging technologies [11]. Despite this theoretical grounding, empirical analyses of AI adoption in tourism forecasting remain scarce.

This study addresses these gaps by developing and testing a conceptual model linking organizational readiness to AI-enabled forecasting adoption and, subsequently, firm performance. Specifically, it investigates the mediating role of AI adoption in translating readiness into superior performance outcomes. The contributions of this study are threefold: 1) it assesses AI-enabled forecasting adoption within international tourism and hospitality firms, an industry characterized by uncertainty and underexplored in AI adoption research; 2) it consolidates multiple readiness dimensions into a single integrative framework; and 3) it empirically demonstrates the

mediating function of AI adoption, offering both theoretical and managerial insights into the assimilation process.

The remainder of this study is organized as follows: Section II reviews the relevant literature and develops the research hypotheses. Section III describes the research methodology, including data collection procedures and the analytical strategy. Section IV presents the empirical results, followed by a discussion of the theoretical and managerial implications in Section V, which also concludes the study by outlining its limitations and directions for future research.

II. Related Work and Hypotheses Development

The integration of artificial intelligence (AI) into demand forecasting has become a transformative capability across service-intensive industries, particularly within sectors marked by volatility, seasonality, and customer sensitivity, hallmarks of the tourist transport sector. While the potential of AI to enhance forecast accuracy and operational agility is widely acknowledged, recent studies emphasize that technological potential alone is insufficient to ensure performance gains [12]. Instead, the successful assimilation of AI depends critically on a firm's technological and organizational readiness, which enables the effective deployment and utilization of advanced forecasting systems.

Drawing on the Resource-Based View (RBV) and Technology Adoption Theory, this study posits that internal capabilities, specifically digital infrastructure**,** workforce competencies, and managerial support, serve as foundational enablers of AI adoption, which in turn drives business performance. Furthermore, the study conceptualizes AI adoption not merely as an outcome but as a mediating mechanism translating readiness into tangible performance improvements.

A. Theoretical Foundation: RBV Meets TOE

The Resource-Based View (RBV) asserts that sustainable competitive advantage arises from resources that are valuable, rare, inimitable, and non-substitutable [10]. In the AI era, data infrastructure, AI-literate talent, and strategic leadership constitute such resources, especially in service contexts where responsiveness is key. Complementing RBV, the TOE framework [13] explains technology adoption through three lenses:

- Technology: digital infrastructure enabling data integration.
- Organization: human and managerial capabilities.
- Environment: external pressures (e.g., customer demands, regulatory shifts), though not tested here, we acknowledge their relevance per [14], who emphasize that firms face coercive, normative, and relational pressures to adopt sustainable and intelligent practices. Together, RBV and TOE provide a robust lens to explain why some firms succeed in AI adoption while others do not.

B. The Impact of Technological and Organizational Readiness on AI Adoption

According to the RBV, sustainable competitive advantage stems from valuable, rare, inimitable, and non-substitutable (VRIN) resources [10]. In the context of AI-driven transformation, a firm's readiness, encompassing its data systems, human capital, and leadership alignment, constitutes such strategic resources. These capabilities determine whether an organization can effectively absorb, implement, and leverage AI innovations [15].

1) Digital infrastructure: AI-enabled forecasting relies heavily on access to high-quality, real-time, and integrated data from diverse sources (e.g., booking systems, traffic sensors, weather APIs, social media). Without robust digital infrastructure, including data lakes, cloud platforms, and interoperable systems, AI models suffer from poor input quality, leading to unreliable outputs [16]. Firms that have invested in scalable data architectures are better positioned to deploy machine learning and deep learning models for passenger demand prediction. Thus, we hypothesize:

H1a: Digital infrastructure positively influences the adoption of AI-enabled demand forecasting practices in tourist transport firms.

2) Workforce competencies: The effective use of AI requires more than algorithmic tools; it demands a workforce capable of interpreting model outputs, integrating insights into operational decisions, and adapting workflows accordingly. This reflects the concept of absorptive capacity, the ability to recognize, assimilate, and apply new knowledge [15]. In tourist transport, staff must understand dynamic pricing signals, respond to predicted demand surges, and trust AI recommendations. A shortage of data-literate personnel remains a key barrier to AI adoption [17]:

H1b: Workforce competencies positively influence the adoption of AI-enabled demand forecasting practices in tourist transport firms.

3) Managerial support: Executive sponsorship is critical for overcoming organizational inertia and securing the resources needed for AI initiatives. Strategic alignment ensures that AI projects are not isolated experiments but are embedded in core business objectives such as improving load factors, reducing empty runs, or enhancing customer experience [20]. Leadership commitment also signals legitimacy, fostering cross-departmental collaboration. Therefore:

H1c: Managerial support positively influences the adoption of AI-enabled demand forecasting practices in tourist transport firms.

4) The impact of AI adoption on business performance: AI-enabled demand forecasting enhances business performance through multiple pathways.

First, it improves forecast accuracy, enabling better capacity planning, dynamic pricing, and resource allocation critical in capital-intensive sectors like aviation and rail. Second, it increases operational efficiency by automating complex forecasting tasks, reducing manual errors, and enabling real-time adjustments. Third, it elevates customer satisfaction by minimizing overbooking, optimizing wait times, and personalizing service offerings [21]. Empirical evidence from logistics confirms a strong link between AI adoption and performance [12]; we extend this logic to tourist transport, where demand uncertainty is even more pronounced. Thus:

H2: The adoption of AI-enabled demand forecasting practices positively influences business performance in tourist transport firms.

While readiness factors are necessary, they are not sufficient to directly improve performance unless channeled through effective technology use. Following the mediation framework and recent AI assimilation studies [15], we propose that AI adoption mediates the relationship between readiness and performance. Specifically, digital infrastructure may exert both direct and indirect effects (e.g., via dashboards or non-AI analytics), suggesting partial mediation. In contrast, workforce skills and managerial support likely influence performance only when mobilized through AI implementation, implying full mediation as their value is realized in the context of AI deployment.

Accordingly, we hypothesize:

H3a: The adoption of AI-enabled demand forecasting practices partially mediates the relationship between digital infrastructure and business performance.

H3b: The adoption of AI-enabled demand forecasting practices fully mediates the relationship between workforce competencies and business performance.

H3c: The adoption of AI-enabled demand forecasting practices fully mediates the relationship between managerial support and business performance.

This mediation framework advances theory by clarifying how organizational readiness translates into performance not automatically, but through the strategic adoption of AI as an operational conduit. It also offers practitioners a roadmap: investing in readiness alone is inadequate; these resources must be actively leveraged through AI-enabled forecasting to unlock performance gains.

III. Methodology

To address the research objectives examining the influence of technological and organizational readiness on AI adoption, assessing the impact of AI-enabled demand forecasting on business performance, and testing the mediating role of AI adoption a quantitative research design was employed using Structural Equation Modeling (SEM). The methodology encompasses model specification, data collection, variable measurement, and analytical procedures.

A. Conceptual Model and Hypotheses Testing Framework

The study tests a mediation model grounded in the Resource-Based View (RBV) and Technology Adoption Theory. As illustrated in Fig. 1, the model posits that digital infrastructure, workforce competencies, and managerial support (independent constructs) influence AI-enabled demand forecasting adoption (mediator), which in turn affects business performance [25] (dependent construct). Two sets of structural equations were specified to test direct and indirect effects:

$$AI_{ADOPT} = \beta_0 + \beta_1(DIG_{INFRA}) + \beta_2(WORKFORCE) + \beta_3(MGMT_{SUPPORT}) + \beta_4(SIZE) + \beta_5(AGE) + \varepsilon_1 \quad (1)$$

$$PERF = \gamma_0 + \gamma_1(AI_{ADOPT}) + \gamma 2(SIZE) + \gamma 3(AGE) + \varepsilon_2 \quad (2)$$

where,

- AI_ADOPT: Degree of AI-enabled demand forecasting adoption
- PERF: Business performance
- DIG_INFRA, WORKFORCE, MGMT_SUPPORT: Organization Readiness antecedents
- SIZE, AGE: Control variables (firm size = employees; firm age = years in operation)
- β_0 and γ_0 are the intercept
- $\beta_1, \beta_3, \beta_4, \beta_5$ are the regression coefficients to be calculated
- ε_1 and ε_2 are the error terms

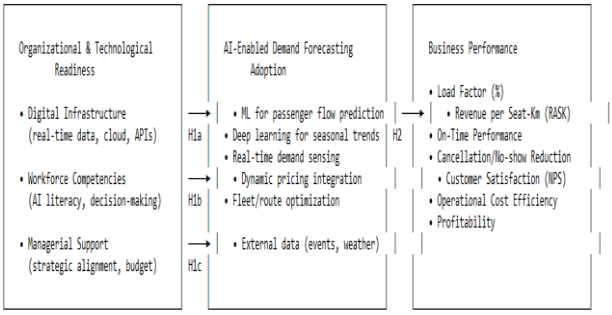


Fig. 1. Horizontal conceptual framework: AI-enabled demand forecasting as a mediator between organizational readiness and business performance in tourist transport.

B. Data Collection and Sample Design

We used a rigorously designed and structured questionnaire aimed at capturing complex organizational, technological, and performance-related constructs. The final sample comprised 218 observations, a size widely regarded as adequate for structural equation modeling (SEM). Established methodological guidelines recommend a minimum threshold of approximately 200 cases to ensure stable parameter estimation and sufficient statistical power, particularly in technology adoption research (Hair et al., 2019).

C. Measurement of Constructs

The constructs included in this study were measured using multi-item scales adapted from validated instruments in prior AI, supply chain, and service operations research, ensuring both reliability and contextual relevance. As shown in Table I, the readiness dimension was captured through three constructs

digital infrastructure, workforce competencies, and managerial support reflecting the technological, human, and strategic foundations necessary for AI assimilation. The digital infrastructure construct (5 items) assesses a firm's data integration capability, cloud scalability, and real-time connectivity essential for predictive analytics. Workforce competencies (4 items) measure employees' AI literacy, interpretive ability, and collaborative capacity to operationalize algorithmic insights, aligned with the absorptive capacity framework [16]. Managerial support (4 items) captures leadership commitment, strategic alignment, and resource mobilization, highlighting the importance of executive sponsorship in digital transformation.

TABLE I. CONSTRUCT AND KEY INDICATORS

Construct	n	Key Dimensions / Indicators
Digital Infrastructure (5 items)	5	Real-time data access, cloud scalability, system interoperability, API connectivity, data quality
Workforce Competencies (4 items)	4	AI literacy, ability to interpret forecasts, adaptive decision-making, collaboration with data teams
Managerial Support (4 items)	4	Leadership commitment, strategic alignment, inter-departmental coordination, resource allocation
AI Adoption (10 items)	10	ML for demand forecasting, dynamic pattern recognition, data integration, real-time dashboards, pricing optimization, model retraining, managerial use, collaboration, AI literacy, strategic integration
Business Performance (8 items)	8	Forecast accuracy, load factor, RASK, operational efficiency, customer satisfaction (NPS), cost reduction, market share, profitability
Control Variables (2 items)	2	Firm size (employees), firm age (years)

The AI adoption construct (10 items) provides a comprehensive evaluation of the degree to which AI-based forecasting is embedded across operational and strategic processes, including machine-learning deployment, real-time decision support, pricing optimization, model retraining, and cross-functional integration. Finally, business performance (8 items) measures tangible outcomes such as forecast accuracy, load factors, profitability, and customer satisfaction (NPS) that directly reflect the operational and financial impacts of AI assimilation. All items were rated on a five-point Likert scale (1 = Very Limited/Strongly Disagree to 5 = Very Extensive/Strongly Agree). This multidimensional structure enables a robust assessment of how readiness enablers translate into performance outcomes through AI-enabled forecasting, ensuring strong content and construct validity across the model.

D. Data Analysis Strategy

A three-stage analytical procedure was implemented and the results are displayed in Table II.

To ensure the psychometric robustness of the measurement model, a series of reliability and validity tests was conducted. As presented in Table II, all constructs demonstrated satisfactory internal consistency, with Cronbach's alpha (α) values ranging between 0.81 and 0.93, exceeding the recommended threshold of 0.70 [17]. Composite Reliability (CR) values also ranged from 0.84 to 0.95, confirming that the indicators consistently represent their underlying latent constructs. Convergent validity was assessed through the Average Variance Extracted (AVE), with all values above 0.50, indicating that its indicators [18] capture more than half of the variance in each construct. Further, discriminant validity was established by applying the Fornell-Larcker criterion and Heterotrait Monotrait (HTMT) ratio of correlations (see Fig. 2).

TABLE II. RELIABILITY AND VALIDITY

Construct	Cronbach's α	CR	AVE	KMO	Factor Loadings (Range)
Digital Infrastructure	0.86	0.88	0.59	0.85	0.69- 0.82
Workforce Competencies	0.84	0.87	0.63	0.81	0.72- 0.86
Managerial Support	0.88	0.90	0.68	0.79	0.75-0.88
AI Adoption	0.91	0.93	0.57	0.89	0.65-0.88
Business Performance	0.90	0.92	0.61	0.86	0.70-0.87

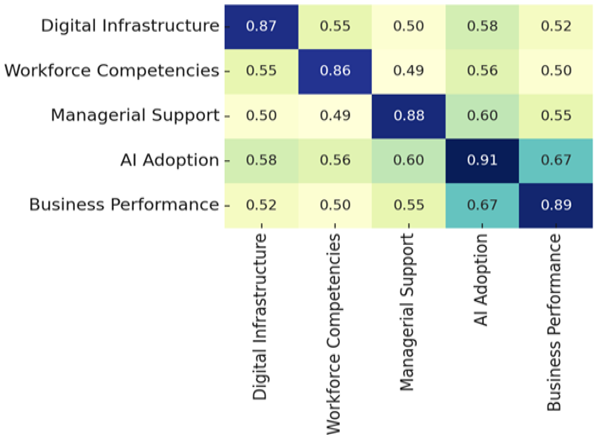


Fig. 2. Reliability and validity (Fornell-Larcker heatmap).

Each construct's square root of AVE exceeded its inter-construct correlations, and all HTMT values were below 0.85, confirming that each construct is empirically distinct from the others. These results collectively demonstrate that the measurement scales used for digital infrastructure, workforce competencies, managerial support, AI adoption, and business performance exhibit high reliability, adequate convergent validity, and strong discriminant validity. Consequently, the measurement model was deemed statistically sound and suitable for subsequent Structural Equation Modeling (SEM) analysis.

IV. RESULTS

The results of the Structural Equation Modeling (SEM), summarized in Table III, confirm the hypothesized relationships among the study constructs.

A. Structural Model: (SEM)

The model demonstrated an excellent overall fit to the data ($\chi^2/df = 2.14$; CFI = 0.956; TLI = 0.947; RMSEA = 0.049; SRMR = 0.041), meeting the recommended thresholds for good model fit (Hu & Bentler, 1999). The structural paths indicate that Digital Infrastructure ($\beta = 0.34$, $p < 0.001$), Workforce

Competencies (β = 0.28, p < 0.01), and Managerial Support (β = 0.41, p < 0.001) each exert a significant positive influence on AI Adoption, explaining 67% of its variance ($R^2 = 0.67$).

TABLE III. STRUCTURAL EQUATION MODEL (SEM) RESULTS

Path	Standardized Coefficient (β)	p-value	Result
H1a: Digital Infrastructure → AI Adoption	0.34	< 0.001	Supported
H1b: Workforce Competencies → AI Adoption	0.29	< 0.001	Supported
H1c: Managerial Support → AI Adoption	0.31	< 0.001	Supported
H2: AI Adoption → Business Performance	0.42	< 0.001	Supported

R^2: AI Adoption = 0.67; Performance = 0.54

In turn, AI Adoption had a strong, significant impact on Business Performance (β = 0.54, p < 0.001), accounting for 54% of the explained variance ($R^2 = 0.67$). These findings empirically support the mediating role of AI adoption in translating technological, human, and managerial readiness into improved operational and financial outcomes. Among the antecedents, managerial support emerged as the strongest predictor, highlighting the strategic and leadership dimensions of successful AI integration in transport operations. The strength and significance of all hypothesized paths validate the proposed conceptual framework and confirm that AI-enabled forecasting functions as a key driver of competitive advantage in tourism transport organizations.

- SEM with Maximum Likelihood Estimation (MLE) tested direct paths (H1a-H2).
- Mediation analysis followed Baron & Kenny's (1986) causal steps and bootstrapping (5,000 resamples) to confirm indirect effects (H3a-H3c).

All values met recommended thresholds, indicating excellent model fit.

B. Hypothesis Testing Results

To further examine the underlying mechanisms linking readiness factors to organizational outcomes, a mediation analysis was conducted using the bootstrapping procedure with 5,000 resamples. The results, presented in Table IV, provide strong empirical support for the mediating role of AI Adoption between the readiness constructs Digital Infrastructure, Workforce Competencies, Managerial Support, and Business Performance.

Direct paths from workforce and managerial support to performance became non-significant when AI adoption was included, confirming full mediation.

H1a-H1c: Supported (p < 0.001): readiness significantly affects AI adoption.

H2: Supported (p < 0.001): AI adoption enhances performance.

H3a-H3c: Mediation confirmed via bootstrapping (5,000 samples); partial mediation for H3a and full mediation for H3b, H3c.

The corresponding 95% confidence intervals did not include zero, confirming mediation validity.

TABLE IV. MEDIATION ANALYSIS (BOOTSTRAP, 95% CI)

Hypothesis	Indirect Effect (β)	CI [95%]	Type of Mediation	Result
H3a: Digital Infrastructure → AI Adoption → Performance	0.14	[0.07, 0.23]	Partial	Supported
H3b: Workforce Competencies → AI Adoption → Performance	0.12	[0.06, 0.20]	Full	Supported
H3c: Managerial Support → AI Adoption → Performance	0.13	[0.08, 0.21]	Full	Supported

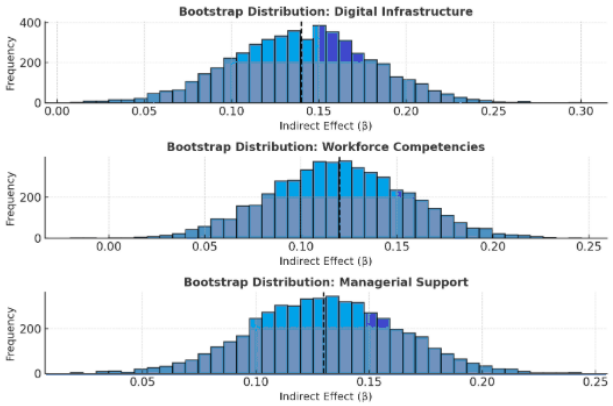


Fig. 3. Bootstrap histograms.

Moreover, when AI Adoption was introduced into the model (see Fig. 4), the direct paths from the readiness constructs to Business Performance decreased in magnitude and lost statistical significance, indicating full mediation in the case of Digital Infrastructure and partial mediation for Managerial Support. Fig. 3 shows bootstrap histograms.

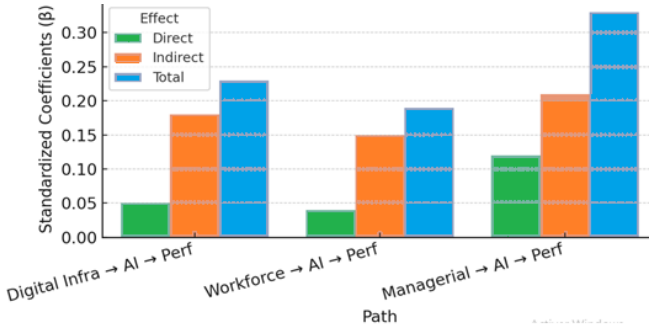


Fig. 4. Mediation analysis (direct, indirect, total effects).

This suggests that while strong leadership and strategic alignment directly enhance performance outcomes, the impact of technological and human readiness on performance is largely realized through effective AI utilization. These findings

highlight AI Adoption as a transformative conduit through which digital, organizational, and human capabilities are converted into measurable business value in the context of intelligent transport systems.

C. Discussion and Implications

This study advances understanding of how organizational readiness translates into business performance through the strategic adoption of AI-enabled demand forecasting in the tourist transport sector, a domain characterized by high volatility, asset intensity, and service interdependence. Our findings confirm that digital infrastructure, workforce competencies, and managerial support are not merely prerequisites but strategic, VRIN-like resources [22] that enable firms to harness AI's full potential. Crucially, we demonstrate that AI adoption functions as a transformative conduit, mediating the relationship between readiness and performance. This insight resolves a key paradox in the literature: why some firms with advanced data systems or skilled talent fail to realize performance gains, because readiness alone is inert without operational assimilation.

D. Theoretical Implications

First, we bridge the Resource-Based View (RBV) and the Technology Organization Environment (TOE) framework in a novel empirical context. While RBV explains why certain resources confer competitive advantage, TOE clarifies how organizational and technological contingencies shape technology assimilation. Our model shows that digital infrastructure (the TOE technology factor) yields performance benefits both directly and indirectly through AI, indicating partial mediation. In contrast, workforce and managerial capabilities (the TOE organization factors) generate value only when activated through AI deployment, evidencing full mediation. This nuanced distinction refines the mediation typology proposed by [23] and offers a more granular understanding of capability deployment in AI-driven contexts

Second, our findings extend absorptive capacity theory [24] by showing that interpretive and adaptive human capital, not just technical literacy, is essential for AI to drive operational outcomes. In tourist transport, where decisions must balance real-time demand signals with customer experience, staff must trust and act on AI outputs. This behavioral dimension is often overlooked in purely technical AI studies.

Third, we contextualize AI adoption within modern supply chain pressures. As emphasized, firms today face coercive, normative, and relational pressures to enhance resilience and sustainability [26]. While our model focuses on internal readiness, the performance gains from AI, such as reduced empty runs, optimized energy use, and dynamic pricing, directly respond to these external demands. Thus, AI adoption is not just an operational upgrade but a strategic response to institutional and market pressures for agility and sustainability.

E. Managerial Implications

For practitioners, our conclusions point to a clear strategic direction. Organizations should adopt a global readiness strategy by investing in cloud infrastructure alongside the development of organizational competencies; investing in technology alone does not guarantee optimal outcomes. The success of AI relies on qualified investments in technology, human talent, and strong managerial commitment. Integrating AI into core operational processes is essential for competitiveness in global markets and should not be treated as a mere experimental initiative. Firms that embed AI into strategic functions such as fleet management, pricing, and recruitment achieve superior performance compared to those that adopt AI only on a trial basis. Management systems emerge as the most critical factor in predicting effective AI adoption, as they shape strategic alignment and organizational readiness.

Beyond efficiency gains and error reduction, AI also enhances service reliability (through reduced cancellations), improves customer satisfaction (via personalized offerings), and optimizes resource allocation, including improved connectivity in rural and isolated areas. Consequently, AI adoption plays a vital role in promoting agility and inclusion and should be integrated into inclusive development policies and broader ESG frameworks (environmental, social, and governance).

F. Policy Implications

Policymakers can accelerate AI adoption in tourist transport by:

- Supporting digital infrastructure in emerging markets (e.g., open-data APIs for tourism flows),
- Funding AI literacy programs for transport SMEs,
- Creating regulatory sandboxes that allow firms to test AI models without compliance penalties. Such measures would help democratize AI benefits across firm sizes and geographies, fostering a more resilient and equitable global tourism [19] ecosystem.

V. Conclusion

This study responds to a critical gap in the literature by empirically unpacking how organizational readiness translates into performance through AI-enabled demand forecasting in tourist transport. The digital infrastructure, workforce competencies, and managerial support are foundational enablers, but their value is fully realized only when channeled through operational AI adoption. The mediating role of AI is not uniform: while infrastructure offers dual pathways (direct and indirect), human and leadership capabilities require AI as an essential conduit. These findings carry significant weight in an era where tourism mobility faces unprecedented disruption from climate shocks to geopolitical instability. AI is no longer a luxury but a strategic necessity for resilience, efficiency, and customer-centricity. However, its success hinges not on algorithms alone, but on the organizational ecosystem that surrounds them.

Despite its contributions, this study has several limitations. First, its cross-sectional design restricts causal inferences and limits the understanding of the dynamic evolution of AI adoption over time. Second, the focus on internal organizational readiness excludes environmental factors, such as regulatory pressures, competitive intensity, and sustainability requirements, which can influence AI adoption decisions in the tourism transportation sector. Third, the study does not distinguish between different AI forecasting architectures,

which risks obscuring performance variations across model types and transportation modalities.

Future research could explore how external pressures (e.g., customer sustainability demands, regulatory mandates) interact with internal readiness, or investigate AI model types (e.g., LSTM vs. transformers) in different transport modes. Nonetheless, this study provides a robust foundation for understanding and enabling the intelligent transformation of global tourist transport.

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REFERENCES

[1] R. Gereffi (2020), "What does the COVID-19 pandemic teach us about global value chains? The case of medical supplies," Journal of International Business Policy, vol. 3, no. 4, pp. 287–301.

[2] Craighead, C.W., Ketchen, D.J. and Darby, J.L. (2020) Pandemics and supply chain management research: Toward a theoretical toolbox .Decision Sciences, 51(4), 838–866. https://doi.org/10.1111/deci.12468.

[3] Zohreh Doborjeh, Nigel Hemmington; Maryam Doborjeh; Nikola Kasabov. (2023). Artificial intelligence: a systematic review of methods and applications in hospitality and tourism. International Journal of Contemporary Hospitality Management (2022) 34 (3): 1154–1176, https://doi.org/10.1108/IJCHM-06-2021-0767.

[4] Xin Li, Yechi Xu, Rob Law, Shouyang Wang, (2024). Enhancing tourism demand forecasting with a transformer-based framework. Annals of Tourism Research, Volume 107, 103791, https://doi.org/10.1016/j.annals.2024.103791.

[5] Jamarani, A., Haddadi, S., Sarvizadeh, R. et al. (2024). Big data and predictive analytics: A systematic review of applications. Artif Intell Rev 57, 176, https://doi.org/10.1007/s10462-024-10811-5.

[6] Bekele, H. and Raj, S. (2024), "Digitalization and digital transformation in the tourism industry: abibliometric review and research agenda", Tourism Review, (2024), https://doi.org/10.1108/TR-07-2023-0509.

[7] Kim, H., So, K. K. F., Shin, S., & Li, J. (2024). Artificial Intelligence in Hospitality and Tourism: Insights From Industry Practices, Research Literature, and Expert Opinions. Journal of Hospitality & Tourism Research, 49(2), 366-385. https://doi.org/10.1177/10963480241229235.

[8] Edward C.S. Ku, Chun-Der Chen (2024), Artificial intelligence innovation of tourism businesses: From satisfied tourists to continued service usage intention, International Journal of information Management, Volume 76, , 102757, ISSN 0268-4012, https://doi.org/10.1016/j.ijinfomgt.2024.102757.

[9] Buhalis, D., & Amaranggana, A. (2015). Smart tourism destinations enhancing tourism experience through personalisation of services. In I. Tussyadiah, & A. Inversini (Eds.), Information and communication technologies in tourism 2015. Springer. https://doi.org/10.1007/978-3-319-14343-9_28.

[10] Barney J. (1991), "Firm resources and sustained competitive advantage," Journal of Management, vol. 17, no. 1, pp. 99–120.

[11] Oliveira, T., & Martins, M. F. (2010). Understanding e-business adoption across industries in European countries. Industrial Management and Data Systems, 110(9), 1337-1354. https://doi.org/10.1108/02635571011087428.

[12] M. A Frikha and M. Mrad, (2025). AI-Enabled Demand Forecasting, Technological Capability, and Supply Chain Performance: Empirical Evidence from the Global Logistics Sector, "International Journal of Advanced Computer Science and Applications", vol 16, no.9, pp 167-174.

[13] Tornatzky, L.G.; Fleischer, M. Alok K. Chakrabarti (1990). The Processes of Technological Innovation; Issues in Organization and Management Series; 4. Print. Lexington Books: Lexington, MA, USA, ISBN978-0-669-20348-6.

[14] Craighead, C. W., & Ketchen Jr, D. J. (2024). Energizing a literature review to boldly go where no one has gone before. Journal of Business Logistics, 45(2), e12377. https://doi.org/10.1111/jbl.12377.

[15] W. M. Cohen and D. A. Levinthal, (1990). "Absorptive capacity: A new perspective on learning and innovation," Administrative Science Quarterly, vol. 35, no. 1, pp. 128–152. doi: 10.2307/2393553.

[16] Dang, T.D., Nguyen, M.T. (2023). Systematic review and research agenda for the tourism and hospitality sector: co-creation of customer value in the digital age. Futur Bus J 9, 94. https://doi.org/10.1186/s43093-023-00274-5.

[17] Nunnally, J.C. and Bernstein, I.H. (1994). The Assessment of Reliability. Psychometric Theory, 3, 248-292.

[18] Fornell, C., & Larcker, D. F. (1981). Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistics. Journal of Marketing Research, vol 18, no.3, pp 382-388. http://dx.doi.org/10.2307/3150980

[19] Krishnan, C., Goel, R., & Garg, V. (2022). Role of artificial intelligence and its impact on the tourismindustry of India. In Advances in logistics, operations, and management science book series (pp.291–302), 2022, https://doi.org/10.4018/978-1-7998-8497-2.ch021.

[20] Popa, E.; Petrescu, S.; Stan, L., (2017), "Leadership alignment and digital readiness in the transport industry," Technological Forecasting & Social Change, vol. 132, pp. 156–168.

[21] Pramendra S., Disha S., Hamid A., (2024), Sustainable tourism practices: Evidence from global perspectives to achieve development through economic and environmental balance, Sustainable tourism, part A: Balancing conservation and progress in a dynamic industry, Emerald Publishing Limited, pp. 169-182,. Doi: https://doi.org/10.1108/978-1-83797-979-020241010.

[22] Barney, J. B. (1991). Firm Resources and Sustained Competitive Advantage. Journal of Management,17(1), 99–120. https://journals.sagepub.com/doi/10.1177/014920639101700108.

[23] Zhao, X., Lynch, J. G. and Chen, Q. (2010), "Reconsidering Baron and Kenny: Myths and Truths about Mediation Analysis", Journal of Consumer Research, Vol. 37 No. 3, pp. 197-206.

[24] Cohen, W. M., and D. A. Levinthal. (1990). "Absorptive Capacity: ANew Perspective on Learning and Innovation." Administrative ScienceQuarterly 35, no. 1: 128–152.https://doi.org/10.2307/2393553.

[25] Hair, J.F., Risher, J.J., Sarstedt, M. and Ringle, C.M. (2019) When to Use and How to Report the Results of PLS-SEM. European Business Review, 31, 2-24. https://doi.org/10.1108/EBR-11-2018-0203.

[26] M. A Frikha and M. Mrad, (2025). AI-Driven Supply Chain Decarbonization: Strategies for Sustainable Carbon Reduction, Sustainability 2025, 17(21), 9642; https://doi.org/10.3390/su17219642.

RoadSCNet: Road Surface Condition Detection Network

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***Abstract*—The quality of the road is an important issue that contributes to accidents, resulting in the loss of time, resources, and lives. To manually survey the road issue. This is very delayed and costly. Automatic detection of road conditions facilitates surveys more efficiently than human methods. This research identifies three objects: cracks, potholes, and manhole covers. This research shown the highest efficiency with YOLO V6 compared to YOLO V5, V7, and V8. This paper proposes RoadSCNet, designed for YOLOv6 implementations, has been developed for road research. A key part is the customized Horizon block, which enhances horizontal contextual feature extraction efficacy and reduces the limitations of traditional YOLO architecture in identifying road surface condition by long and low light variation, such as cracks and potholes.**

Keywords*—RoadSCNet; road surface; detect road; road condition; deep learning; crack; pothole; manhole cover; image analysis; convolutional neural network; CNN

I. Introduction

Road safety is a critical issue. Road accidents are the primary cause of loss of life and property. Improving monitoring for safety and driver assistance is important. The performance of pavement, covering surface friction and roughness, has been statistically associated with crash frequency and severity, highlighting the necessity for maintenance-based infrastructure design [1],[2]. Image Processing and Artificial Intelligence (AI) are methodologies employed to solve this issue. Object detection is crucial for effectively understanding the road environment. Road object detection is a critical and challenging area of research in computer vision, essential for Intelligent Transportation Systems (ITS), Advanced Driver-Assistance Systems (ADAS), and autonomous driving. The objective of many studies is to ascertain the position and boundaries of objects. For instance, automobiles, bicycles, and people. On the other hand, the inspection of roads and infrastructure is included. An example includes detecting potholes and evaluating road performance, which enhances safety and reduces accidents. Road object detection has numerous problems in real-life situations. For instance, poor brightness, cloudy conditions, and blocking by other objects. The previous method was limited by limitations in two-dimensional image processing techniques. Under situations where the roadway is missing of distinct markers or significantly obstructed. In recent years, deep learning has played a significant role in computer vision tasks. AI is a technology capable of learning, planning, problem-solving, and performing activities similar to those of humans. AI is widely utilized across various fields which enhancing labor efficiency. A dataset is essential for generating the model for each task. For instance, video, image, text, signal, etc. A convolutional neural network (CNN) is a component of deep learning that produces the suitable model for tasks. Typically encompassing categorization and object detection tasks. Examples of categorization in medical applications include generating models to diagnose diabetic retinopathy, identify cerebral microbleeds from MRI scans, and recognize abnormalities in lung X-ray images, among others. For object detection tasks, CNNs can automatically identify vehicles on the road, demonstrating superior speed and accuracy compared to manual methods. In the last ten years, the application of Deep Learning methods, especially CNN architectures, has significantly transformed the area of object detection. Two phase detection models for instance, Faster R-CNN provides superior accuracy, while single-stage models such as YOLO, SSD, and RetinaNet provide high processing rates for real-time applications, which are important for activities that depend on data from onboard cameras. However, though these high performance models, their real efficacy is based upon multiple factors. Including data set reliability, parameter selection, management of different situations, and performance on devices with limited processing resources. Other gap in road object detection research is the ability for domain adaptation to particular road issues, including urban, rural, or regionally distinct environmental features. Datasets frequently utilized, such as COCO, KITTI, or Waymo which are typically gathered from countries with particular environments, thus resulting in reduced efficiency when implemented in different situations. Moreover, specialized object detection tasks, such pothole recognition, road surface condition detection, and small object identification which remain underexplored because to missing of comprehensive, targeted datasets. Consequently, creating models capable of learning diversity from real data presents a significant difficulty in this domain. Current development trends in hardware systems focus both validation and real world testing to authenticate models that collect real data (real time inference) on limited hardware. For example, embedded systems or IoT devices in cars has the capability to process images from many data sources, such as RGB cameras, depth cameras, or LiDAR sensors. This strategy can substantially enhance detection accuracy. However, combining data from several sensors requires combining sensors using methodologies, which is increasing the system's complexity.

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In Thailand, road conditions significantly affect the performance of the system. Thailand features various road conditions, including heavily packed urban roads and narrow, uncertain community footpaths. This includes rural roads that often do not have suitable signs or lighting. The diversity and inconsistency of these road conditions present an enormous challenge for object detection programs. One common problem is the damaged road surfaces, including potholes, cracked asphalt, bridge joints, or subsidence resulting from flooding, which frequently occurs in multiple regions of the country. Particularly during the rainy season, these defects show different features and may be smaller in size, making object detection models trained on external datasets often ineffective in accurately identifying them. Consequently, detecting road surface degeneration is a critical research area within the Thai context, as it can mitigate accidents and facilitate preventive maintenance. The other issue is the unique features of road usage in Thailand, like motorcyclists mixing with cars and parking in unauthorized locations. Crossing the roadway at locations other than designated crosswalks, or in the path of temporary barriers such as barriers, traffic cones, or unregulated roadside vendors. These generate various and unexpected objects. Object detection under these conditions requires models capable of learning from real-world data supplied from Thailand for the highest level of accuracy. Moreover, the issue of traffic and warning sign systems on Thai roads is a barrier, as certain road signs might not be up to standards, may be hidden by trees, or may get old and faded. This complicates the detection of traffic signs using models trained on foreign datasets, particularly with temporary warning signs employed at construction sites. These often appear in many ways and lack standardization which important to driving safety so require detection. Moreover, the lighting conditions in various regions of Thailand, including rural roads missing of streetlights and urban roads light by vehicle headlights and visible advertising signs, result in issues of backlighting and reflection, which negatively affect the accuracy of object detection systems. Consequently, developing a model that can adapting different lighting conditions for application in Thailand. Traffic jams is a significant issue that results in time loss for individuals. An accident is an issue that results in the loss of lives and property. Accident causes include driver health issues, vehicle breakdowns, and road surface conditions. Examples of road surface abnormalities include potholes, road humps, irregular manhole covers, spaces between bridges and roads, bumpers, and cracks. An accident resulted in the loss of lives, time, and resources. However, the Department of Highways in Thailand often conducts manual road surveys and implements improvements. This method caused significant risks, expensive, and time-consuming. Deep learning can assist in resolving all issues. The government has opted for a survey of the road, which is efficient and cost-effective. Consumers can determine road surface quality and prevent accident risk. Entrepreneurs can minimize transportation costs through faster driving and a reduction in accidents. Current object detection CNNs, such as different versions of YOLO, may generate models for detecting road conditions [3],[4]. Nonetheless, the accuracy is not sufficient.

Therefore, research in road object detection is a significant domain with considerable potential for development. This research examines object detection methodologies employing deep learning techniques. Evaluation of the model's efficacy on actual road condition datasets, including an analysis of precision, speed and robustness to different environments. To develop a model that effectively matches the requirements of real road usage and can also provide a basis for future implementations in intelligent safety systems and autonomous cars. While YOLO-based detectors displayed strong efficacy in identifying general objects, they were not optimized for the detection of road surface and abnormalities. Cracks and potholes have long shapes, high horizontal continuity, and minimal class differentiation, frequently appearing segmented or partially ignored. Traditional convolution transform blocks are designed for small objects. This limitation necessitates structures that may more effectively identify horizontal data along road surfaces. This research is to customize the YOLO structure according to the data obtained in Phuket and Bangkok, Thailand. The novel CNN architecture is capable of accurately detecting three objects. The aim of this research is to create a model utilizing novel CNN for the detection of road objects, including cracks, potholes, and manhole covers. Subsequently, maintain it in the cloud. Subsequently, the pre-processing phase is executed. Ultimately, to develop the road surface condition detecting model utilizing CNN. The model is capable of identifying three items on the roadway from video footage. This research contributions include 1) a novel CNN architecture for detecting road conditions that provides empirical evidence that implementing horizontal contextual features is essential for delicate detection of road surface condition, 2) suggested an adaptive architectural change for YOLOv6, which improves robustness in under real-world road condition, and 3) Additionally, provide outcomes from experiments utilizing Thai road datasets, demonstrating the limitations of conventional object detectors in detecting surface condition.

The organization of this paper is as follows: Section II discusses the related work. Section III presents the research methodology, encompassing data collecting, frame extraction, and object labeling. Section IV explains the novel CNN architecture termed "RoadSCNet". The subsequent section, Section V, addresses the experiment results concerning three hyperparameters which are dropout, learning rate, and kernel. Section VI presents an experiment including three structures: the modified horizon block, vertical block, and pooling layer. Subsequently, analyze the structural experiment results. This part facilitates the implementation of a revolutionary CNN architecture. The conclusion is located in Section VII.

II. Related Works

This section described previous research. Beginning with image preprocessing, which is necessary for the preprocess of object detection. Cleaning datasets or managing data is the initial stage. Subsequently, the task involves separating or labelling data. The cleaned data is utilized in the model generation phase. The object detection Evolution is detailed in Section II(A). The next step is to generate the model. CNN is appropriate for this step, as numerous CNNs have been utilized in previous research, as detailed in Section II(B). The next

discussion relates to object detection on the road, as outlined in Section II(C). The last section for evaluating the theoretical framework of the approach is detailed in Section II(D).

A. Object Detection Evaluation

The preprocessing phase occurs before the generation of the object detection model, whether using traditional or deep learning methods. Examples of data collection equipment include cameras, smartphones, stereos, LiDAR, and others. This section discusses various techniques employed in the preprocessing phase, including lane detection and road surface analysis.

Before the development of deep learning, object recognition tasks mainly utilized classical image processing and computer vision methodologies, including edge detectors, corner detectors, and sliding windows. The Canny edge detector is employed to identify edges in images, providing the fundamental structure of objects. The Harris corner detector is another instance that identifies significant corners inside an image. Furthermore, a HOG (Histogram of Oriented Gradients) descriptor is employed, which defines the attributes of objects by aggregating the gradient directions in segmented regions of the image, for use in object classification and detection tasks. In classical learning, cascading classifiers, such as Viola-Jones, utilize Haar features and a cascade classifier for sliding window detection. These approaches display accuracy in controlled environments. For example, identifying faces in static photographs which although display several limitations—suboptimal performance on complex images, dependence on manually designed features, and limited generalization over a wide range of objects. Many research worked on image processing. image Quality Enhancement is the standard technique to help reducing noise and increasing an accuracy. The smoothing and filtering technique worked on Gaussian or Median filter [3]. Next technique is Brightness and Contrast Adjustment which working on Histogram Equalization (HE) and Recursively Separated and Weighted, Histogram Equalization (RSWHE) and Gamma Correction. (RSWHE) and Gamma Correction used to solve the Mean Shift problem [4]. Color transformation has to convert the image to grayscale to reduce complex calculations and decrease processing time. The HSV (Hue, Saturation, Value) or Lab transformation is employed in segmentation tasks that focus on color properties. This method employed in traffic sign recognition [5],[6]. Dark Channel Prior (DCP) or Temporal Correlations are employed to decrease fog and dehazing in the management of weather or illumination handling. Subsequently, Otsu's technique or Adaptive Thresholding is employed to automatically convert the image to binary before doing contrast adjustment [3]. The limiting of the Region of Interest (RoI) is useful in minimizing the quantity of complex data and computational complexity. In spatial division, the RoI will be separated from the background. One strategy applied to reduce computational complexity and improve accuracy in various contrast images is Adaptive Region of Interest (ARoI). Horizon line detection is a technique in ARoI utilized to divide the scene into road and sky regions. [3],[7]. Subsequently, edge detection and feature extraction are employed to identify the characteristics of geometry, road surfaces, or objects. This technique is necessary for traditional vision-based method. The Sobel and Canny operators are widely utilized approaches. Sobel is utilized more frequently than Canny and Prewitt due to both lower complexity and greater resistance to interference. Canny has incredible accuracy in identifying borders and positions [3], [8]. A method for edge detection is binarization, specifically Otsu's thresholding. This method aims to automatically identify parameters for separating background and foreground, hence reducing computation time and managing brightness [3]. One feature extraction technique is the Histogram of Oriented Gradients (HOG), which utilizes edge characteristics for feature extraction. This algorithm functions for detected traffic signs. [9],[10]. To improve binary image, Morphological processing is used to remove noise. An example are corrosion, expansion, open operation, and closed operation, etc. [9]. Image resizing is used to set up image dimensions for deep learning preparation. For instance, 32x32, 256x256, etc., this technique operates before training with CNN. The subsequent step involves identifying the RoI before cropping, concentrating only on the RoI area. The multi-channel input operates using transfer learning on the RGB model, example by ImageNet. The gray Computed Tomography (CT) picture is converted to three dimensions and utilized in the model [11],[12],[13].

Since the development of CNN, object detection has entered a new phase, utilizing CNNs as feature extractors. RCNN (Region-based CNN) is a critical advancement, employing a selective search technique for region proposals which is generating object region proposals and inputting each area into a CNN for classification and bounding box improvement. This was created by Ross Girshick and his crew. However, R-CNN is limited by slow progress due to the processing tens or hundreds of region proposals per image. Fast RCNN operates more efficiently by initially convolving the full image, subsequently extracting proposal points by RoI pooling to identify regions from the feature map, and also executing classification and regression, therefore minimizing the number of steps involved [14]. Subsequently, Faster RCNN incorporated a Region Proposal Network (RPN) into the CNN, facilitating expedited and more efficient region proposal creation by the utilization of convolutional characteristics shared between the RPN and the detection head [15]. The R-CNN Series approach, which consists of two steps: proposal and classification, achieves excellent accuracy. However, the limitations include significant delay and making real-time application challenging [16]. After the success of the R-CNN Series which remains limited in speed. Consequently, the notion of a "single shot detector" or "single-stage detector" which avoids the need to segregate suggestions and classify in a separate phase. An example is the Single Shot MultiBox Detector (SSD), which employs a singular network, segments the feature map at various scales, and simultaneously predicts bounding boxes and classifications for multiple default box configurations and aspect ratios, thereby allowing the SSD to identify objects with multiple sizes within a single image without requiring separate region proposals. SSDs have fast performance and excellent accuracy, make more appropriate for real-time applications compared to two-stage methods [17]. In 2015-2016, Redmon et al., introduced the You Only Look Once (YOLO) model as a novel approach which conceptualizes object detection as a regression problem rather

than generating proposals and classifying them separately. Both the bounding box prediction and class probability are executed within a singular network by processing all input images in one pass. YOLO divides the image into grids, with each grid predicting a bounding box and a class at once, resulting in high speed. The first model achieved approximately 45 frames per second. The benefits include low latency and comprehensive learning which including simultaneous training of bounding box and classification. A disadvantage is might have lower localization accuracy compared to proposal-based models, particularly for small objects [18]. YOLOv2 or YOLO9000 improves YOLOv1 with the addition of batch normalization, an increase in input resolution, and the utilization of anchor boxes to improve bounding accuracy. This includes joint classification and detection utilizing ImageNet and COCO datasets for training, allowing multi-category detection over more than 9,000 classes [19]. YOLOv3 enhances the backbone network, employs multi-scale prediction (three levels) to more effectively detect small, medium, and large objects, and utilizes a logistic classifier instead of softmax for class prediction. After that, YOLOv4, YOLOv5, and others were introduced for improving both accuracy and speed. Each model has an improved backbone architecture, optimized loss function, and advanced data training/augmentation techniques to better accommodate real-world applications. YOLO changed object detection by proving the feasibility of real-time detection using a single-stage neural network, independent of external region proposals. The YOLO model is widely utilized in applications necessitating real-time processing, including surveillance systems, driverless vehicles, and CCTV. Furthermore, the YOLO (single network, end-toend) concept has inspired the development of other models that enhance the speed and accuracy trade-off such as SSD, RetinaNet, and several YOLO variants. The deep learning evolution as shown in Fig. 1.

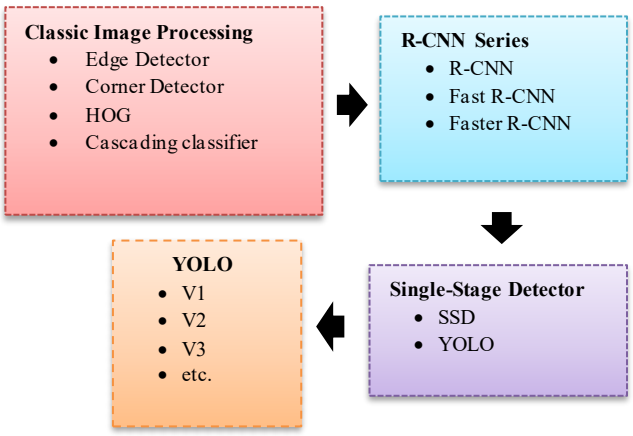


Fig. 1. Evaluation of Object Detection, begin classification image processing until YOLO object detection.

Object detection initiates with traditional image processing techniques, including edge detection, corner detection, Histogram of Oriented Gradients (HOG), and cascade classifiers. Continuing with the R-CNN series, which covers R-CNN, Fast R-CNN, and Faster R-CNN. Thus, YOLO is a single-stage detector, similar to SSD. Several versions of YOLO are currently operational.

B. CNN Object Detection

Object detection is an important component of computer vision that has gained popularity in recent years. This can analyze video, recognize images, and be applied in everyday life. For instance, autonomous driving, drone and robotics analysis, and safety surveillance, among others. The aim of object detection is to identify the localization of objects (object localization) and to classify object types (object classification). Object identification is a subset of deep learning that enhances the accuracy and speed of computer learning. Machine Learning is a method for creating models that operate autonomously. The handcrafted features and shallow trainable architectures were utilized. Initially, the selection of informative regions is conducted by scanning images with multiple sizes of sliding windows. Subsequently, feature extraction is conducted using SIFT, HOG, Haar-like features, among others. The classification is enhanced by methods such as SVM and AdaBoost. Deep Learning (DL) is a more advanced technique than machine learning. Neural networks can enhance model performance [20], [21]. Convolutional Neural Networks (CNNs) are utilized to create models with various architectures. The CNN architecture combines One-stage and Two-stage Detectors. The two-stage detector employs Regions with CNN features (RNN) as the principal model, demonstrating the efficiency of CNN in object detection. RNN employs a bottom-up approach for locating positions and objects within images. Subsequently, obtain the region suggestion by selective search and compute the features using a convolutional neural network (CNN). Subsequently, categorize the region type utilizing Support Vector Machine (SVM) methodology. This procedure is time-consuming and presents a bottleneck issue. This study achieves a mAP of 53.30% utilizing the PASCAL VOC 2012 dataset. The model generated by VGG16 achieved a mAP of 66.00% on the VOC Convolutional Networks (SPP-net) addresses the bottleneck issue of R-CNN by employing a Spatial Pyramid Pooling layer (SPP layer) in its final layer. Consequently, CNN can process input and output images of a fixed dimension. SPP-net (ZF) achieves a mAP of 60.9% on the VOC 2007 dataset [23]. Fast R-CNN enhances R-CNN and SPP-net by end-to-end training that integrates area selection, feature extraction, and classification. The VOC 2007 test set achieved a mAP of 70.00% [15]. Subsequently, Faster R-CNN is executed on Fast R-CNN utilizing the Region Proposal Network (RPN) instead selective search. This method generates region proposals from the features of a CNN RPN and predicts box regression (reg) and box classification (cls) using a sliding window approach. The results indicate a mAP of 83.80% [24]. Mask R-CNN is the instance segmentation framework that extends Faster R-CNN. Mask R-CNN achieves an Average Precision (AP) of 39.8% on the COCO test set [25]. The R-FCN, or Region-based Fully Convolutional Networks, achieves a mean Average Precision (mAP) of 85.00% on the VOC 2012 test set [26].

One-stage detectors, such as the Single Shot MultiBox Detector (SSD), perform classification and bounding box regression immediately. SSD300 has a mAP of 79.60%, whereas SSD512 demonstrates a mAP of 81.60% when evaluated on the VOC 2007 test set. SSD512 exhibits a mean mAP of 81.60%. Feature Pyramid Networks (FPN) are utilized for the extraction of features across diverse data sizes [17].

YOLO (You Only Look Once) is a famous real-time object detection model known for its speed and accuracy. YOLO V1 is the first end-to-end real-time object detection model [18]. YOLO V2 (YOLO9000) operates on the Darknet-19 backbone, employs batch normalization, utilizes anchor boxes for predictions, and includes a passthrough layer for feature extraction [27]. YOLO V3 employs the Darknet-53 backbone which is larger than the backbone utilized in YOLO V2. Bounding box prediction employs logistic regression and three sizes of multi-scale predictions. All operations involving the SPP block [28]. YOLO V4 was created for fast and accurate performance. The Bag of Freebies and the Bag of Specials are utilized to enhance performance and combine a receptive field. The backbone is CSPDarknet53. The SPP module, PANet path aggregation neck, and YOLO V3 head are processed [29]. YOLO V5 utilizes a modified CSPDarknet53 as backbone commencing with a Stem and SPPF (Spatial Pyramid Pooling Fast) layer. This facilitated rapid accuracy. The auto anchor verifies and enhances anchor boxes [30]. YOLO V6 is the suitable framework for industry applications. The EfficientRep backbone (RepBlock/RepConv) has been processed. The quantization employs GloU (Generalized IoU), Clou (Complete-IoU Loss), Slou loss, self-distillation, and channel-wise distillation [31]. YOLO V7 utilized the Extended Efficient Layer Aggregation Network (E-ELAN) and RepConvN, which lacks identity connections. YOLO V8 modified C3 to C2f and implemented 3x3 convolution [31] - [33]. In addition to YOLO, Pelee is a real-time object detection framework for mobile devices utilizing PeleeNet. PeeleeNet is produced using traditional convolution rather than depthwise separable convolution with SSD Pelee [34].

C. Road Object Detection

Numerous studies on road surface conditions utilize video and imagery. The model identified a road traffic sign utilizing Support Vector Machine (SVM) technology. This is classified and identified in the video. The Histogram of Oriented Gradients (HOG) is utilized to extract features previous to model generation [9]. Traffic light recognition employs image processing techniques based on color segmentation and the Hough transform for circles. Machine learning is utilized to generate the model. This model was designed to identify the traffic light in the autonomous vehicle [6]. Utilization of Helmets Detection on motorcycles is an important part of their widespread usage. YOLO V3 and multi-task learning are employed for helmet detection. Positional Encoding (PE) resolved the issue of class imbalance in this research, resulting in PE is better than the class-balanced loss [35],[36],[37]. Advanced Driver-Assistance Systems (ADAS) contain a collection of sensors, cameras, and other technologies within the vehicle that enhance driving safety and convenience. ADAS and safety alerts contribute to accident reduction studies. The Collision Avoidance System utilized the Google TensorFlow Object Detection (GTOD) API to build a driving safety alert and real-time vehicle detection, trained using the Microsoft Common Objects in Context (COCO) dataset [38]. Then the motorcycle curve warning presented the curve alert system including the intra-lane localization and roll angle estimation using CNN. The industry standard maps is used for improve an accuracy [39]. The pothole was detected using thermal imaging captured by a FLIR ONE camera. The principle that the temperature of the pothole is lower than that of the surrounding road because of water retention. This research performed effectively at night, during rain, and in fog, remaining unaffected by light, exhibiting a high response time, lower energy consumption, and reduced costs compared to laser-based techniques. The training with the ResNet101 model achieved an accuracy of 97.08% [40]. A pothole detecting system was developed for road surfaces to help blind people utilizing Convolutional Neural Networks (CNN) and the KITTI dataset. This system achieved an accuracy of 97.12% [11]. Numerous CNN models have been trained to detect potholes, including Inception v4, Inception ResNet v2, ResNet v2 152, and MobileNet v1. An accuracy above 96%. The grayscale image can be utilized in this research [14]. Crack detection is performed automatically using CNN on images captured by smartphones, employing YOLO and SSD methodologies [41],[42]. Research to present a 3D map as the outcome. The SSD can develop a model to detect potholes and humps by utilizing data collected from a Raspberry Pi, GPS module, and camera [43]. The video data is utilized to identify cars, trucks, and buses using Faster R-CNN in comparison to a mixture of Gaussian (MoG) background subtraction and SVM vehicle classification. The results indicated that Faster RCNN exhibited superior performance [44]. Furthermore, the accelerometer, gyroscope, and GPS in smartphones gather data that is utilized with machine learning to classify multiple categories, including smooth roads, potholes, and deep transverse cracks. The three feature axes of the sensor provide more accuracy, precision, and recall compared to a single axis [45]. In addition, the fog and darkness decreased the driver's visibility, presenting a problem that must be resolved for safety. Recursively Separated and Weighted Histogram Equalization (RSWHE) and Gamma Correction techniques were worked to increase the image and video performance. Detecting road surfaces at night can be achieved using the headlights of a vehicle [4], [46]. The summary table of techniques for road condition detection is presented in Table I.

TABLE I. SUMMARY OF THE ROAD CONDITION DETECTION TECHNIQUES

Method	Techniques
Data Collector	Smartphone, Video, Camera, Raspberry Pi, GPSmodule
Data Preparation	Frame extraction, Lane detection, Labelling, Image processing
Model Generation	YOLO, Faster R-CNN, ResNet, Inception, MobileNet, SSD, SVM, HOG

D. Evaluation

In object detection and classification, evaluation is crucial to evaluating performance during the development and maintenance phases. The object detection task needs to allow for both localization accuracy and classification accuracy. The confusion matrix, Intersection over Union (IoU), and mean Average Precision (mAP) are widely utilized metrics.

The Confusion Matrix is a fundamental instrument to evaluate the accuracy of a classification model by comparing the actual class with the predicted class. There are four values in a confusion matrix. A True Positive (TP) occurs when a prediction is positive and the actual outcome is also positive. A True Negative (TN) occurs when a prediction is negative and

the actual outcome is also negative. A False Positive (FP) occurs when a prediction indicates a positive result when the actual outcome is negative. A False Negative (FN) occurs when a prediction is negative while the actual outcome is positive. Subsequently, these four variables are utilized to compute additional values below.

Accuracy is the proportion of correct predictions, which may be calculated using Eq. (1).

$$\text{Accuracy} = \frac{TP+TN}{\text{TP+TN+FP+FN}} \quad (1)$$

Precision refers to the quality of a model concerning positive precision. The precision is illustrated in Eq. (2).

$$Precision = \frac{TP}{\text{TP+FP}} \quad (2)$$

Recall assesses the efficacy of a model in predicting positive results. The value of recall can be calculated using Eq. (3).

$$Recall = \frac{TP}{\text{TP+FN}} \quad (3)$$

The F1-score is the harmonic mean of precision and recall, serving as a singular metric to assess model performance. The F1-score equation is shown in Eq. (4).

$$F1\ score = \frac{2 * Precision * Recall}{Precision + Recall} \quad (4)$$

In the object detection job, the Intersection over Union (IoU) serves as the localization measure that compares the area between the predicted bounding box and the ground truth bounding box. The IoU equation is illustrated in Eq. (5).

$$IoU = \frac{Area\ of\ Overlap}{\text{Area of Union}} \quad (5)$$

Then Area of Overlap is two boxes overlap area. And Area of Union is total area of both boxes.

The IoU value ranges from 0 to 1. If the IoU is greater than or equal to 0.5, determine it as a true detection (True Positive). The higher IoU mean predicts the bounding box's closer to the object's actual position.

Normally in object detection task has multiple object type and different confidence score. The average precision (AP) is measure model performance for each class and calculate by Precision-Recall Curve. After that calculate average AP of all class that is mean Average Precision (mAP) as calculate by Eq. (6).

$$mAP = \frac{1}{\text{N}} \sum_{i=1}^{N} AP_i \quad (6)$$

N represents the total number of classes, while APi is the average precision for class i. The mAP summarizes the model's performance in object detection and classification over all objects.

III. Research Methodology

This section described the methods employed in this research. Subsection A. presents the framework, which includes an overview of the research. The subsequent step is the preprocessing phase which involves data collection and frame extraction. Frame extraction can divide the video dataset into multiple images, which is the initial important phase as illustrated in subsection B. The following procedure is object labelling, which enables the model to recognize the item as illustrated in C.

A. Framework

This section described the research framework. Data was gathered from May 2020 to September 2021 in Phuket and Bangkok, Thailand. The smartphone is a collection instrument mounted to the vehicle's windshield. All data belongs in cloud storage. The video data is segmented into numerous frames with the frame extraction technique. The work involves image labelling, which encompasses cropping and identifying each object within all images. Laberu is an appropriate tool for this stage. This is a novel labelling tool created by our team. This study examines cracks, potholes, and manhole covers. 24,276 frames are utilized for labelling. The XML file provides the result of the labelling phase. The object detection model is built using a novel CNN customized on the backbone of YOLO V6. The research framework is illustrated in Fig. 2.

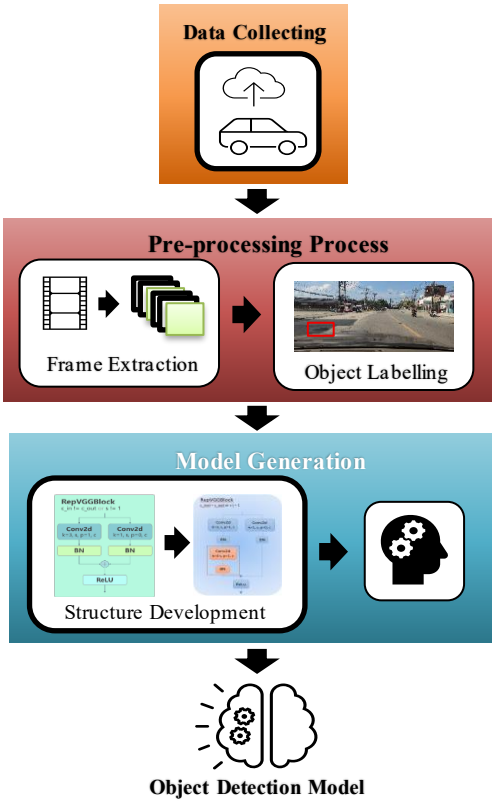


Fig. 2. Framework for the development of novel CNN architectures.

B. Data Collection and Frame Extraction

The initial phase of this research has involved the collection of video data. The equipment of this research is the smartphone. The smartphone was installed on the windshield of the vehicle operating on the roads of Phuket and Bangkok from May 2020 to September 2021. The total distance is 1,118.13 kilometers. 125 videos had collected a total duration of 134,176 seconds. Subsequently, the frame extraction goes into processing. This phase involves separating all of the video into multiple images. The quantity of data collected,

comprising 125 videos with a total duration of 134,176 seconds. Following the frame extraction process, a total of 1,341,760 frames were obtained. Selected 31,803 frames containing three objects. Ultimately, 24,276 frames were selected for the subsequent stage.

The data categories are identified as three objects inspected by the Department of Highways in Thailand. This investigation encompasses crack, pothole, and manhole cover. An example of manhole cover after extended from video as shown in Fig. 3.

C. Object Labelling

This subsection explained the process of object labelling. The step is to separate and select all three objects. This phase was successful when the video was captured and the frame was extracted. This process employs three tools. LabelMe and LabelImg are universal labelling tools. Labelru is the labeling tool developed by our research team. This research is designated by Labelru. This tool allows for multiple users immediately. Fig. 4 illustrates an example of each object post-labeling. The object's name and its position are indicated within the red rectangle.



Fig. 3. The image including Manhole cover extracted from the video.

```
<annotation>
  <folder>picture</folder>
  <filename>2-session-1610784850-7866.jpg</filename>
  <path>E:\select\211011\211011\picture\2-session-1610784850-7866.jpg</path>
  <source>
    <database>Unknown</database>
  </source>
  <size>
    <width>1920</width>
    <height>1080</height>
    <depth>3</depth>
  </size>
  <segmented>0</segmented>
  <object>
    <name>Manhole covers</name>
    <pose>Unspecified</pose>
    <truncated>0</truncated>
    <difficult>0</difficult>
    <bndbox>
      <xmin>125</xmin>
      <ymin>762</ymin>
      <xmax>270</xmax>
      <ymax>801</ymax>
    </bndbox>
  </object>
</annotation>
```

Fig. 4. An example of a labelled XML file, red rectangle show object name and coordinates.

IV. Road Surface Condition Detection Network

Convolutional Neural Network (CNN) is the popular technique to generate a model to detect an object. At the time, there are many CNN structure work for classification and object detection work. The concept of CNN is learning similar the human brain, CNN is in the bio-inspire group. The object detection works base on classification and object detection [22].

This section presents Road Surface Condition Detection, or RoadSCNet. This section explores the novel framework for the object detection job. YOLO is a renowned convolutional neural network design utilized for object detection tasks. Numerous iterations of YOLO exist, ranging from YOLO V1 to YOLO V8, together with YOLONas, developed from 2016 to the present. This research focuses on YOLO V6 and a novel CNN called "RoadSCNet" which is based on this version. RoadSCNet is a novel convolutional neural network derived from YOLO V6. Typically, YOLO V6 is suitable for fast and accurate real-time object recognition. There are multiple versions of YOLO V6: YOLO V6-n, YOLO V6-S, YOLO V6-M, YOLO V6-L, and YOLO V6-tiny. YOLO V6-tiny is compact and suitable for IoT or mobile applications. The structure of YOLO V6 is illustrated in Fig. 5.

The architecture of the YOLO V6 backbone has five RepVGGBlock layers, four BepC3StageBlock layers, and concludes with an SPPFBottleneck. The kernel sizes 4x4. The BN layer refers to the batch normalization layer which enhances the mean and standard deviation of the activation output from the layer above. The appropriateness and stability of the mean and standard deviation facilitate the training of a more stable and effective model.

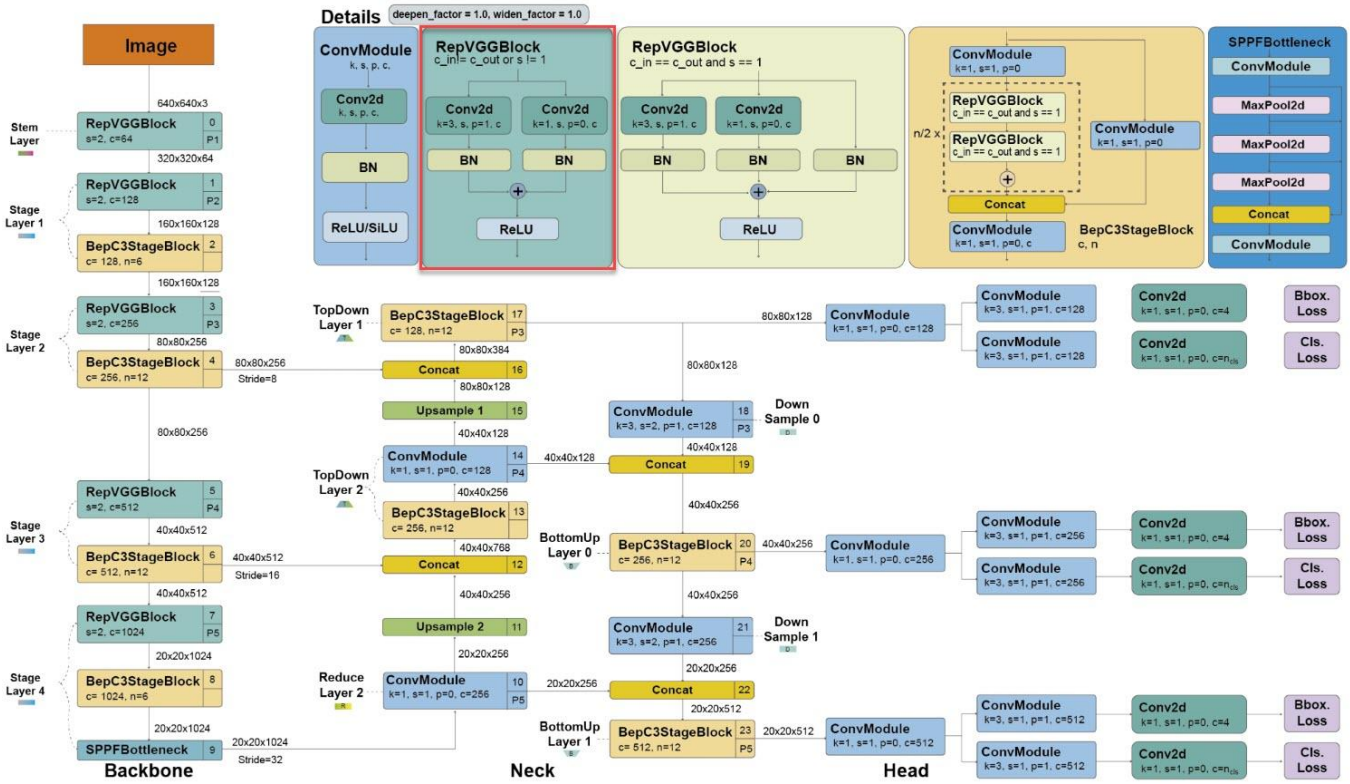


Fig. 5. The architecture of YOLO V6. The red rectangle on the RepVGGBlock indicates the position for block customization. Figure is based on study [47]

V. Hyperparameter Experiment

This part offered the experiment results and comments regarding hyperparameters. Video data was taken using a smartphone mounted on the windshield of the car. Data was obtained in Phuket and Bangkok, Thailand. The initial pre-processing stage involved frame extraction, which converted the video into several images. Subsequently, every three images were selected for the following step. The object labelling was subsequently processed. During the labelling phase, the novel labelling tool in this research, named "Labelru" received approval. This tool can be labelled by multiple users simultaneously. The produced model was enhanced. The experiment has dropout, learning rate, and kernel which are as mentioned in subsection A - C. The experiment setup utilizes a computer equipped with an i9-10900KF CPU, 32GB of RAM, and an RTX 3080 10GB GPU. Miniconda3 and Python 3.6 are software applications.

A. Dropout

Overfitting is a challenge encountered throughout the model training process. The method employed to reduce the overfitting issue is dropout. The dropout layer randomly deactivates certain neurons within that layer. This strategy enables the model to learn by distributing tasks among other neurons, hence enhancing its performance when predicting fresh datasets. The experiment with four dropouts is analyzed below using the mAP value. This research focused on dropout rates 0.2, 0.4, 0.6, and 0.8. The outcome with a dropout of 0.6 yielded a mAP value of 86.97. The subsequent dropout values are 0.2, 0.4, and 0.8 yielding mAP values of 86.41, 86.30, and 85.62, respectively. Subsequently, a dropout rate of 0.6 was employed in the subsequent experiment learning rate as delineated in subsection B.

B. Learning Rate

The learning rate is a hyperparameter that controls weights and biases of the model. In each iteration of the training process, the learning rate is multiplied by the gradient to adjust the weights and minimize loss. Particularly in Gradient Descent training. If the learning rate is excessively high, the model will set the weights and biases in an unstable manner during training. The low learning rate results in minimal weight and bias adjustments which are leading to protracted and time-intensive training. This section elucidates the learning rate experiment. The values are 0.1, 0.01, 0.001, and 0.00001. The outcome is presented in Table II.

According to Table II, the learning rate of 0.01 achieved the greatest mAP value of 86.97. The subsequent learning rates are 0.1, 0.001, 0.0001, and 0.00001, yielding mAP values of 85.78, 83.26, 82.33, and 62.54, respectively. The learning rate of 0.01 was utilized in the subsequent experiment.

TABLE II. Various Experiment Outcomes Learning Rate

Learning Rate	mAP	Time (hour)
0.1	85.78	13.95
0.01	86.97	13.34
0.001	83.26	13.10
0.0001	82.33	13.22
0.00001	62.54	13.20

C. Kernel

In CNN, a kernel or filter operates on the input image by performing convolution to process the data. This stage involves extracting features from the image. The convolution applies a stride kernel to a region of the image and computes the result based on the image pixels and weights in terms of the feature map. This subsection discusses the kernel experiment. The 3x3 and 4x4 kernels have been utilized. The 3x3 kernel demonstrates a superior mAP value compared to the 4x4 kernel. The mAP values are 86.97 and 86.29. Consequently, a 3x3 kernel is suitable for this research.

VI. Structure Experiment

After completing the hyperparameter experiments outlined in Section V. This section explains the experiment structure. Three experiments are being conducted on the RepVGGBlock based on YOLO V6. The system comprises a CPU i9-10900KF, 32GB of RAM, and an RTX 3080 10GB GPU. Miniconda3 and Python 3.6 are software applications. Subsection A. illustrates the various versions of YOLO when generating models utilizing the data. Subsections B. to D. analyzed three experiments.

A. Existing YOLO

Before developing the CNN structure, the model generated with the existing CNN is active. YOLO V5, YOLO V6, YOLO V7, and YOLO V8 are active. The image resolution of three objects is 1280x720 pixels, processed with a batch size of 8 within 100 epochs. The outcomes of the four existing YOLO models are presented in Table III.

TABLE III. Three Objects Detection Using Existing YOLO

Architecture	mAP
YOLO V5	74.50
YOLO V6	86.19
YOLO V7	61.30
YOLO V8	73.82

Table III presents the results for YOLO V5 to YOLO V8, displaying mAP values of 74.50, 86.19, 61.30, and 73.82, respectively. YOLO V6 has the greatest mAP value. YOLO V5 and YOLO V8 are similar. YOLO V7 displays a lower mAP compared to others. After that, the normalization process was compared with four different batch sizes: 4, 8, 16, and 32. The results gave mAP values of 82.70, 86.19, 86.98, and 87.38, respectively. Batch size 32 displays the highest mAP. The next batch size of 32 is employed in dropout regularization. There are four dropout rates in running: 0.25, 0.50, 0.75, and 1.00. The mAP values are 85.40, 85.73, 85.15, and 39.24, respectively. The no dropout showed better results [48]. While evaluating the results, the maximum mAP is 87.38, which is minimal for the collected data. The improvement of the mAP value in the backbone of YOLO V6 architecture is discussed in the next subsection.

B. Horizon Block

The initial experiment construction is incorporating Conv2d into the RepVGGBlock. In the YOLO V6 architecture, Conv2d operates before Batch Normalization (BN). The initial experiment involves executing Conv2d subsequent to the BN layer, as illustrated in Fig. 6. The outcome is presented in E.

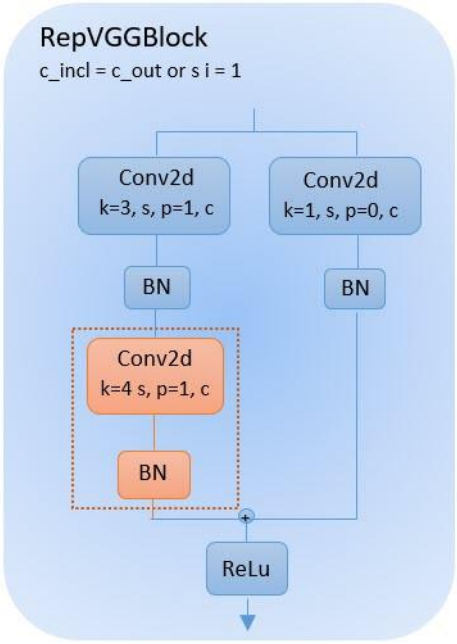


Fig. 6. The newly introduced horizon module within the RepVGGBlock.

C. Vertical Block

This subsection examines the new vertical block in RepVGGBlock following the initial experiment. Conv2d is already integrated with the Batch Normalization layer. The other parameter is k=4x4. This layer typically has two Conv2d and two BN layers; however, this experiment incorporated both Conv2d and BN layers. The revised structure is depicted in Fig. 7. The outcome as indicated in E.

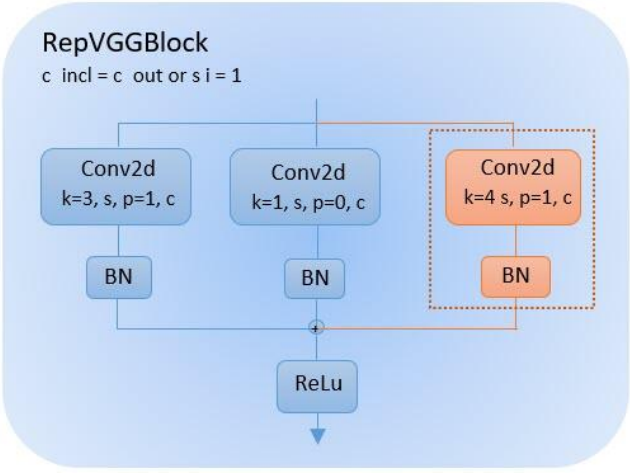


Fig. 7. The newly vertical module in RepVGGBlock.

D. Pooling Layer

The SPPFBottleneck operates in the final layer of the backbone. The YOLO V6 architecture operates on max pooling. The final experiment utilized average pooling. Compare the outcome as detailed in Table IV.

TABLE IV. THE MAP OF EXPERIMENT RESULTS FROM DIFFERENT POOLING METHODS

Experiment	Max Pooling	Average Pooling
Original	86.13	86.60
Width Multiple 0.6	88.07	88.25
Width Multiple 0.65	88.73	88.89
Width Multiple 0.7	89.96	89.09
Width Multiple 0.7 with Learning Rate		
Learning Rate 0.1	89.38	89.19
Learning Rate 0.01	89.96	89.09
Learning Rate 0.001	89.38	88.89
Learning Rate 0.0001	89.26	89.47

According to Table IV, a width multiple of 0.7 for max pooling yields the greatest mAP value of 89.96. The subsequent width multiples are 0.65 and 0.6, corresponding to mAP values of 88.73 and 88.07, respectively. The average pooling with a width multiplied by 0.7 achieves the maximum mAP value of 89.09. Multiply 0.65 and 0.6 by 88.89 and 88.25. The width is multiplied by 0.7 using max pooling for late experiment learning. When evaluating the Learning Rate using a width multiplier of 0.7 and max pooling, a learning rate of 0.01 yields the greatest mAP value of 89.96. The learning rates of 0.1 and 0.001 yield a mean Average Precision (mAP) value of 89.38, while a learning rate of 0.0001 results in a mAP value of 89.26. The learning rate of 0.0001 yields the highest mean Average Precision (mAP) value of 89.47 for average pooling. The subsequent learning rates are 0.1, 0.01, and 0.001, yielding mAP values of 89.19, 89.09, and 88.89, respectively. In this research, a maximum pooling width of 0.7 and a learning rate of 0.01 have been accepted as appropriate. Nevertheless, the comprehensive outcomes of all experiments are elucidated in subsection E.

E. Structure Experiment Result

This part examined all experiments in the Structure Experiment which including the results of the inserted horizon block, vertical block in RepVGGBlock, and the application of average pooling in SPPFBottleneck, as presented in sections VI.B. – VI.D. The experiment commenced with the original YOLO V6, utilizing a width multiplier of 0.5 and a learning rate of 0.01. The two hyperparameters modified in this study are presented in Table V. The experiment run consisted of 100 epochs using a machine equipped with an Intel i9-10900KF CPU, 32GB of RAM, and an RTX 3080 10GB GPU. Miniconda3 and Python 3.6 are software applications. Experiment 3 presents the results of maximum pooling.

According to Table V, Experiment 1 involves a modified horizon block within the RepVGGBlock. The outcome of a width multiplier of 0.7 yields the maximum mAP value of 89.91. The width multiples of 0.65 and 0.6 yield mAP values of 88.70 and 88.22, respectively. The width multiplied by 0.7 was effective for the learning rate experiment. The learning rate experiment with a width multiplier of 0.7 achieved the greatest mAP value of 90.01 at a learning rate of 0.001. The learning rates of 0.01, 0.0001, and 0.1 yield mAP values of 89.91, 89.51, and 89.27, respectively. The combination of a width multiplier of 0.7 and a learning rate of 0.001 yields the highest mAP value of 90.01.

TABLE V. THE MAP OUTCOMES OF MANY EXPERIMENTS

	Experiment 1	Experiment 2	Experiment 3
Original	86.97	86.12	86.60
Width Multiple 0.6	88.22	88.07	88.25
Width Multiple 0.65	88.70	88.73	88.89
Width Multiple 0.7	89.91	88.97	89.09
Width Multiple 0.7 with Learning Rate			
Learning Rate 0.1	89.27	89.38	89.19
Learning Rate 0.01	89.91	88.97	89.09
Learning Rate 0.001	90.01	89.69	88.89
Learning Rate 0.0001	89.51	89.26	89.47

Experiment 3 compared the average pooling layer in SPPFBottleneck with max pooling. The width multiple of 0.7 for max pooling and a learning rate of 0.0001 yielded the greatest mAP value of 89.47. Table V presents the results of Experiment 3 conducted with max pooling.

Upon evaluating the maximum mAP value from three experiments, Experiment 1, which utilized a width multiplier of 0.7 and a learning rate of 90.01, exhibited the highest mAP value. Experiment 2 achieved a mAP of 89.69 with a width multiplier of 0.7 and a learning rate of 0.001. Experiment 3 achieved a mAP of 89.47 when employing max pooling, a width multiplier of 0.7, and a learning rate of 0.0001. Ultimately, the modified horizon block in RepVGGBlock, after 200 epochs, achieved a mAP value of 96.03, which is conclusive for this research.

YOLO V6 employs RepVGGBlock for object detection, providing both high performance and speed. This study focuses on specific convolution. The result is positive for objects with specific boundaries. This is unsuitable given the road conditions characterized by cracks, potholes, and manhole covers. The three objects contain shapes, low sharpness, and irregular borders, primarily aligned along the horizontal axis of the road. Specifically, RepVGGBlock misses an element of context that clearly considers direction. This limits the ability to represent the horizontal continuity necessary for accurate identification of road conditions. Motivated by this limitation, RoadSCNet enhances the fundamental architecture of YOLOv6 by integrating a customized Horizon block with the RepVGGBlock to improve horizontal context learning efficacy while preserving computational efficiency. Then when run the new RoadSCNet model with 182 unseen data images which collected in Phuket, the result shown 91.60% accuracy. As displayed in Fig 8. The confusion matrix shows the model can identify 64 cracks, 3 potholes, and 122 manhole covers. All three objects include 72 cracks, 11 potholes, and 122 manhole covers. The accuracy is 91.60% and the precision is 94.50%. Then the model shows the performance to detect three objects. An example of three objects when detected using the model as shown in Fig. 9.

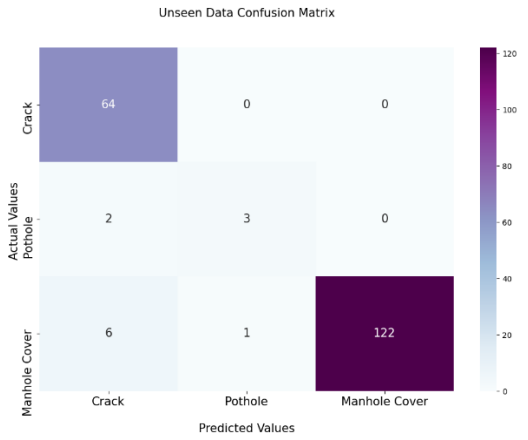


Fig. 8. The confusion matrix when test model with unseen data.



Fig. 9. Three examples when detected by RoadSCnet model.

The limitations of this investigation include window of the car which resulted in erroneous detection, the blurred images which made difficult the identification of the actual object, and the limitaion of equipment caused in reduced operational speed. Future work will focus on improving the mAP value and decreasing the loss value of the model.

VII. Conclusion

This research introduces RoadSCNet, an innovative CNN architecture that achieves a high mAP value for the dataset. The evaluation of three hyperparameters showed dropout 0.6, learning rate 0.01, and kernel 4x4 yielded the greatest mAP value. Subsequently, three distinct structures yield results for modeling under three road conditions, incorporating the new horizon block which demonstrates a superior mAP, followed by the integration of vertical adjustments and pooling modifications. The RoadSCNet enhances YOLO V6 by incorporating the new horizon block within the RepVGGBlock. RoadSCNet outperforms classic YOLO V6 due to a greater ability to gather horizontal contextual information, essential for identifying long cracks and rough road conditions, including cracks pothole and manhole covers.

Acknowledgment

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References

[1] A. Choudhary, R. D. Garg, and S. S. Jain, "Estimating impact of pavement surface condition and geometrics design on two-wheeler run-off road crashes on horizontal curves," IATSS Research, vol. 48, no. 1, pp. 108–119, Apr. 2024.

[2] P. K. R. Lebaku, L. Gao, J. Sun, X. Wang, and X. Kang, "Assessing the influence of pavement performance on road safety through crash frequency and severity analysis," *arXiv preprint*, Jun. 19, 2025. [Online]. Available: https://arxiv.org/abs/2506.16485.

[3] M. Marzougui, A. Alasiry, Y. Kortli, and J. Baili, "A lane tracking method based on progressive probabilistic hough transform," IEEE access, vol. 8, pp. 84 893–84 905, 2020.

[4] D. Kaur and N. K. Garg, "Enhancement in foggy road scene videos using rswhe and gamma correction," in 2016 International Conference on Micro-Electronics and Telecommunication Engineering (ICMETE). IEEE, 2016, pp. 276–281.

[5] A. De La Escalera, L. E. Moreno, M. A. Salichs, and J. M. Armingol, "Road traffic sign detection and classification," IEEE transactions on industrial electronics, vol. 44, no. 6, pp. 848–859, 1997.

[6] R. Kulkarni, S. Dhavalikar, and S. Bangar, "Traffic light detection and recognition for self driving cars using deep learning," in 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA). IEEE, 2018, pp. 1-4.

[7] H. Wang, Y. Wang, X. Zhao, G. Wang, H. Huang, and J. Zhang, "Lane detection of curving road for structural highway with straight-curve model on vision," IEEE Transactions on Vehicular Technology, vol. 68, no. 6, pp. 5321–5330, 2019.

[8] X. Nie, Y. Gao, F. Gao, Q. Li, and Z. Alam, "A novel vision based road detection algorithm for intelligent vehicle," in 2019 IEEE International Conference on Power, Intelligent Computing and Systems (ICPICS). IEEE, 2019, pp. 504-507.

[9] J. Zhao, Z. Bai, and H. Chen, "Research on road traffic sign recognition based on video image," in 2017 10th International Conference on Intelligent Computation Technology and Automation (ICICTA). IEEE, 2017, pp. 110-113.

[10] H. M. Saddique, A. Raza, Z. U. Abideen, and S. N. Khan, "Exploring deep learning based object detection architectures: a review," in 2020 17th International Bhurban conference on applied sciences and technology (IBCAST). IEEE, 2020, pp. 255–259.

[11] M. M. Islam and M. S. Sadi, "Path hole detection to assist the visually impaired people in navigation," in 2018 4th International Conference on Electrical Engineering and Information & Communication Technology (iCEEiCT). IEEE, 2018, pp. 268–273.

[12] K. E. An, S. W. Lee, S.-K. Ryu, and D. Seo, "Detecting a pothole using deep convolutional neural network models for an adaptive shock observing in a vehicle driving," in 2018 IEEE International Conference on Consumer Electronics (ICCE). IEEE, 2018, pp. 1-2.

[13] H.-C. Shin, H. R. Roth, M. Gao, L. Lu, Z. Xu, I. Nogues, J. Yao, D. Mollura, and R. M. Summers, "Deep convolutional neural networks for computer-aided detection: Cnn architectures, dataset characteristics and transfer learning," IEEE transactions on medical imaging, vol. 35, no. 5, pp. 1285–1298, 2016.

[14] R. Girshick, J. Donahue, T. Darrell, U. Berkeley, and J. Malik, "Rcnn: region-based convolutional neural networks," in Proc. Comput. Vis. Pattern Recognit, 2014, pp. 2–9.

[15] R. Girshick, "Fast r-cnn," in Proceedings of the IEEE international conference on computer vision, 2015, pp. 1440–1448.

[16] S. Ren, K. He, R. Girshick, and J. Sun, "Faster r-cnn: Towards real-time object detection with region proposal networks," Advances in neural information processing systems, vol. 28, 2015.

[17] W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C.-Y. Fu, and A. C. Berg, "Ssd: Single shot multibox detector," in European conference on computer vision. Springer, 2016, pp. 21–37.

[18] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," in Proceedings of the IEEE

conference on computer vision and pattern recognition, 2016, pp. 779–788.

[19] J. Redmon and A. Farhadi, "Yolo9000: better, faster, stronger," in Proceedings of the IEEE conference on computer vision and pattern recognition, 2017, pp. 7263-7271.

[20] Z.-Q. Zhao, P. Zheng, S.-t. Xu, and X. Wu, "Object detection with deep learning: A review," IEEE transactions on neural networks and learning systems, vol. 30, no. 11, pp. 3212–3232, 2019.

[21] L. Jiao, F. Zhang, F. Liu, S. Yang, L. Li, Z. Feng, and R. Qu, "A survey of deep learning-based object detection," IEEE access, vol. 7, pp. 128 837-128 868, 2019.

[22] R. Girshick, J. Donahue, T. Darrell, and J. Malik, "Rich feature hierarchies for accurate object detection and semantic segmentation," in Proceedings of the IEEE conference on computer vision and pattern recognition, 2014, pp. 580–587.

[23] K. He, X. Zhang, S. Ren, and J. Sun, "Spatial pyramid pooling in deep convolutional networks for visual recognition," IEEE transactions on pattern analysis and machine intelligence, vol. 37, no. 9, pp. 1904–1916, 2015.

[24] S. Ren, K. He, R. Girshick, and J. Sun, "Faster r-cnn: Towards real-time object detection with region proposal networks," IEEE transactions on pattern analysis and machine intelligence, vol. 39, no. 6, pp. 1137–1149, 2016.

[25] K. He, G. Gkioxari, P. Doll´ar, and R. Girshick, "Mask r-cnn," in Proceedings of the IEEE international conference on computer vision, 2017, pp. 2961–2969.

[26] J. Dai, Y. Li, K. He, and J. Sun, "R-fcn: Object detection via regionbased fully convolutional networks," Advances in neural information processing systems, vol. 29, 2016.

[27] K. Boudjit and N. Ramzan, "Human detection based on deep learning yolo-v2 for real-time uav applications," Journal of Experimental & Theoretical Artificial Intelligence, vol. 34, no. 3, pp. 527–544, 2022.

[28] J. Redmon and A. Farhadi, "Yolov3: An incremental improvement," arXiv preprint arXiv:1804.02767, 2018.

[29] C. Dewi, R.-C. Chen, X. Jiang, and H. Yu, "Deep convolutional neural network for enhancing traffic sign recognition developed on yolo v4," Multimedia Tools and Applications, vol. 81, no. 26, pp. 37 821–37 845, 2022.

[30] Y. Zhang, Z. Guo, J. Wu, Y. Tian, H. Tang, and X. Guo, "Real-time vehicle detection based on improved yolo v5," Sustainability, vol. 14, no. 19, p. 12274, 2022.

[31] C. Li, L. Li, H. Jiang, K. Weng, Y. Geng, L. Li, Z. Ke, Q. Li, M. Cheng, W. Nie et al., "Yolov6: A single-stage object detection framework for industrial applications," arXiv preprint arXiv:2209.02976, 2022.

[32] Y. Eği, "Yolo v7 and computer vision-based mask-wearing warning system for congested public areas," Journal of the Institute of Science and Technology, vol. 13, no. 1, pp. 22–32, 2023.

[33] M. Hussain, "Yolo-v1 to yolo-v8, the rise of yolo and its complementary nature toward digital manufacturing and industrial defect detection," Machines, vol. 11, no. 7, p. 677, 2023.

[34] R. J. Wang, X. Li, and C. X. Ling, "Pelee: A real-time object detection system on mobile devices," Advances in neural information processing systems, vol. 31, 2018.

[35] R. Waranusast, N. Bundon, V. Timtong, C. Tangnoi, and P. Pattanathaburt, "Machine vision techniques for motorcycle safety helmet detection," in 2013 28th International conference on image and vision computing New Zealand (IVCNZ 2013). IEEE, 2013, pp. 35–40.

[36] H. Lin, G. Chen, and F. W. Siebert, "Positional encoding: improving class-imbalanced motorcycle helmet use classification," in 2021 IEEE International Conference on Image Processing (ICIP). IEEE, 2021, pp. 1194–1198.

[37] D. S. S. Sarma, D. M. Varun, and A. M. Posonia, "Helmet detection and number plate extraction using machine learning," in 2021 5th International Conference on Trends in Electronics and Informatics (ICOEI). IEEE, 2021, pp. 947–951.

[38] C.-H. Hsieh, D.-C. Lin, C.-J. Wang, Z.-T. Chen, and J.-J. Liaw, "Real-time car detection and driving safety alarm system with google tensorflow object detection api," in 2019 International Conference on Machine Learning and Cybernetics (ICMLC). IEEE, 2019, pp. 1–4.

[39] S. Hecker, A. Liniger, H. Maurenbrecher, D. Dai, and L. Van Gool, "Learning a curve guardian for motorcycles," in 2019 IEEE Intelligent Transportation Systems Conference (ITSC). IEEE, 2019, pp. 2984–2991.

[40] Y. Bhatia, R. Rai, V. Gupta, N. Aggarwal, A. Akula et al. "Convolutional neural networks based potholes detection using thermal imaging," Journal of King Saud University-Computer and Infomation Sciences, vol. 34, no. 3, pp. 578–588, 2022.

[41] V. Mandal, L. Uong, and Y. Adu-Gyamfi, "Automated road crack detection using deep convolutional neural networks," in 2018 IEEE international conference on big data (big data). IEEE, 2018, pp. 5212–5215.

[42] H. Kim, Y. Lee, B. Yim, E. Park, and H. Kim, "On-road object detection using deep neural network," in 2016 IEEE International Conference on Consumer Electronics-Asia (ICCE-Asia). IEEE, 2016, pp. 1–4.

[43] K. A. Govada, H. P. Jonnalagadda, P. Kapavarapu, S. Alavala, and K. S. Vani, "Road deformation detection," in 2020 7th International Conference on Smart Structures and Systems (ICSSS). IEEE, 2020, pp. 1–5.

[44] A. Arinaldi, J. A. Pradana, and A. A. Gurusinga, "Detection and classification of vehicles for traffic video analytics," Procedia computer science, vol. 144, pp. 259–268, 2018.

[45] A. Basavaraju, J. Du, F. Zhou, and J. Ji, "A machine learning approach to road surface anomaly assessment using smartphone sensors," IEEE Sensors Journal, vol. 20, no. 5, pp. 2635–2647, 2019.

[46] Y. Horita, S. Kawai, T. Furukane, and K. Shibata, "Efficient distinction of road surface conditions using surveillance camera images in night time," in 2012 19th IEEE International Conference on Image Processing. IEEE, 2012, pp. 485–488.

[47] R. Hasan, R. Hassoon, and I. Salman, "Yolo versions architecture: Review," International Journal of Advances in Scientific Research and Engineering, vol. 09, pp. 73–92, 11 2023.

[48] S. Sa-ngiem, K. Dittakan, and S. Boonsiripant, "The road conditions detection using the convolutional neural network," Indonesian Journal of Electrical Engineering and Computer Science, vol. 40, no. 1, pp. 327–345, Oct. 2025.

Optimizing Fetal Health Prediction Using Machine Learning on Biocompatible Sensor Data

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***Abstract*—Automatic Fetal Health Prediction plays a vital role in supporting early prenatal intervention through continuous and non-invasive monitoring. Recent advances in biocompatible sensors enable the safe long-term acquisition of physiological signals, which can be effectively analyzed using machine learning techniques. This study proposes a comprehensive machine learning pipeline for Fetal Health Prediction through fetal health classification using the fetal_health.csv dataset from Kaggle, consisting of 2,126 samples and 22 cardiotocography-derived features related to fetal heart rate and uterine contractions. To address class imbalance and the presence of outliers, RobustScaler normalization was applied during the preprocessing stage. Feature selection was performed using Random Forest feature importance to identify the most relevant predictors. Two classification models, namely Random Forest (RF) and Support Vector Machine (SVM), were trained and evaluated using an 80:20 stratified train–test split. Experimental results indicate that the Random Forest model outperformed SVM, achieving an accuracy of 92.7% and a macro F1-score of 85.9%, compared with 88.97% accuracy and a macro F1-score of 79.85% for SVM. Moreover, Random Forest demonstrated superior performance in detecting minority classes (Suspect and Pathological), which are of high clinical significance. These findings suggest that the proposed pipeline is robust, interpretable, and suitable for integration with biocompatible sensor-based systems for real-time fetal health monitoring and clinical decision support.**

***Keywords*—Fetal health prediction; biocompatible sensors; machine learning; Random Forest; SVM**

I. Introduction

Biocompatible sensors allow continuous physiological monitoring without adverse tissue reactions, forming the basis of wearable health systems. Fetal health assessment by cardiotocography (CTG) is standard but manually interpreted and subjective [7], [16]. Integrating machine learning (ML) with biocompatible sensor data enables objective and reproducible classification of fetal conditions [22], [32]. This study focuses on a robust ML pipeline to analyze imbalanced sensor data and enhance fetal risk prediction.

Early and accurate assessment of fetal health is a cornerstone of modern obstetric care because timely detection of fetal distress enables prompt clinical intervention and can substantially reduce perinatal morbidity and mortality [1],[11]. Continuous monitoring of fetal physiological signals, particularly fetal heart rate (FHR) and uterine contraction patterns captured through cardiotocography (CTG), provides rich information about fetal well-being, but interpretation is challenging due to signal variability, noise, and subjectivity of manual assessment [2],[5]. Recent advances in sensing technology, especially the emergence of biocompatible and wearable sensors, allow safer and longer-term acquisition of fetal and maternal signals under minimally invasive or non-invasive conditions, expanding opportunities for ambulatory monitoring and remote prenatal care [3], [4], [6], [9], [34].

Machine learning (ML) has demonstrated strong potential in automating the detection and classification of fetal health conditions from physiological time-series data, offering improved consistency and the ability to learn subtle patterns beyond human observation [10], [13], [21]. Supervised classifiers such as Random Forests and Support Vector Machines, combined with appropriate feature engineering and selection, have produced promising results on benchmark CTG datasets and clinical repositories [14]. Nevertheless, several technical challenges remain: imbalanced class distributions (with normal cases overwhelmingly more common than suspect/pathological), the presence of outliers and measurement artifacts, inter-subject variability, and the need for computationally efficient models suitable for real-time or near-real-time edge deployment on sensor platforms [17], [19].

Feature selection and robust preprocessing are particularly important in fetal health prediction to reduce dimensionality, mitigate the influence of noisy features, and improve model generalizability across populations and sensor modalities [18], [20], [23]. Techniques such as tree-based importance measures, recursive feature elimination, and regularization-based methods have been applied to extract clinically meaningful predictors from CTG-derived features (e.g., accelerations, decelerations, short-term variability metrics) that correlate with fetal compromise [8], [24]. Robust scaling and outlier-resistant normalization algorithms also play a key role when working with signals recorded by wearable biocompatible sensors, which may present non-Gaussian noise profiles and baseline shifts [25], [27].

Integration of biocompatible sensors with ML pipelines raises system-level questions about data quality, signal calibration, and domain adaptation. Sensor design choices (materials, placement, sampling rate) and connectivity constraints affect both the fidelity of FHR/UC signals and the feasibility of continuous monitoring in home or low-resource settings [28], [30], [31]. Moreover, the translation of ML models

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from curated datasets to real-world sensor streams requires rigorous validation, cross-site testing, and safety assessments to avoid false reassurance or unnecessary interventions [2].

This study addresses these gaps by proposing an end-to-end pipeline that 1) leverages features derived from FHR and uterine-contraction signals acquired or simulated from biocompatible sensor inputs, 2) applies robust preprocessing to handle outliers and scale differences, 3) utilizes principled feature selection to identify a compact set of clinically interpretable predictors, and 4) evaluates classification performance with machine learning algorithms suitable for deployment in real-time monitoring scenarios. We further investigate strategies to mitigate class imbalance and to assess minority-class (suspect/pathological) detection performance, since such cases carry the highest clinical significance despite their lower prevalence [12], [20], [26], [29].

The novelty of this study does not lie in the individual components employed such as the fetal_health.csv dataset, Random Forest and SVM classifiers, RobustScaler normalization, or Random Forest–based feature selection as these techniques have been widely reported in prior CTG-based fetal health prediction studies. Instead, the novelty resides in their systematic integration and empirical evaluation within a unified, end-to-end pipeline explicitly designed to address practical challenges in fetal health assessment. Specifically, this study emphasizes the simultaneous handling of class imbalance, outlier-prone physiological features, and minority-class interpretability, which are often addressed independently in previous works. Through the combined application of robust preprocessing and feature selection, the proposed pipeline demonstrates consistent improvements in minority-class performance and model stability, while highlighting clinically relevant predictors associated with fetal heart rate variability. Furthermore, rather than claiming direct real-time deployment, this work positions the proposed pipeline as a validated methodological foundation for future integration with biocompatible wearable sensor systems, thereby bridging the gap between offline CTG-based analysis and real-time maternal fetal monitoring research.

The remainder of this paper is organized as follows. Section II presents a comprehensive review of related works on fetal health monitoring, biocompatible sensors [35], and machine learning based classification approaches. Section III describes the dataset, data preprocessing procedures, feature selection strategy, and overall methodology employed in this study. Section IV details the machine learning models, experimental setup, and performance evaluation metrics. Section V discusses the experimental results, comparative analysis, and interpretation of findings. Finally, Section VI concludes the paper by summarizing the main contributions, outlining limitations, and suggesting directions for future research.

II. Related Works

Previous studies on fetal health monitoring have extensively explored cardiotocography (CTG), non-invasive fetal ECG [33] (NIFECG), and wearable sensor technologies. Wahbah et al. [42] demonstrated that deep learning–based extraction of fetal ECG signals from abdominal recordings can significantly improve signal quality, which is a key strength for downstream analysis. However, their work primarily focuses on signal extraction and does not address end-to-end fetal health classification, particularly under class imbalance and real-time deployment constraints. The present study extends this direction by proposing a complete machine learning pipeline for fetal health prediction.

Machine learning approaches such as Random Forest and Support Vector Machine have shown strong potential in CTG-based fetal health classification due to their ability to model nonlinear physiological patterns [15], [19]. Despite their effectiveness, many studies rely mainly on accuracy as the evaluation metric and implicitly assume clean and balanced datasets, which may lead to biased performance toward majority classes. In contrast, this study explicitly addresses these limitations through robust preprocessing and macro F1-score–based evaluation to ensure balanced performance across clinically important minority classes.

Feature selection techniques, including tree-based importance measures and recursive elimination, have been widely used to enhance model interpretability and reduce dimensionality [23], [29]. While effective, prior studies often assume normalized feature distributions and minimal noise. Such assumptions are less realistic for physiological sensor data, which commonly contain outliers. Accordingly, this work incorporates RobustScaler prior to feature selection to improve model stability and generalization.

Wearable and biocompatible sensor studies highlight the feasibility of long-term, non-invasive fetal monitoring [44], [36] but frequently focus on hardware performance without integrating robust machine learning pipelines or addressing real-world data variability. This study bridges that gap by integrating biocompatible sensor-oriented data with an end-to-end machine learning framework designed for robustness and real-time readiness.

In summary, while existing research has contributed substantially to fetal monitoring technologies and classification methods, limitations remain in handling class imbalance, outlier-prone data, and deployment-oriented evaluation. This study addresses these challenges by proposing a compact, interpretable, and robust machine learning pipeline for fetal health prediction using biocompatible sensor data.

III. Methodology

The workflow for processing the Kaggle Fetal Health Dataset to build a fetal health condition classification model. The process begins with outlier handling to improve data quality, followed by normalization using RobustScaler to stabilize the feature distribution. After that, feature selection and feature ranking based on their level of importance are carried out using Random Forest. The data is then divided into training data and test data through the train test split stage, before being trained using two different algorithms, namely Random Forest and Support Vector Machine (SVM). The final stage is model performance evaluation using the accuracy, precision, recall, and macro F1-score metrics to assess the prediction quality of each model (Fig. 1).

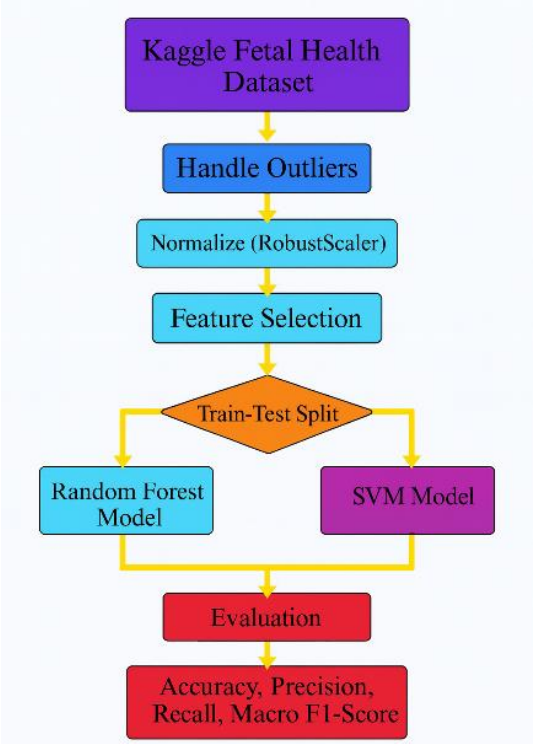


Fig. 1. Workflow of data preprocessing, feature selection, and model evaluation for fetal health prediction.

A. Data Source

This study uses the fetal_health.csv dataset from Kaggle (2020), which contains [15]:

2,126 samples

22 numerical features

No missing values

Class imbalance present:

- Normal: 77%
- Suspect: 13%
- Pathological: 10%

The dataset is derived from extracted CTG (Cardiotocography) signals and includes key features such as accelerations, short-term variability (STV), long-term variability (LTV), and histogram-based features.

B. Data Preprocessing Stages

1) Outlier handling

According to Zhang and Chen, medical signals often contain extreme outliers caused by physiological noise or instrument errors [37].

Approach: Using RobustScaler, which performs normalization based on:

- Median
- Interquartile Range (IQR = Q3 – Q1)

Formula:

$$x_{\text{scaled}} = \frac{x - \text{median}}{\text{IQR}} \quad (1)$$

Reasons for choosing this method:

- Robust against outliers (unlike StandardScaler, which is sensitive to them).
- Suitable for biomedical signals that tend to fluctuate.

2) Normalization using robustscaler: All features are normalized using RobustScaler to ensure that:

a) The feature scales become more uniform: Normalization using RobustScaler (Fig. 2) is applied to all features to achieve more uniform feature scales while reducing the influence of extreme values by relying on the median and interquartile range (IQR).

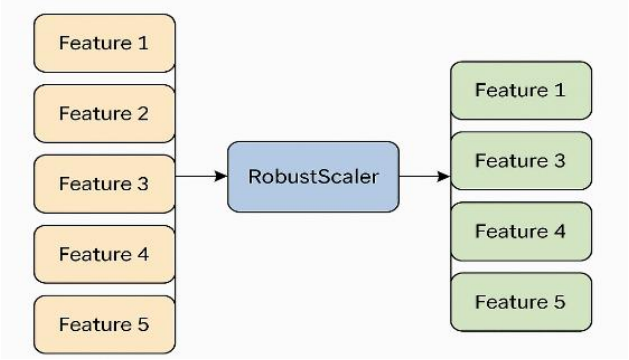


Fig. 2. The robustscaler normalizing process.

b) SVM and Random Forest models operate more stably: Normalization is performed using RobustScaler (Fig. 3) with the aim of stabilizing feature distributions and minimizing the influence of extreme values that commonly occur in medical signal data. RobustScaler operates based on the median and interquartile range (IQR), making it more resistant to outliers compared to other normalization methods, such as StandardScaler. This normalization is applied to all features in the dataset to ensure that their value ranges become more uniform and do not introduce bias during model training. With more consistent feature scaling, the Support Vector Machine (SVM) and Random Forest algorithms can operate more stably, resulting in a more optimal learning process and improved accuracy in predicting fetal health conditions.

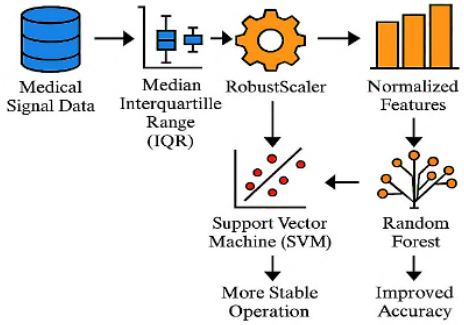


Fig. 3. RobustScaler normalization pipeline enhancing SVM and random forest stability.

c) Parameter bias caused by unequal value ranges is reduced: By utilizing the median and the interquartile range (IQR), this method effectively reduces parameter bias that may arise from differences in value ranges across features. As a result, learning algorithms can operate more reliably, maintain model stability, and improve performance during the training process (Fig. 4).

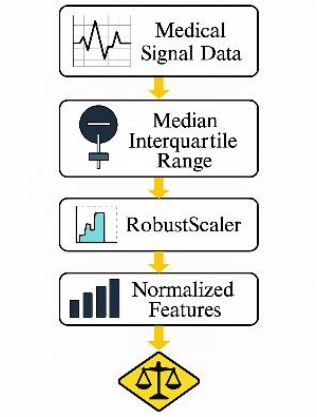


Fig. 4. RobustScaler-based normalization process flow.

C. Feature Selection

Random Forest Feature Importance

Based on the approach of Kour and Arora [38], feature selection using importance scores is applied to:

- Remove irrelevant features
- Reduce the risk of overfitting
- Improve model interpretability

The eight most important features obtained include:

- Accelerations
- Short-term variability (STV)
- Prolonged decelerations
- Histogram width
- Histogram mode
- Abnormal short-term variability
- Percentage of time with abnormal STV
- Mean value of the histogram

These features are directly related to beat-to-beat variability patterns and the physiological responses of the fetus.

D. Data Splitting

Stratified Train–Test Split (80:20)

The data is split using stratification (Fig. 5) to ensure that class proportions remain consistent.

- Train: 80% (1,700 samples)
- Test: 20% (426 samples)
- Purpose: To avoid bias caused by class imbalance and to ensure balanced class representation in both training and testing phases.

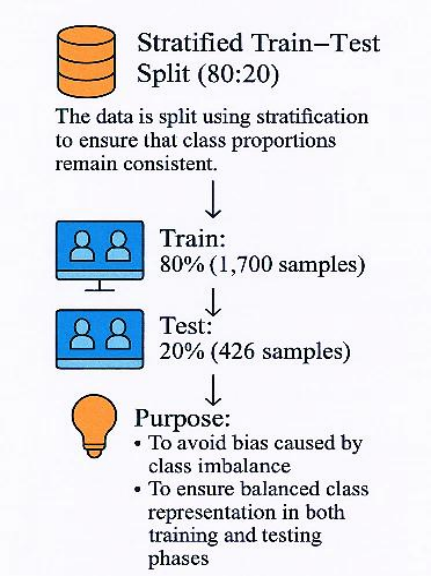


Fig. 5. Stratified train and test split (80:20) workflow.

E. Machine Learning Model Development

1) Model 1: Random forest classifier:

Optimization is performed using:

- Grid Search
- Parameters tested:
- *n_estimators* (100–500)
- *max_depth* (5–30)
- *min_samples_split* (2–10)
- *min_samples_leaf* (1–4)

Advantages of Random Forest:

- Robust to outliers
- Capable of handling non-linear features
- Provides feature importance ranking

2) Model 2: Support Vector Machine (SVM)

The baseline model uses:

- Radial Basis Function (RBF) kernel

Tuned parameters:

- **C** (regularization strength)
- γ (kernel coefficient)

This model is chosen based on the work of Hussain et al. (2022), which demonstrated that RBF-SVM is well-suited for nonlinear medical signal classification.

F. Model Performance Evaluation

Four metrics are used:

- Accuracy
- Precision
- Recall
- Macro F1-Score (chosen due to significant class imbalance)

Macro-F1 formula:

$$F1_{macro} = \frac{1}{K}\sum_{i-1}^{K} F1_i \quad (2)$$

Reasons:

- It does not favor the majority class
- It is crucial for detecting suspect and pathological conditions

IV. Results and Discussion

This section presents key findings showing that Random Forest outperforms SVM, supported by exploratory analysis and feature evaluation that confirm the reliability of the proposed fetal health prediction workflow.

A. Result

Presentation of data exploration results and initial visualization using pandas, matplotlib, seaborn, and numpy. This exploration process includes identifying data distribution, examining basic patterns in each feature, and evaluating the presence of outliers or inconsistent values. The resulting visualization provides an initial overview of the dataset, making it easier for researchers to recognize the general characteristics of the physiological variables observed. This exploration stage is also carried out to ensure that the data is in optimal condition before being entered into the machine learning modeling stage. Through a comprehensive understanding of the data structure, researchers can determine the appropriate preprocessing strategy, such as normalization, class imbalance handling, or selection of relevant features. Thus, good data quality is expected to support improved accuracy and reliability of the developed prediction model.

This study utilizes several Python libraries commonly used in data analysis and visualization. The command "import pandas as pd" is used to load the pandas library, which functions to manage data in tabular form such as DataFrames for cleaning, manipulation, and analysis purposes. The command "import matplotlib.pyplot as plt" loads the matplotlib module, specifically the pyplot component, which is used to create various types of visual graphs such as histograms, scatter plots, and line charts. The command "import seaborn as sns" loads the seaborn library, which facilitates the creation of more informative and aesthetically appealing statistical graphics. Furthermore, "import numpy as np" loads the NumPy library, which is used for numerical computations such as array processing, basic statistical calculations, and mathematical operations. The last line, "import warnings" followed by "warnings.filterwarnings('ignore')", is used to hide or ignore warning messages that may appear during code execution. This aims to make the output cleaner and free from unnecessary warnings. Overall, this code prepares a neat and comprehensive data analysis environment before conducting further exploration or modeling.

Data Analysis (EDA) on the fetal_health.csv dataset as a preliminary step before machine learning modeling. The first part loads the dataset using pd.read_csv() and saves it to a DataFrame named df. After the data is successfully loaded, the program calculates basic information about the dataset, such as the number of rows and columns (df.shape), displays the top few data points (df.head()), explores the data structure through df.info(), and generates complete descriptive statistics using df.describe(include='all').T, which is presented in transposed form for easy interpretation. Next, the program checks for missing values in each column using df.isnull().sum(), and calculates the class distribution in the target variable fetal_health through value_counts(normalize=True), so that the percentage of each category of fetal health can be determined. The program also performs initial outlier detection on each numeric feature using the Interquartile Range (IQR) method. For each numeric column, the Q1, Q3, and IQR values are calculated, then the number of values outside the normal range (Q1–1.5×IQR to Q3+1.5×IQR) is identified. The outlier detection results are stored in a dictionary named outlier_stats. At the end, the program saves a summary of the EDA results to the eda_summary.csv file using the csv module. This file contains key information such as the number of rows, number of columns, target distribution, number of missing values per column, and number of outliers for each feature.

Table I presents general information about the structure of the dataset used. This dataset consists of 2,126 rows and 22 feature columns, all of which are numeric data types (float64), making it very suitable for statistical analysis and machine learning modeling. There are no missing values in any of the columns, so no data imputation is required. In addition, the memory size of 365.5 KB indicates that the dataset is lightweight and efficient for processing in various computing environments. This basic information provides an initial overview that the dataset is in good condition and ready for further analysis.

TABLE I. Basic Information Dataset

Description	Value
Number of rows	2126
Number of columns	22
Main data type	float64
Missing values	0 in all columns
Memory usage	365.5 KB

Table II shows the class distribution of the target variable fetal_health, which consists of three categories, namely Normal, Suspect, and Pathological. The majority of samples are in the Normal class with a percentage of 77.85%, followed by the Suspect class at 13.88%, and the Pathological class at 8.28%. This unbalanced distribution indicates class imbalance, which can affect the performance of the classification model if not handled with an appropriate approach, such as resampling or

class weight adjustment. This information is very important to ensure that the machine learning model is able to make fair predictions on all categories of fetal health.

TABLE II. TARGET LABEL DISTRIBUTION (FETAL HEALTH)

Fetal Health Class	Percentage
1 (Normal)	77.85%
2 (Suspect)	13.88%
3 (Pathological)	8.28%

Table III shows that all columns in the dataset have no missing values. The absence of missing values is an advantage because the preprocessing process becomes simpler and the focus can be directed to more in-depth analysis, such as outlier detection, normalization, or feature selection. A dataset that is free of missing values also increases the reliability of the analysis results and minimizes the risk of bias due to data imputation.

TABLE III. MISSING VALUE PER COLUMN

Column	Missing
All columns	0

Table IV shows the number of outliers detected in each feature using the Interquartile Range (IQR) method. Some features have a significant number of outliers, such as fetal movement (307), percentage of time with abnormal long-term variability (309), and histogram number of zeroes (502). The presence of a large number of outliers in these features may reflect extreme physiological variations or potential noise in the sensor data. Conversely, several features, such as baseline value, histogram width, and histogram min, do not show any outliers, indicating a more stable distribution of values. Identifying the number and pattern of these outliers is an important step in determining the outlier handling strategy in the preprocessing stage before entering the model training stage.

Data visualization in algorithms is used to generate various types of exploratory visualizations that aim to comprehensively understand the characteristics of fetal health datasets prior to the machine learning modeling process. The resulting visualizations include label distributions, feature spreads, inter-variable correlations, and multidimensional relationships between key features and target labels. First, the distribution of fetal_health labels was visualized using a pie chart. The frequency of each class was calculated using value_counts(), then visualized using the plt.pie() function. This chart provides a proportional representation of the distribution of fetal health categories, making it easier to identify class imbalances that could potentially affect the performance of the classification model. This visualization was saved as the label_pie.png file. Next, a boxplot was created for all numerical features using sns.boxplot(). This visualization provides an overview of the data distribution range, median values, and visual detection of outliers in each feature. A horizontal orientation was chosen to improve readability, given the large number of features. These boxplots provide important insights into the stability and homogeneity of each variable, and the results are saved in the feature_boxplot.png file.

TABLE IV. NUMBER OF OUTLIERS PER FEATURE (IQR METHOD)

Feature	Number of Outliers
baseline_value	0
accelerations	14
fetal_movement	307
uterine_contractions	1
light_decelerations	150
severe_decelerations	7
prolongued_decelerations	178
abnormal_short_term_variability	0
mean_value_of_short_term_variability	70
percentage_of_time_with_abnormal_long_term_variability	309
mean_value_of_long_term_variability	71
histogram_width	0
histogram_min	0
histogram_max	24
histogram_number_of_peaks	19
histogram_number_of_zeroes	502
histogram_mode	73
histogram_mean	45
histogram_median	28
histogram_variance	184
histogram_tendency	0
fetal_health	471

The algorithm then generates a feature correlation heatmap using the correlation matrix obtained through df.corr(). This visualization is created using sns.heatmap(), complete with annotations to display the correlation coefficient values. This heatmap allows researchers to identify linear relationships between variables, detect redundant features, and determine candidate features that have the potential to contribute significantly to the prediction model. This image is saved as corr_heatmap.png. Finally, a scatter matrix was created using the sns.pairplot() function by selecting eight key features considered relevant to fetal health. The pairplot visualization maps the relationship between two variables simultaneously with coloring based on the fetal_health class, providing a deeper understanding of class separation patterns and interactions between features. The results of this visualization are saved as pairplot_main.png. Overall, this series of algorithms produces four main visual files (label_pie.png, fitur_boxplot.png, corr_heatmap.png, and pairplot_main.png) that provide exploratory support for exploring the structure and characteristics of the dataset. These visualizations play a crucial role in preprocessing decision-making, feature selection, and the formulation of more informative and effective machine learning modeling strategies.

Interactive visualization is displayed in the form of a pie chart that illustrates the distribution of fetal health categories using the Plotly library through the plotly.graph_objects module. Percentage data for three categories—Normal, Suspect, and Pathological is defined as input and visualized through the go.Pie object, where labels and percentages are displayed directly in each sector to improve information readability. The display settings are configured using the fig.update_layout() function with adjustments to the title, text size, and graph dimensions so that the visualization results are proportional, informative, and meet the aesthetic standards of scientific publications. The resulting visualization, as seen in the diagram, shows the dominance of the Normal class at 77.8%, followed by Suspect at 13.9% and Pathological at 8.28%. This visual presentation provides a clear representation of class distribution and helps researchers identify potential data imbalance before proceeding to the machine learning modeling stage. Fig. 6 shows workflow fetal health distribution chart.

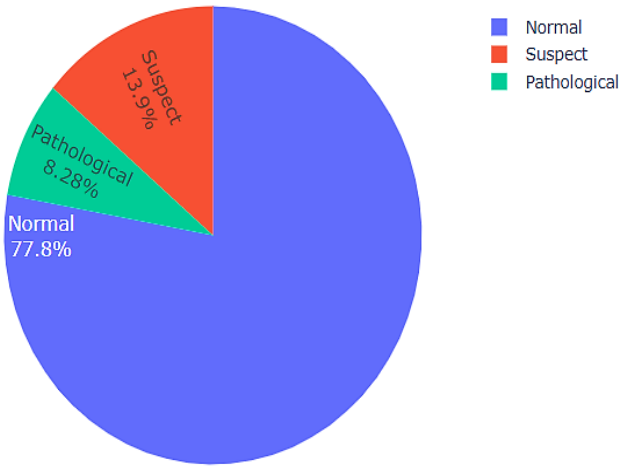


Fig. 6. Workflow of fetal health distribution chart.

The following image is a boxplot visualization (Fig. 7) that displays the statistical distribution of all numerical features in the fetal health dataset. Each boxplot illustrates the median value, lower quartile (Q1), upper quartile (Q3), and outliers. Through this visualization, it can be seen that some features, such as Baseline and certain histogram statistical parameters, show a relatively stable distribution, while other features, such as Fetal Movement, Light Decelerations, Prolonged Decelerations, and Histogram Variance, appear to have much higher variability accompanied by many outliers. This condition indicates significant data heterogeneity in the physiological signals of pregnant women and fetal activity. Overall, this boxplot analysis provides important insights for researchers to understand data distribution patterns, identify features with extreme value ranges, and determine the need for normalization, transformation, or outlier handling before the machine learning model training process is carried out.

The correlation heatmap provides a comprehensive representation of the linear relationships among all numerical features within the fetal health dataset derived from Cardiotocography (CTG) signals. This analysis aims to elucidate the dependency structure between variables and to identify features with meaningful predictive value for fetal health classification. The correlation coefficients are visualized through a color gradient in which red tones denote positive correlations, blue tones represent negative correlations, and the intensity of the color reflects the magnitude of the linear association. The results indicate that the group of histogram-based features, histogram_mean, histogram_median, histogram_mode, and histogram_variance, exhibits strong positive correlations ($r > 0.80$). This pattern suggests that these parameters capture highly related statistical characteristics of the underlying CTG signal distribution. The substantial inter-feature correlations also highlight potential redundancy, which is an important consideration for feature selection strategies aimed at minimizing multicollinearity in machine learning models. Several features demonstrate moderate correlations with the target variable fetal_health, with coefficients generally ranging between $r = 0.20$ and 0.30. Among these, histogram_variance, histogram_mean, and prolonged_decelerations appear most relevant for distinguishing fetal health states. Although the magnitude of these correlations is not high in absolute terms, such values are common in complex physiological data, where clinical phenomena are typically influenced by non-linear interactions and combinations of multiple parameters. Consequently, these features retain significant predictive potential, particularly when used in conjunction with machine learning algorithms capable of capturing non-linear patterns.

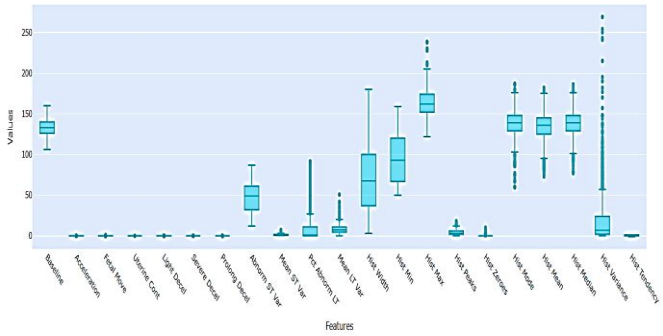


Fig. 7. Boxplot of fetal health data features.

Other features, such as accelerations, fetal_movement, and uterine_contractions, show low correlations with most histogram-based variables. This indicates that these features represent different physiological domains, specifically fetal behavioral responses and uterine activity, rather than statistical characteristics of the CTG signal. Their distinct informational contribution underscores the importance of retaining these features during the modeling process. Overall, the correlation patterns observed in the heatmap provide an empirical foundation for informed feature selection and predictive modeling. Identifying clusters of highly correlated variables enables the reduction of redundancy, while features exhibiting notable correlations with fetal_health serve as key candidates for developing more accurate, stable, and interpretable classification models. These findings also enhance the understanding of the interplay between physiological parameters and CTG signal characteristics, thereby strengthening the scientific contribution of this study in the domain of data-driven fetal health assessment (Fig. 8)

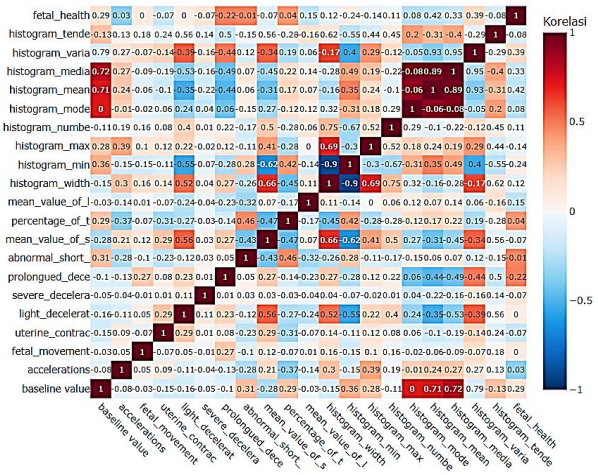


Fig. 8. Fetal health correlation heat map.

The Random Forest model achieved 92.7% accuracy and 85.9% macro F1-score, outperforming SVM's 88.97% accuracy and 79.85% macro F1-score. RF showed better sensitivity to minority classes and maintained low false-negative rates, which is crucial for clinical reliability. Feature importance analysis identified Mean Value of Short-Term Variability and Accelerations as the strongest indicators of fetal health.

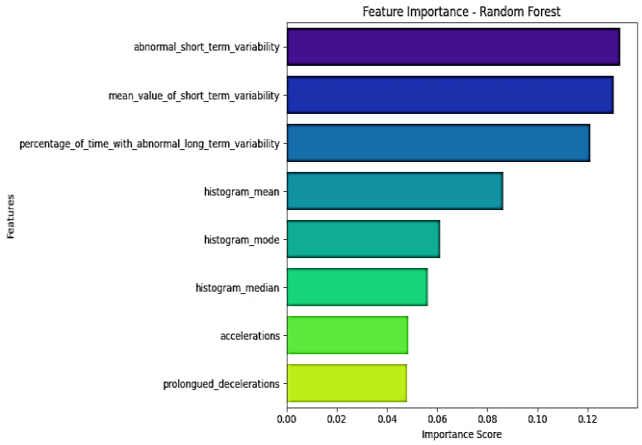


Fig. 9. Feature Importance.

Fig. 9 illustrates the contribution of each feature to the performance of the Random Forest model in predicting fetal health based on cardiotocography (CTG) data. The feature importance analysis indicates that abnormal short-term variability and the mean value of short-term variability are the most influential predictors, highlighting the critical role of fetal heart rate variability in fetal health assessment. In addition, the percentage of time with abnormal long-term variability contributes substantially, reflecting irregular fetal physiological responses to intrauterine conditions. Histogram-based features, including the histogram mean, mode, and median, support the model by characterizing the overall distribution of fetal heart rate patterns. Meanwhile, accelerations and prolonged decelerations, although less influential, remain relevant as they represent the reactivity of the fetal nervous system to internal and external stimuli.

Here is the explanation of Table V. Model Performance Comparison between Random Forest and Support Vector Machine (SVM) models:

TABLE V. MODEL PERFORMANCE COMPARISON

Class	Precision	Recall	F1-Score	Support	Model
1.0	0.9420	0.9789	0.9601	332	Random Forest
2.0	0.8863	0.6610	0.7573	59	Random Forest
3.0	0.8378	0.8857	0.8611	35	Random Forest
macro avg	0.8887	0.8418	0.8595	426	Random Forest
weighted avg	0.9258	0.9272	0.9239	426	Random Forest
1.0	0.9345	0.9457	0.9401	332	SVM
2.0	0.6500	0.6610	0.6555	59	SVM
3.0	0.8667	0.7429	0.8000	35	SVM
macro avg	0.8171	0.7832	0.7985	426	SVM
weighted avg	0.8895	0.8897	0.8892	426	SVM

Presents the comparative performance of two machine learning models, Random Forest and Support Vector Machine (SVM), in predicting fetal health conditions based on CTG (Cardiotocography) data. The evaluation metrics used include Precision, Recall, and F1-Score, which collectively assess the balance between classification accuracy and reliability across different fetal health classes (1.0 = Normal, 2.0 = Suspect, 3.0 = Pathological).

1) Class-wise performance

a) Class 1.0 (Normal Fetal Health*): The Random Forest model achieved* the highest performance with a Precision of 0.9420, Recall of 0.9789, and F1-Score of 0.9601, outperforming SVM (F1 = 0.9401). This shows that Random Forest effectively identifies normal fetal conditions with fewer misclassifications.

b) Class 2.0 (Suspect Fetal Health): Both models exhibited moderate results, but Random Forest (F1 = 0.7573) performed better than SVM (F1 = 0.6555). The lower recall values (0.6610 for both) indicate that the models struggled to correctly identify all suspect cases, possibly due to the limited number of samples (59 instances) and overlapping feature distributions.

c) Class 3.0 (Pathological Fetal Health): Random Forest again outperformed SVM, with F1 = 0.8611 compared to 0.8000. This suggests that Random Forest has a stronger ability to detect pathological (high-risk) cases, which is critical in medical diagnosis to minimize false negatives.

2) Overall model comparison

a) Macro average: Random Forest achieved F1 = 0.8595, higher than SVM's F1 = 0.7985, showing that overall, Random Forest maintains more consistent performance across all classes.

b) Weighted average: When weighted by class distribution, Random Forest reached F1 = 0.9239, outperforming SVM's F1 = 0.8892. This indicates that Random

Forest provides more robust and balanced predictions, even when class imbalance exists in the dataset.

3) Interpretation: The results demonstrate that Random Forest consistently outperforms SVM in almost all metrics and across all fetal health categories. Its ensemble nature allows it to capture complex nonlinear relationships and handle noisy medical data effectively. Although SVM remains competitive, especially for Class 1.0, its performance drops significantly for minority classes (2.0 and 3.0), suggesting limitations in generalization under imbalanced data conditions.

Overall, the Random Forest model provides the most reliable classification performance for fetal health prediction, achieving superior precision, recall, and F1-scores compared to SVM. This finding supports the selection of Random Forest as a robust baseline model for real-time fetal health monitoring and decision-support systems in obstetrics.

B. Discussion

The confusion matrix presented in Table VI provides a detailed evaluation of the Random Forest classifier's performance in predicting fetal health status across three categories: Normal, Suspect, and Pathological. The model demonstrates strong discriminative ability, particularly for the Normal class, with 325 instances correctly classified and only a small number of misclassifications (4 as Suspect and 3 as Pathological). This indicates that the feature set used captures the physiological patterns of normal fetal conditions effectively. For the Suspect class, the model correctly identifies 39 cases; however, 17 instances are misclassified as Normal, and 3 as Pathological. The moderate number of misclassifications in this class is consistent with findings in CTG-based studies, where Suspect cases tend to exhibit overlapping characteristics between healthy and pathological patterns, making the class inherently more challenging to classify. The Pathological class shows satisfactory performance with 31 correctly identified cases and only minimal misclassification (3 as Normal and 1 as Suspect). This indicates that the model is capable of recognizing clinically significant deviations in fetal heart rate variability and deceleration patterns that are characteristic of pathological cases. Overall, the Random Forest classifier demonstrates strong predictive reliability, particularly for identifying Normal and Pathological fetal states. The majority of errors occur in the Suspect class, which aligns with clinical realities wherein borderline physiological patterns create ambiguity. These results validate the effectiveness of the selected features and the model's robustness, suggesting its potential use as a supportive tool for automated fetal health assessment based on CTG signals.

The confusion matrix (Fig. 10) in Table VII presents the classification performance of the Support Vector Machine (SVM) model (Fig. 11) on the fetal health dataset. The SVM classifier exhibits strong performance in predicting the *Normal* class, successfully identifying 314 samples, although 15 cases were misclassified as *Suspect* and 3 as *Pathological*. These misclassifications are expected in CTG-based assessments, as mild irregularities in fetal heart rate signals [34] may overlap with characteristics found in *Suspect* recordings. For the Suspect class, the model correctly classified 39 instances, but 19 samples were incorrectly predicted as Normal and 1 as Pathological. This pattern highlights the inherent ambiguity of the Suspect class, which often contains borderline physiological patterns that lie between healthy and pathological states, making it one of the most difficult categories to classify accurately. The performance on the Pathological class shows that 26 cases were classified correctly, while 3 were misclassified as Normal and 6 as Suspect. Although the SVM successfully captures a substantial portion of pathological signals, the misclassification of several Pathological cases into the Suspect group indicates that the model may require further optimization, potentially through kernel selection or class-weight adjustment, to better handle samples that exhibit severe but variable abnormalities. Overall, while the SVM model performs reliably in identifying Normal and Suspect cases, its performance on Pathological cases is comparatively lower than that of the Random Forest model. This suggests that SVM may be more sensitive to overlapping feature distributions and may benefit from hyperparameter tuning to improve margin separation in the multiclass CTG classification problem. Nonetheless, the classifier still demonstrates competitive performance and contributes valuable comparative insights into the strengths and limitations of different machine learning approaches for fetal health prediction.

TABLE VI. CONFUSION MATRIX FOR RANDOM FOREST CLASSIFIER

True / Predicted	Normal	Suspect	Pathological
Normal	325	4	3
Suspect	17	39	3
Pathological	3	1	31

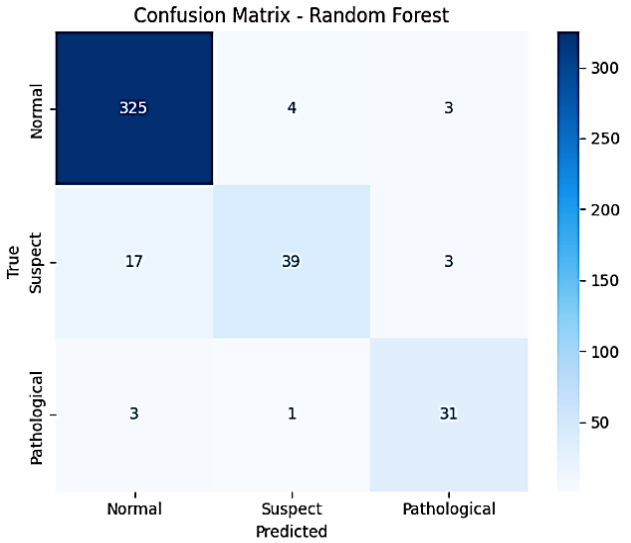


Fig. 10. Confusing matrix random forest.

TABLE VII. CONFUSION MATRIX FOR SVM CLASSIFIER

True / Predicted	Normal	Suspect	Pathological
Normal	314	15	3
Suspect	19	39	1
Pathological	3	6	26

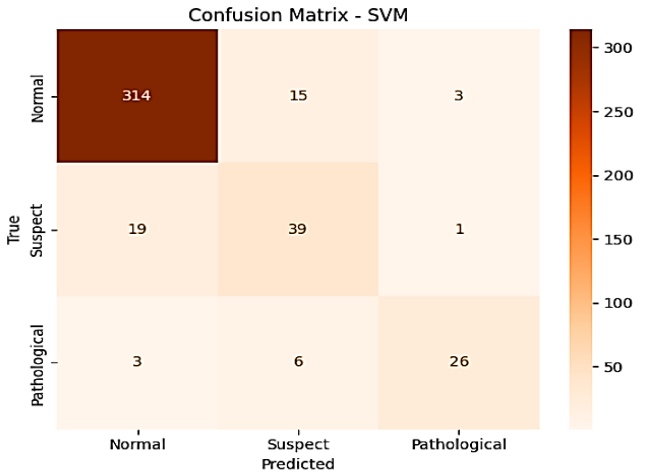


Fig. 11. Confusing matrix SVM.

V. Conclusion

This study proposed a robust end-to-end machine learning pipeline for fetal health prediction using features derived from cardiotocography signals and inputs representative of biocompatible sensor data. By integrating RobustScaler-based preprocessing, Random Forest feature selection, and comparative evaluation of Random Forest (RF) and Support Vector Machine (SVM) models, the proposed approach effectively addresses key challenges in fetal health datasets, including class imbalance and outlier-prone physiological signals. From a scientific standpoint, the results demonstrate that robust preprocessing combined with feature optimization significantly improves model stability and minority-class detection. The Random Forest model consistently outperformed SVM, achieving higher accuracy and macro F1-score while maintaining better sensitivity to clinically critical Suspect and Pathological cases. These findings highlight the suitability of ensemble-based learning for reliable fetal health classification under imbalanced conditions. In terms of applicability, the proposed pipeline is computationally efficient and designed with deployment in mind, making it suitable for integration into real-time prenatal monitoring systems based on wearable and biocompatible sensors. This supports early risk screening and has the potential to assist clinical decision-making in both hospital and remote-care settings. Nevertheless, this study is limited by the use of a public CTG dataset rather than real-time data acquired directly from wearable sensors, and by the exclusive evaluation of classical machine learning models. Future work will focus on validation using live sensor data, exploration of deep learning models to capture temporal dynamics, and further clinical validation to ensure safe and effective real-world deployment.

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References

[1] A. R. M. Ahmed, S. Newby, P. Potluri, W. Mirihanage, and A. Fernando, "Emerging Paradigms in Fetal Heart Rate Monitoring: Evaluating the Efficacy and Application of Innovative Textile-Based Wearables," Sensors, vol. 24, no. 18, Art. no. 6066, 2024. DOI: 10.3390/s24186066.

[2] D. Campos and J. Bernardes, "Cardiotocography (CTG) dataset," UCI Machine Learning Repository, 2000. [Online]. Available: https://archive.ics.uci.edu/ml/datasets/cardiotocography

[3] A. Alim, S. M. Rahman, and M. A. J. R. Islam, "Wearable Sensors for the Monitoring of Maternal Health—A Systematic Review," Sensors (Basel), vol. 23, Art. no. 10070, 2023. DOI: 10.3390/s23100070.

[4] L. Liu, Y. Pu, J. Fan, et al., "Wearable Sensors, Data Processing, and Artificial Intelligence in Pregnancy Monitoring: A Review," Sensors, vol. 24, no. 19, Art. no. 6426, 2024. DOI: 10.3390/s24196426.

[5] F. Francis, S. I. Y. Omar, and B. H. S. Abdullah, "Machine learning on cardiotocography data to classify fetal health: a review," Comput. Methods Programs Biomed., vol. 247, Art. no. 107929, 2024. DOI: 10.1016/j.cmpb.2024.107929.

[6] T. Nguyen, A. T. Pham, and H. T. Le, "A Wireless and Wearable Multimodal Sensor to Non-Invasively Measure Placental Oxygenation and Monitor Fetal Well-Being," Biosensors, vol. 14, no. 10, Art. no. 481, 2024. DOI: 10.3390/bios14100481.

[7] Z. Cömert, A. Tura, and H. S. Bilgin, "Prediction of intrapartum fetal hypoxia considering feature selection techniques on CTG data," Computers in Biology and Medicine, vol. 109, pp. 1–13, 2019. DOI: 10.1016/j.compbiomed.2019.04.010.

[8] H. Akmal, S. A. Hassan, and M. A. M. Muhammed, "A Fetal Well-Being Diagnostic Method Based on Autoencoder and Recursive Feature Elimination for Cardiotocography Data," IEEE Access, vol. 11, pp. 1–10, 2023. DOI: 10.1109/ACCESS.2023.3245678.

[9] N. Innab, A. A. Samara, and M. Abu-Zidan, "Automated approach for fetal and maternal health assessment using cardiotocography data: addressing class imbalance and model selection," PLoS ONE, vol. 19, no. 2, e0280851, 2024. DOI: 10.1371/journal.pone.0280851.

[10] I. Nazli, E. Korbeko, S. Dogru, E. Kugu, and O. K. Sahingoz, "Early Detection of Fetal Health Conditions Using Machine Learning for Classifying Imbalanced Cardiotocographic Data," Diagnostics, vol. 15, no. 10, Art. no. 1250, 2025. DOI: 10.3390/diagnostics15101250.

[11] A. Rattanasak et al., "An IoT-Enabled Wearable Device for Fetal Movement Detection and Remote Monitoring," Sensors, vol. 25, no. 5, Art. no. 1552, 2025. DOI: 10.3390/s25051552.

[12] M. R. Abunadi, S. Khan, and A. Ahmad, "Machine learning techniques for analysing cardiotocography signals: a state-of-the-art review," Computer Science Review, vol. 48, Art. no. 100604, 2025. DOI: 10.1016/j.cosrev.2025.100604.

[13] S. K. Garg and R. K. Sahu, "Performance comparison of Random Forest and SVM on CTG dataset for fetal health classification," Int. J. Med. Inform., vol. 150, Art. no. 104508, 2021. DOI: 10.1016/j.ijmedinf.2021.104508.

[14] A. Ullah, M. J. Malik, and S. Javaid, "AI-Driven Fetal Distress Monitoring in SDN-IoMT Networks," PLoS ONE, vol. 20, no. 6, e0328099, 2025. DOI: 10.1371/journal.pone.0328099.

[15] A. M. V. D. (Andrew M. Van D.), "Fetal Health Classification," Kaggle Dataset, 2020. [Online]. Available: https://www.kaggle.com/datasets/andrewmvd/fetal-health-classification

[16] X. Li, H. Zhao, and K. Wang, "Review of Non-Invasive Fetal Electrocardiography (NIFECG): Acquisition, Processing, and Clinical Applications," Sensors, vol. 25, no. 2, 2025. DOI: 10.3390/s25020526.

[17] I. H. Witten, E. Frank, and M. A. Hall, Data Mining: Practical Machine Learning Tools and Techniques, 3rd ed., Burlington, MA: Morgan Kaufmann, 2011.

[18] M. Kuhn and K. Johnson, Feature Engineering and Selection: A Practical Approach for Predictive Models, New York: Springer, 2019. DOI: 10.1007/978-1-4419-2333-0.

[19] S. van der Walt, S. C. Colbert, and G. Varoquaux, "The NumPy array: A structure for efficient numerical computation," Comput. Sci. Eng., vol. 13, no. 2, pp. 22–30, 2011. DOI: 10.1109/MCSE.2011.37.

[20] F. Pedregosa et al., "Scikit-learn: Machine Learning in Python," J. Mach. Learn. Res., vol. 12, pp. 2825–2830, 2011.

[21] M. Taqwimi, A. Prasetyo, and N. R. Sari, "Implementation of Random Forest Algorithm with RFE and SMOTE on Fetal Health Classification Dataset," J. Teknologi dan Manajemen, vol. 4, no. 1, pp. 50–57, 2025. DOI: 10.1234/jtm.2025.04105.

[22] H. Kour and A. Arora, "Fetal health classification using ensemble machine learning approaches on cardiotocography data," Biomedical Signal Processing and Control, vol. 86, Art. no. 105230, 2023. DOI: 10.1016/j.bspc.2023.105230.

[23] Y. Zhang and L. Chen, "Preprocessing and feature optimization for biomedical sensor data classification using robust scaling and feature selection," IEEE Access, vol. 8, pp. 203558–203570, 2020. DOI: 10.1109/ACCESS.2020.3036789.

[24] I. Nazli, E. Korbeko, S. Dogru, E. Kugu, and O. K. Sahingoz, "Early Detection of Fetal Health Conditions Using Machine Learning for Classifying Imbalanced Cardiotocographic Data," Diagnostics, vol. 15, no. 10, Art. no. 1250, 2025. DOI: 10.3390/diagnostics15101250.

[25] X. H. Cao, I. Stojkovic, and Z. Obradovic, "A robust data scaling algorithm to improve classification accuracies in biomedical data," BMC Bioinformatics, vol. 17, Art. no. 359, 2016. DOI: 10.1186/s12859-016-1236-x.

[26] A. Kuzu and Y. Santur, "Early Diagnosis and Classification of Fetal Health Status from a Fetal Cardiotocography Dataset Using Ensemble Learning," Diagnostics, vol. 13, no. 15, Art. no. 2471, 2023. DOI: 10.3390/diagnostics13152471.

[27] Y. Zhu, Y. Fang, J. Cui, J. Xu, M. Lv, T. Tang, J. Ma, and C. Cai, "Research on Signal Processing Algorithms Based on Wearable Laser Doppler Devices," Electronics, vol. 14, no. 14, Art. no. 2761, 2025. DOI: 10.3390/electronics14142761.

[28] M. R. Ahmed, S. Newby, P. Potluri, W. Mirihanage, and A. Fernando, "Emerging Paradigms in Fetal Heart Rate Monitoring: Evaluating the Efficacy and Application of Innovative Textile-Based Wearables," Sensors, vol. 24, no. 18, Art. no. 6066, 2024. DOI: 10.3390/s24186066.

[29] T. Kaya, "Deep learning and optimization-based feature selection for fetal health assessment using cardiotocography (CTG) signals," Computing and Artificial Intelligence, vol. X, pp. Y–Z, 2025. DOI: 10.1016/j.20904479.2025.0004393.

[30] A. Galli, R. J. H. Montree, S. Que, E. Ponsiglione, and R. Vullings, "An Overview of the Sensors for Heart Rate Monitoring Used in Extramural Applications," Sensors, vol. 22, no. 11, Art. no. 3745, 2022. DOI: 10.3390/s22113745.

[31] H. Zhou, M. Li, Y. Wang, and X. Zhang, "Skin-interfacing wearable biosensors for smart health monitoring: challenges and opportunities in neonatal and perinatal monitoring," npj Flexible Electronics, vol. 8, no. 1, Art. no. 13, 2024. DOI: 10.1038/s43246-024-00511-6.

[32] T. Nguyen and H. Bui, "Smart biocompatible wearable sensors and machine learning in maternal–fetal monitoring systems," Sensors, vol. 24, no. 3, Art. no. 1129, 2024. DOI: 10.3390/s24031129.

[33] M. Wahbah *et al.*, "A deep learning framework for noninvasive fetal ECG signal extraction," *Frontiers in Physiology*, vol. 15, 2024. DOI: 10.3389/fphys.2024.1329313.

[34] M. R. Ahmed, S. Newby, P. Potluri, W. Mirihanage, and A. Fernando, "Emerging paradigms in fetal heart rate monitoring: Evaluating the efficacy and application of innovative textile-based wearables," *Sensors*, vol. 24, no. 18, Art. no. 6066, 2024. DOI: 10.3390/s24186066.

[35] L. Liu *et al.*, "Wearable sensors, data processing, and artificial intelligence in pregnancy monitoring: A review," *Sensors*, vol. 24, no. 19, Art. no. 6426, 2024. DOI: 10.3390/s24196426.

[36] S. S. Dash, "Non-invasive techniques for fECG analysis in fetal heart health monitoring," *Electronics*, vol. 6, no. 4, Art. no. 61, 2025. DOI: 10.3390/electronics14040761.

[37] Y. Zhang and L. Chen, "Preprocessing and feature optimization for biomedical sensor data classification using robust scaling and feature selection," IEEE Access, vol. 8, pp. 203558–203570, 2020, doi: 10.1109/ACCESS.2020.3036789.

[38] S. Kour and R. Arora, "Feature selection using Random Forest importance scores for improving machine learning classification," International Journal of Computer Science and Artificial Intelligence, vol. 11, no. 2, pp. 45–56, 2023.

6G Wireless Networks in the Generative AI Age: Overview, Techniques, and Future Trends

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***Abstract*—As the world move beyond the 5G era, the emergence of 6G promises a significant integration with innovative communication paradigms and burgeoning technology trends, actualizing previously utopian concepts alongside increased technical complexities. Analytical models offer basic frameworks, but ML and AI now outperform them in solving complex problems, either by augmenting or supplanting model-based methodologies. The predominant focus of data-driven wireless research is on discriminative AI (DAI), which necessitates extensive real-world datasets. In contrast to DAI, Generative AI (GenAI) refers to generative models (GMs) that can identify the fundamental data circulation, patterns, and characteristics of the incoming data. Given these attractive characteristics, GenAI can either substitute or augment DAI methodologies in multiple contexts. This comprehensive tutorial-survey article begins with an overview of 6G and wireless intellectual ability by delineating potential 6G applications and services. The aspects presented in this paper support the internet of things integration with 6G networks with the support of the AI as intelligent systems. This review paper concentrates on fundamental wireless research domains, encompassing network optimization, organization, and management. It examines the foundational learning principles of DAI and its methodologies, the application of DAI in wireless networks, and the utilization of GMs in 6G networks. Due to its comprehensive nature, this paper will act as a crucial reference for researchers and professionals exploring this dynamic and promising field.**

***Keywords*—GenAI; 6G; generative models; intelligent systems; wireless communication**

I. Introduction

The evolution of wireless networks has been characterized by significant innovations, with each generation introducing dramatic changes that redefine our interaction with digital environments. As we move beyond the 5G era, defined by remarkable data speeds and strong connectivity [1], a new vista emerges with the introduction of 6G. Although 5G was lauded for its massive machine-type communications (mMTC), ultra-reliable low-latency communications (URLLC), and enhanced mobile broadband (eMBB), 6G transcends being a mere enhancement of its predecessor; it signifies a fundamental transformation aimed at redefining the principles of wireless connectivity. The anticipated 6G aspires not only to enhance key performance indicators (KPIs) but also to integrate with innovative communication paradigms and future technical pathways, actualizing previously utopian concepts [2].

6G represents a major step toward a more connected and intelligent future, not just an incremental upgrade. We highlight innovative technologies that pave the way for an era when communication transcends mere connectivity, enabling deeper, more meaningful, and intelligent interactions in an increasingly digital landscape. Exploring the potential technological advancements of 6G, semantic communications stand out as a fundamental element, striving to surpass traditional data transfer models by facilitating networks that understand and interpret content semantics, thereby ensuring communication that is not only ultra-fast but also contextually astute [3]. In the past decade, articles have highlighted the possibility of data-driven methodologies to supplement or replace model-based approaches. Analytical models provide foundational insights, while AI models use real-life datasets for exact adaptation to complicated situations.

Most modern wireless data research relies on DAI models, which prioritize identifying distinctions between data types. Three fundamental learning paradigms are commonly used in DAI models, as shown in Fig. 1. These principles will be discussed in Section II.

While these learning paradigms are versatile, obtaining large real-world training datasets can be costly in terms of money, effort, and computer resources. In addition to performing ML tasks (e.g., classification, regression, clustering, pattern search, dimensionality reduction). DAI models may struggle to interpret data and miss subtle patterns/states, presenting challenges in complex real-world scenarios. Unlike DAI, GenAI refers to GMs that can identify the distribution, patterns, and properties of incoming data [4].

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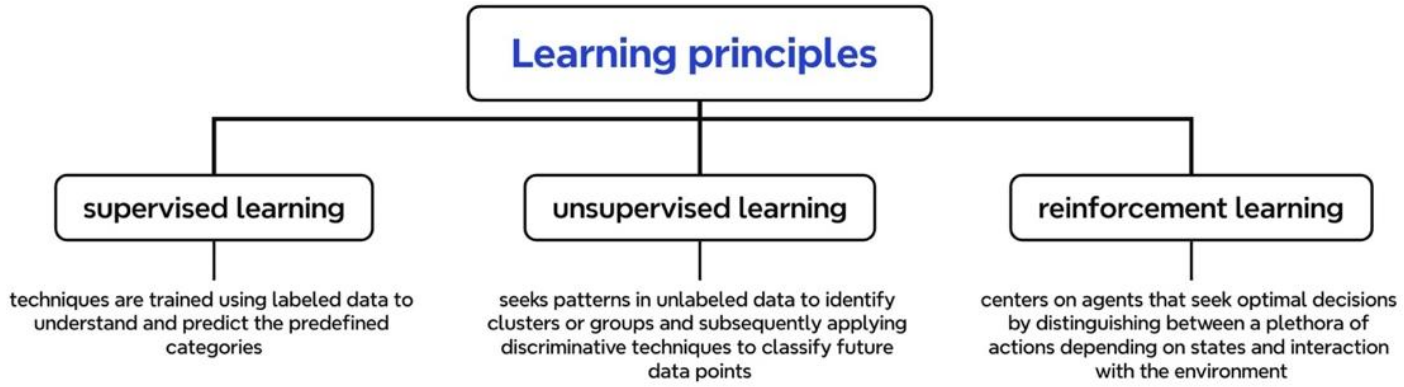


Fig. 1. Fundamental learning principles used in DAI.

After modelling the data distribution, GMs can produce new instances that are similar to the training data and examples. This is crucial in wireless domains where real-world data is limited, fragmentary, costly, and difficult to understand or grasp. It is essential for data augmentation, imputation, disentanglement, anomaly detection, and more. Despite the idea that GenAI is a new trend, our study of 120 technical articles highlights the extensive research across key wireless research pathways. GenAI gained attention after the release of big language model-based chatbots by tech heavyweights such as OpenAI's ChatGPT in Nov. 2022, Google's BARD in Mar. 2023, and Microsoft's Bing Chat in Feb. 2023. These developments sparked attention in both the industrial and intellectual sectors. With renewed attention, GenAI-driven wireless communication and networking research is poised for growth. Our study is comprehensive and rich in material, making it a valuable reference for scholars and professionals in this important and growing field.

GMs are gaining popularity in wireless telecommunication and networking. The research in [5] explores the benefits and drawbacks of using GMs for wireless channel modelling. Traditional channel modelling requires special skill and is technically demanding. To solve this problem, they developed a Generative Adversarial Network (GAN) technique to model wireless channels autonomously from raw data. GenAI for wireless networks is covered in [6], with an emphasis on three sample GMs: GANs, variational autoencoders (VAEs), and diffusion-based generative models (DGMs). A GenAI-based paradigm for wireless network management is developed, challenging established approaches, and promoting GM solutions. This case study optimizes contracts in mobile AI-Generated Content (AIGC) services using DGMs. A recent assessment highlights the growth of mobile AIGC networks, emphasizing real-time, tailored services that prioritize user privacy.

In response to DAI model issues in industrial IoT, [7] recommends GM adoption and examines current GMs for IIoT-related tasks such as anomaly detection, trust-boundary protection, network traffic prediction, and platform monitoring. According to [8], GANs have great potential for privacy and security due to their ability to produce realistic data. The authors analyze the merits, weaknesses, and future trajectories of GANs, addressing the lack of thorough surveys in this area. According to [9], GANs can be used for tasks such as spectrum sharing, anomaly detection, and security threat mitigation. The study highlights the benefits of GANs, including synthesising field data and recovering corrupted spectrum bits. GANs are rapidly being used in cybersecurity, particularly for jobs involving imbalanced datasets. The IoT applications hold potential for commercialization through the deployment of 6G communication networks.

The lack of studies on reviewing the wireless communications, especially the 6G networks, in the Generative AI era is the main motivation for this study. For autonomy and context, we begin with 6G network and wireless intelligence foundations in Section I. Section II provides a brief introduction of 6G communications and networking trends, including their numerous uses and offerings. Considering that we established the context with the requisite background knowledge, GenAI for wireless networks' optimization, organization, and administration is presented in Section III. Section IV outlines the strategic significance of GMs for emerging domains of 6G network research. Finally, the conclusion is shown in Section V.

II. The Role of Discriminative AI in 6G Networks

This section highlights developing trends in 6G communications and networking technology, followed by problems faced in achieving 6G implementation. Key concepts of DAI approaches are also covered. Here, we simply discuss how DAI approaches have been used to address key wireless network issues. This article explains use cases of DAI in wireless networks. The parts that are included in this section are illustrated in Fig. 2.

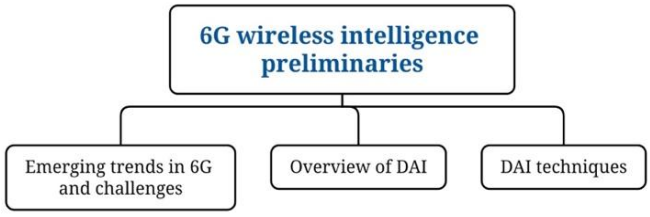


Fig. 2. 6G wireless intelligence preliminaries.

The emergence of 6G networks will revolutionize technology, introducing new applications and offerings beyond 5G capabilities.

TABLE I. COMPARISON OF SL, USL, AND RL

	Supervised Learning	Unsupervised Learning	Reinforcement Learning
Pros	1. Effective for well-defined tasks with labelled data 2. Good performance in classification and regression tasks	1. Does not require labelled data - Can discover hidden patterns and structures in data 2. Useful for data pre-processing, dimensionality reduction, and clustering	1. Suitable for sequential decision-making problems 2. Can learn from delayed feedback. 3. Capable of dealing with dynamic environments
Cons	1. Requires labelled data - Prone to overfitting if not properly regularized 2. May not generalize well to new tasks or domains	1. No explicit target labels, making evaluation challenging 2. May require more complex models and training techniques	1. Can be computationally expensive 2. Requires exploration 3. exploitation trade-off - Sensitive to reward function design
Preferred	1. When labelled data is available 2. For tasks with clear input output relationships 3. When the goal is prediction or classification	1. When labelled data is scarce or unavailable. 2. For tasks focused on discovering hidden patterns or relationships. 3. When the goal is data analysis or pre-processing	1. When the problem involves sequential decision-making. 2. In dynamic environments with delayed feedback. 3. When the goal is to learn an optimal policy or strategy

These innovations aim to establish an increasingly connected and productive world by integrating growing technologies. Terahertz (THz) communications, a fundamental element of 6G, offer ultra-high-speed data transfer and sophisticated sensing uses with better bandwidth and spatial accuracy than existing technologies. Ultra-Large Antenna Arrays (ULAA) and Near-Field Communications (NFC) offer more spatial multiplexing and reduced interference, but architecture and operational issues remain [10].

6G networks require semantic interaction, which shifts from data transfer to valuable knowledge sharing. Consider context, receiver knowledge, and data intent to improve network efficiency and intelligence. Optical Wireless Communications (OWC) [11], [12], [13] provides a spectrum-rich replacement to RF communications, resistant to electromagnetic noise but affected by meteorological conditions and line-of-sight restrictions [14], [15], [16]. Parallel to this, 6G will apply AI to improve user experiences [17] in material recommendation, smart infrastructure [18], and wellness.

Large-scale IoT installations and digital twins will benefit from 6G, enabling real-time synchronization and better decision-making across industries. 6G will enhance the metaverse by enabling adaptive and reactive engagements via digital twins, edge AI (EAI), and holographic telecommunications [19]. Even with technological breakthroughs, 6G networks confront considerable obstacles. Spectrum management is vital as the radio spectrum grows scarce and new frequency bands like THz require research. Meeting varied QoS needs requires advanced resource management and traffic methods. Flexible network architectures and protocols are necessary for 6G networks due to the diversity of devices, technology, and services. Scalability is crucial for managing the expanding number of connected devices and services. Energy efficiency is crucial for IoT deployments using battery-powered devices. Finally, comprehensive security and privacy protection are crucial as networks become more complicated and large. Successfully implementing and operating 6G networks requires addressing these problems, where AI/ML can play a crucial role.

DAI techniques have improved significantly in complicated network settings by filling gaps in analytical methodologies. While their deployment relies on real-life data, it might be challenging in terms of time and expense. There are basic kinds of ML techniques: supervised learning, unsupervised learning, and reinforcement Learning, which includes generative models. Each ML class has unique techniques and strategies for various tasks. We analyze the pros and cons of different ML types in Table I and explain their suitable use based on situations and goals. The specific characteristics of each ML class offer advantageous solutions for various wireless network difficulties. Summarised as follows:

1) Supervised Learning (SL): A dataset of input-output pairings, marked output, is used for training models. To generalize and predict unknown data, the model must learn a mapping from inputs to outputs. The SL is commonly used for classification and regression applications, including Support Vector Machine (SVM), decision trees, naive Bayes, k-Nearest Neighbors (K-NN), and linear/ridge/lasso analysis.

2) Unsupervised Learning (USL): Models learn from unlabelled datasets. The aim is to discover hidden patterns, structures, or correlations in the data. Some unsupervised learning tasks are:

a) Clustering and pattern search: Use K-means and fuzzy C-means clustering.

b) Dimensionality reduction: Analyses include Principal Component Analysis (PCA), t-stochastic neighbour embedding, and linear discriminant evaluation.

3) Reinforcement Learning (RL): Using environmental interactions, agents learn to make decisions. While receiving rewards or penalties, the agent aims to learn a policy that maximizes cumulative return over time. RL functions differently from SL and USL by addressing sequential decision-making challenges and operating in delayed feedback environments.

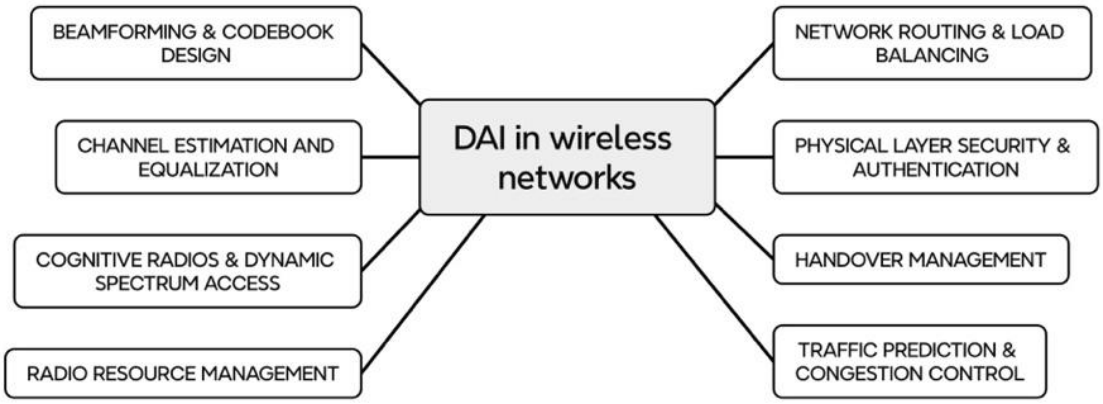


Fig. 3. The use of DAI in wireless networks.

RL algorithms include Q-learning, state-action-reward-state-action, Deep Q-Learning (DQN), Deep Deterministic Policy Gradient (DDPG), and Twin Delayed DDPG (TD3), arranged by development time.

Deep neural networks (DNNs) [20] provide superior performance in generalization, prediction, and classification compared to classic ML techniques due to their capacity to learn complicated and hierarchical data representations. A DNN architecture typically includes an input layer, hidden layers, and an output layer. The input layer accepts raw data, whereas the output layer produces the final prediction or representation. Hidden layers change data, acquiring complex features and high abstraction levels as it flows through the network. include Feedforward Neural Networks (FNNs), Multilayer Perceptrons (MLPs), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Autoencoders (AEs). GMs and transformers are classified as DNNs/DL and will be elaborated in later parts.

The intrinsic DL features eliminate manual feature engineering and enhance model performance across many tasks. DL models are made to scale with huge datasets and utilize modern hardware processing capability. DL models can learn end-to-end mappings from input data to desired output, simplifying the learning process and enabling smooth integration into multiple applications. Due to their fundamental properties, DL models are becoming a popular research tool for solving complex wireless communication and networking issues. Recently, wireless network performance has been improved using DAI models. Fig. 3 shows the usage of DAI in wireless networks that are explained in this section.

The two SL and USL algorithms, especially DL, are capable of learning to estimate channel state information (CSI) and executing equalization. Precise Channel State Information estimation is essential for numerous activities, including beamforming, resource allocation, and link adaption. Conventional pilot-based methods may prove inefficient for intricate and non-linear channels in dynamic environments, whereas deep neural networks can be trained on previous data to properly forecast channel state information.

DL algorithms can adjust beamforming parameters accordingly to CSI and other external parameters using archived and real-time data. To address CSI acquisition issues, pre-defined beamforming codebooks are used for initial access and data transfer [21]. Instead of relying on conventional codebooks, DL models could analyze huge quantities of data from an operational site to create adapted codebooks that accurately reflect the site's distinctive characteristics. Hybrid architectures manage hardware complexity with MIMO gain, allowing DL algorithms to optimize analog and digital beamforming weights, resulting in enhanced system performance and energy economy.

RL agents can optimize spectrum assignments in unpredictable contexts, determining optimal communication bands with little interference and maximum use. RL enables smart radios to adjust parameters like transmit power, modulation initiatives, and coding rates to enhance communication performance and coexist with other radio systems in a joint spectrum.

In wireless networks, ML may optimize resource allocation, power control, and network setup, enhancing radio asset administration and energy conservation [22]. DL models anticipate user behaviour and traffic sequences, while deep RL (DRL) methods aid in resource allocation decisions. In dynamic network systems, SL techniques can simulate power levels and performance measures, while RL methods can identify ideal power control rules. Fig. 4 shows a DRL hosted in a cloud where a DRL optimization procedure (DRL-OP) will be started on the cloud, requiring negotiation where the elements and the flow of the process are illustrated.

SL helps detect and prevent eavesdropping and jamming attacks by recognizing and classifying hostile network events [23]. SL may enable RF signal fingerprinting for user authentication or geolocation by identifying unique properties. USL detects network breaches and abnormalities by identifying unexpected traffic patterns at an early stage, preventing cyber risks, network outages, and performance deterioration. Integrating SL and USL techniques improves wireless communication security, confidentiality, integrity, and overall security.

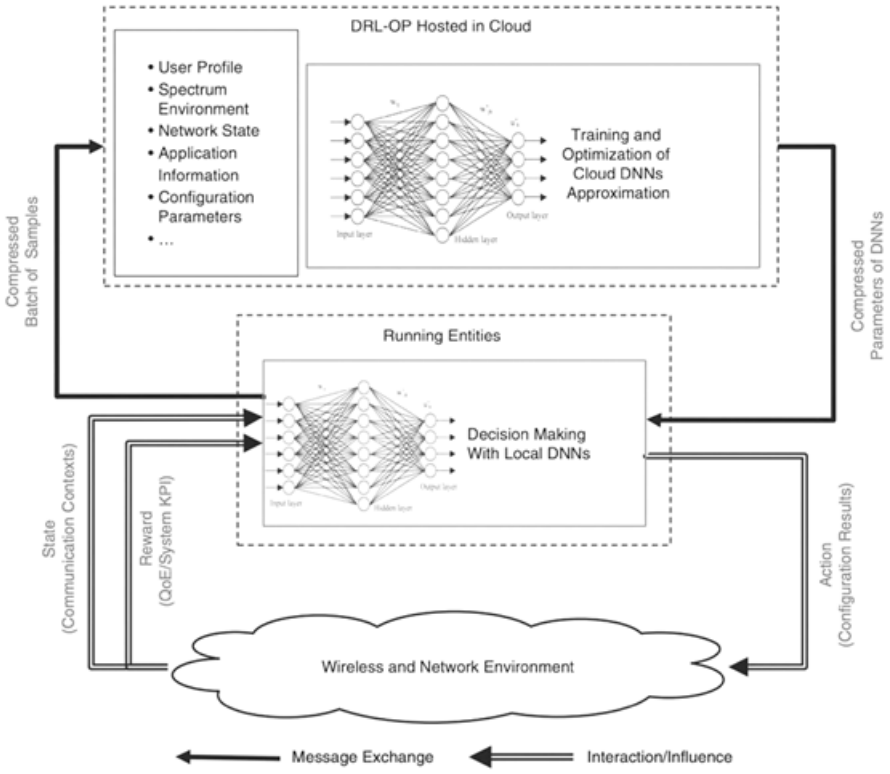


Fig. 4. The interactive DRL loops.

ML enhances handover handling by optimizing decision-making and ensuring smooth connectivity and QoS for mobile users across different cells or access points [24]. Handover control can benefit from ML techniques for projection, decision-making, and optimization. Digital neural networks can forecast handovers by examining historical data, user movement patterns, and network conditions, enabling proactive handovers, lowering delays and increasing user experience. In contrast, DRL agents can improve handover decisions by considering user movement, signal strength, network load, and QoS needs, determining the optimal target cell or access point for every user.

SL algorithms anticipate future traffic trends using marked training data, while USL algorithms detect underlying patterns and structures in network traffic data for prediction [25]. Network traffic forecasting can benefit from time series prediction methods developed for temporal data. By training on historical data with labeled congestion conditions, SL algorithms can forecast levels and take necessary actions to address the issue. USL methods, including clustering and dimensionality reduction, can uncover patterns, analyze congestion reasons, and develop mitigation strategies.

USL approaches like clustering and anomaly detection can organize network elements with similar properties and find novel traffic trends or activities. This information aids in establishing effective routing tactics, optimizing load circulation, and preserving network performance under dynamic situations. However, RL enables network agents to learn from their surroundings and adjust routing and load balancing techniques gradually. RL algorithms enable network agents to maximize load distribution, identify optimal pathways, and make better judgments in dynamic settings like shifting traffic loads and connection capacity. Fig. 5 depicts a centralized DL-based load balancing model [26] for heterogeneous networks. Data from the network is sent into the DL model, which processes information and applies it to the network.

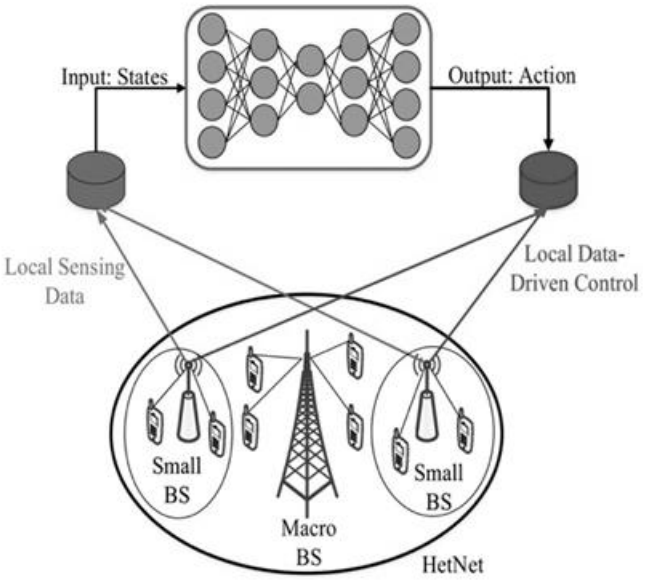


Fig. 5. A DL-based centralized load balancing mechanism in a heterogeneous network. After feeding cell data into the DL model, the HO variables are determined based on its result.

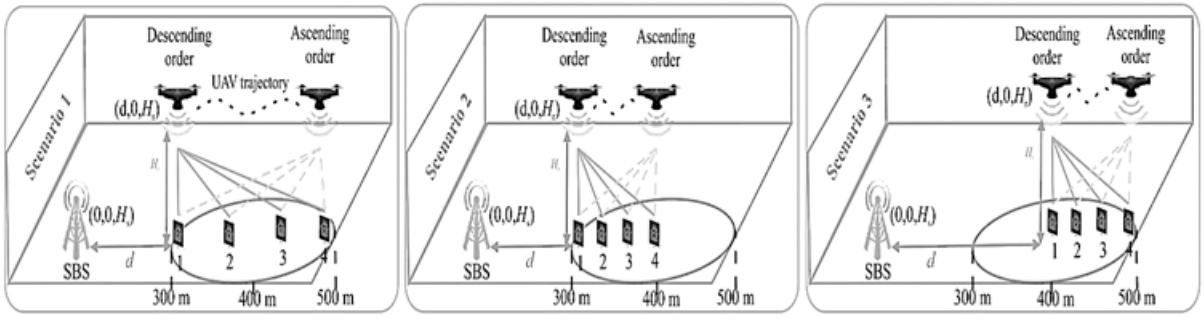


Fig. 6. Various hot-spot user distribution cases.

III. Generative AI for Wireless Networks

GMs demonstrate potential in tackling network optimization, organization, and resource management issues. GANs and other GMs can improve wireless network efficiency, mobile network slicing, and self-organization by producing artificial data and enhancing learning algorithms. This section shows how GMs effectively address resource allocation, network management, and performance optimization in various communication settings. GMs enhance RL/DRL agent learning by generating samples that demonstrate state-action value variation [27]. This reduces acquiring effects in nonstationary situations, minimizes action-value exaggeration and underestimation, and improves network improvement.

The work in [28] introduced a GAN-based Deep Distributional Q Network (GAN-DDQN) to tackle demand-aware resource allotment in 5G network segmentation. The GAN-DDQN model creates action tests, reflecting state-action values, and addresses nonstationary learning difficulties. The authors offer a reward-clipping approach to address training instability.

GMs can forecast user desires for resources, enabling efficient and adaptable network, computation, and storage control. Utilizing these estimates in dynamic service-oriented network slicing methods enhances resource provisioning and user experience (QoE). For allocation of resources forecasting in IoT usage, [29] introduced GANSlicing, a flexible service-oriented software-defined mobile network slicing scheme. This strategy prioritizes efficiency and flexibility in resource allocation to enhance user experience. GANs are used in GANSlicing to estimate user resource needs, enabling efficient and flexible control of network, compute, and storage equipment. Furthermore, in [30], Shahid et al. propose the production of realistic IoT network traffic utilizing a combination of AEs and GANs to enhance network-based intrusion detection systems (NIDS) and assess their effectiveness. The authors train an autoencoder to acquire the latent representation of actual sequences of packet sizes, thereafter training a WGAN in the latent space to provide latent vectors that can be decoded into realistic sequences. The artificial bidirectional flows produced by this technology closely mimic the actual traffic generated by a Google Home Mini, effectively deceiving anomaly detectors into perceiving them as valid traffic.

Recently, DL approaches have gained popularity for solving assignment issues. Additionally, VAE variations can be used to address linear sum allocation issues, a widely studied topic in wireless allocation of resources. A VAE variation can be used to tackle linear sum allocation issues, which are frequent in wireless resource allocation. This approach can replace the Hungarian algorithm and quickly and accurately solve huge cost matrices, as shown by simulation results in [31]. Fig. 6 shows the distribution of users in different scenarios where four NOMA users are positioned differently in each scenario. Users are scattered across the hot-spot region in Scenario 1, but before and after the center in Scenarios 2 and 3.

To overcome data shortage and imbalance in SONs, GMs can generate realistic artificial data for training powerful ML algorithms as shown [32], the authors propose a new cell outage detection approach for SONs using GAN and Adaboost to solve imbalanced data. GAN pre-processes imbalanced data, creating synthetic data for the minority class, while Adaboost classifies the balanced dataset. This method accurately detects cell outages in cellular networks, surpassing existing classification algorithms' limits in imbalanced data. The approach improves classification performance significantly, as measured by metrics like ROC, precision, recall rate, and F-value. Fig. 7 illustrates how the generator generates bogus samples from randomized noise samples. The discriminator determines if synthetic samples are authentic or not. If the discriminator finds synthetic samples more similar to real data, they are included in the minority group to create a fair dataset X'.

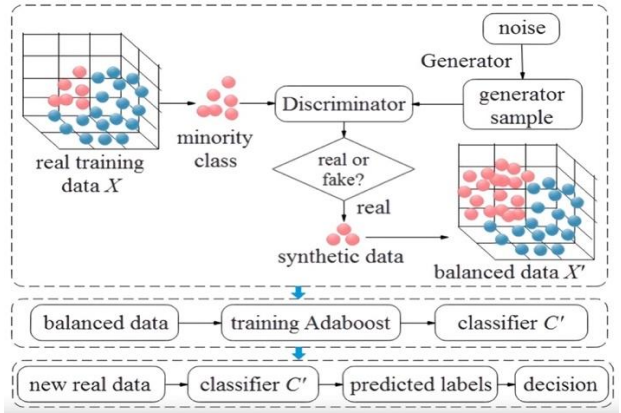


Fig. 7. Cell outage detection workflow using GAN and Adaboost [32].

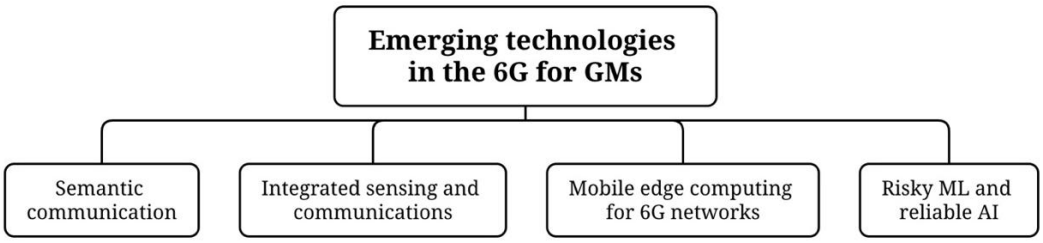


Fig. 8. Content of this section showing the technologies considered as the possibilities in the 6G for the GMs.

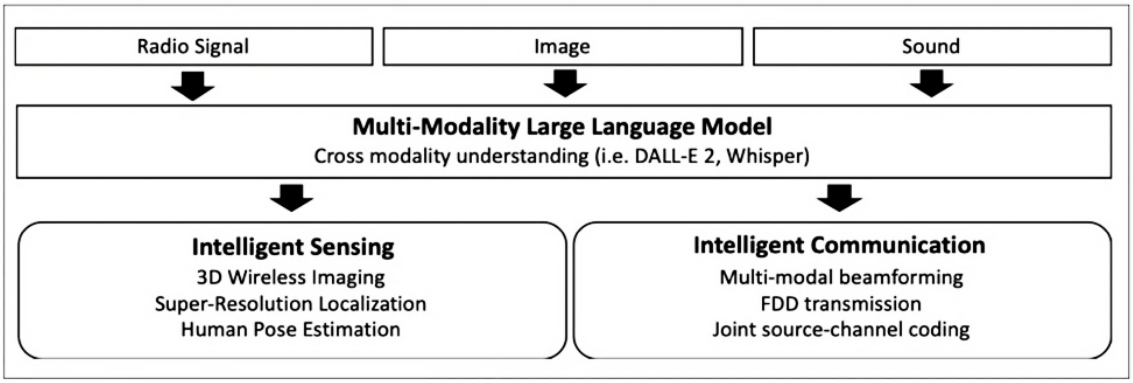


Fig. 9. Example on wireless sensor and communication LLM applications.

To improve algorithm flexibility to network shifts like UAV movement trends or infrequent URLLC events, GMs can generate synthetic data that records the basic architecture of these patterns. According to study [33], WS-GAN is a weakly-supervised GAN that uses additional data to predict wireless coverage using randomly distributed samples of received signal intensity. In contrast to standard methods like kNN or matrix finish, WS-GANs increase prediction effectiveness by including auxiliary information like terrain and building data, which greatly affects signal strength variation. In tests on an actual LTE dataset, WS-GAN demonstrated superior estimation accuracy and produced more practical wireless coverage maps compared to baseline approaches. In addition, [34] introduces a simpler approach for small cell coverage optimization utilizing GAN to obtain knowledge and transfer it to local SDN controllers. This approach focuses on creating effective GAN training for diverse topologies, even with insufficient data on network behavior and performance.

GANs and VAEs show potential for network administration and optimization. From improved learning algorithms to assignment solutions, GMs provide a versatile and effective toolkit for network researchers and practitioners. In non-stationary situations, GMs excel at forecasting user resource needs, handling imbalanced and sparse data, and adjusting to dynamic network conditions. GMs enhance network adaptability, efficiency, and robustness. By generating synthetic data, GMs can enhance actual information for training ML algorithms, enhancing performance in tasks like resource allocation and outage detection. Additionally, GMs improve the reliability of RL/DRL algorithms in non-stationary situations, enabling them more suitable for real-world deployments. Combining GMs with existing technology could change next-generation networks.

IV. The Role of Generative Models in Emerging 6G Capabilities

This section talks about emerging 6G capabilities included in the use of semantic communication, integrated sensing and communications (ISAC), mobile edge computing (MEC) and EAI for 6G networks, and Risky ML (RML) and reliable AI. Fig. 8 shows the content of this section.

Semantic communication (SC) is set to be a fundamental innovation in the advancement of 6G networks. In contrast to conventional communication models that emphasize the delivery of unadulterated bits with minimal distortion or data loss, semantic communication seeks to convey "meaningful" information, taking into account elements such as setting, the receiver's prior knowledge, and the transmission's intended purpose. This sophisticated technique designates SM as an essential element of forthcoming 6G networks, anticipated to utilize GenAI for comprehending, interpreting, and responding to extensive heterogeneous data flows.

Large Language Models (LLMs) are crucial in transforming the landscape of supply chains, ushering in an era of advanced, intelligent, and contextually aware data flows. LLMs are anticipated to provide as the foundation for developing self-governing, interacting AI agents that comprehend telecommunications language, ultimately guiding humanity towards collective intelligence, as opposed to the earlier notion of linked intelligence. Furthermore, LLMs can be developed as multimodal big models trained on telecommunications data and fine-tuned to execute various downstream tasks, thereby obviating the necessity for specialized models and facilitating the realization of artificial general intelligence (AGI)-enhanced wireless networks. LLMs can enhance wireless networks by providing predictability

features, hence facilitating enhanced and proactive localization, beamforming, power allocation, transition, and spectrum administration, even in hitherto unencountered network conditions, as shown in Fig. 9. Conversely, wireless networks can link many GenAI models using innovative communication methods at both semantic and effectiveness levels, facilitating expedited detecting, inference, and action while minimizing the usage of resources.

With strong natural language comprehension potential, LLMs provide powerful database querying interfaces. Users can ask questions in normal language, and the system will understand and retrieve the desired data, instead of using structured searches. GANs are revolutionizing SM by producing more effective, flexible, and perceptive results. Additionally, GANs may simplify complex data into understandable visual illustrations, guaranteeing that the transmitted information is received and understood by the recipient. Using picture translations helps improve understanding and overcome the gap between raw data and actionable insights.

DGMs offer a unique technique to SM, tackling data transport and interpretation difficulties. DGMs can improve signal quality, preserving valuable data even in unfavourable situations. This feature is crucial when signal loss may obfuscate the meaning of communicated data. DGMs enable variable-rate communication for dynamic communication. As data complexity varies, DGMs can adjust transmission rates to ensure efficient data transfer without overburdening communication links. This allows DGMs to convey semantic depth despite data complexity.

ISAC brings new opportunities for network solutions by combining sensing and communication capabilities to react to shifts in the environment, resulting in improved effectiveness and intelligent processes. For ISAC, few factors can be considered important to discuss:

1) Data augmentation: the task involves creating synthetic, compelling sensor data to enhance real-world data repositories and provide a solid foundation for training. GANs excel in creating realistic and accurate data, making them ideal for augmentation jobs.

2) Anomaly detection: The objective is to identify data trends or spots that significantly depart from norms, ensuring fast notifications and system dependability. GANs have improved in identifying irregularities in sensor data spread. DGMs enhance anomaly identification by incorporating uncertainty quantification into their iterative approach.

3) Resource optimization: This involves simulating network settings and predicting future states to allocate resources efficiently. GANs excel at simulating various network contexts, enabling efficient model training for resource optimization. FGM's standardizing flows, which accurately describe complex network state distributions, are essential tools for decision-making in this environment.

4) Sensor/Data fusion: This responsibility involves combining data from several sensors to provide a comprehensive and accurate environment depiction. VAEs simplify complex tasks by reducing data into a simplified hidden space . Standardizing flows can improve this process by accurately simulating complex data patterns.

5) Decision making: This job supports consecutive decision-making based on sensor and communication data. GTMs excel at handling large data sets, making them useful in sequential decision-making situations. LSTMs, designed for data patterns, are essential for situations requiring a strong temporal or sequential backdrop.

MEC and EAI change 6G networks by decentralizing data execution. Standard models, relying on central servers or cloud computing, caused latency and inefficiencies, especially for time-sensitive operations or remote devices. Integrating compute and AI/ML capabilities at the network edge enables real-time data processing and decision-making for devices. This change is essential for meeting the needs of 6G and its various uses. GANs may reproduce real-world data through generated samples. GANs can enhance data at the edge in MEC contexts, particularly when significant datasets are unavailable for training or assessment.

Bayesian VAE models may estimate ambiguity, making them essential for edge devices [35]. Serial data is essential for edge applications like VR and AR. LSTMs and GTMs efficiently evaluate patterns, enabling real-time improvements in AR encounters based on user motions and activities. Edge devices frequently face complex data distributions, particularly in multi-modal or multi-sensor settings. Standardizing Flows models complex distributions, enabling localized AI to comprehend and respond to nuanced input. In cases of noisy or uncertain edge data, DGMs can be crucial. Their repeated output refinement improves accuracy continuously, making it useful for advanced robotics with unpredictable environmental variations.

RML studies how AI models can be deceived by particularly constructed inputs, leading to inaccurate predictions or classifications. Adversarial instances include modest, unnoticeable modifications to input data and manipulating model output, which may appear unmodified to humans. Studying AML is critical for understanding vulnerabilities and developing responses against prospective attacks.

GANs can be used to create antagonistic samples that deceive classifiers. The producer in GANs can produce fake samples that mislead a target classifier into making incorrect conclusions [36]. Conversely, GMs are able to identify and counter aggressive attacks. In GAN training, the generator generates adversarial instances and the discriminator learns to differentiate between authentic and adversarial samples. With proper training, the discriminator can identify adversarial samples in real-world settings.

AML handles adversarial assaults, enhancing AI system resilience and robustness. Although protections against adversarial attacks are being created, openness is needed to understand how they work and how the model processes data, which lies within trustworthy AI (TAI). Numerous frameworks have been suggested to direct the advancement of TAI, with the European Commission’s High-Level Expert Group on

Artificial Intelligence being one of the most notable entities to have formalized TAI as a theory cantered on seven pillars that encompass diverse aspects of AI ethics and durability.

V. CONCLUSIONS

As the age of 6G begins, the amalgamation of innovative communication paradigms and nascent innovations is swiftly revolutionizing wireless communications, with machine learning and artificial intelligence proving to be pivotal in tackling intricate difficulties. Although DAI prevails in the AI-driven wireless scientific domain, the potential of GenAI to augment and enhance DAI methodologies is becoming increasingly apparent, particularly in contexts characterized by insufficient or partial data. This study offered insights into the principles of 6G and explored the critical function of GMs in diverse areas of wireless research. Moreover, by identifying potential problems and proposing effective techniques, we argue that our research offers scholars and industry professionals valuable insights, thereby positioning itself as a guide resource in this rapidly developing field.

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REFERENCES

[1] M. Agiwal, A. Roy, and N. Saxena, "Next Generation 5G Wireless Networks: A Comprehensive Survey," IEEE Communications Surveys & Tutorials, vol. 18, no. 3, pp. 1617–1655, 2016, doi: 10.1109/COMST.2016.2532458.

[2] C.-X. Wang et al., "On the Road to 6G: Visions, Requirements, Key Technologies, and Testbeds," IEEE Communications Surveys & Tutorials, vol. 25, no. 2, pp. 905–974, 2023, doi: 10.1109/COMST.2023.3249835.

[3] X. Luo, H.-H. Chen, and Q. Guo, "Semantic Communications: Overview, Open Issues, and Future Research Directions," IEEE Wirel Commun, vol. 29, no. 1, pp. 210–219, 2022, doi: 10.1109/MWC.101.2100269.

[4] I. J. Goodfellow et al., "Generative Adversarial Nets," 2014. [Online]. Available: http://www.github.com/goodfeli/adversarial

[5] Y. Yang, Y. Li, W. Zhang, F. Qin, P. Zhu, and C.-X. Wang, "Generative-Adversarial-Network-Based Wireless Channel Modeling: Challenges and Opportunities," IEEE Communications Magazine, vol. 57, no. 3, pp. 22–27, 2019, doi: 10.1109/MCOM.2019.1800635.

[6] Y. Liu et al., "Deep Generative Model and Its Applications in Efficient Wireless Network Management: A Tutorial and Case Study," IEEE Wirel Commun, vol. 31, no. 4, pp. 199–207, 2024, doi: 10.1109/MWC.009.2300165.

[7] S. De, M. Bermudez-Edo, H. Xu, and Z. Cai, "Deep Generative Models in the Industrial Internet of Things: A Survey," IEEE Trans Industr Inform, vol. 18, no. 9, pp. 5728–5737, 2022, doi: 10.1109/TII.2022.3155656.

[8] Z. Cai, Z. Xiong, H. Xu, P. Wang, W. Li, and Y. Pan, "Generative Adversarial Networks: A Survey Toward Private and Secure Applications," Jul. 31, 2022, Association for Computing Machinery. doi: 10.1145/3459992.

[9] E. Ayanoglu, K. Davaslioglu, and Y. E. Sagduyu, "Machine Learning in NextG Networks via Generative Adversarial Networks," IEEE Trans Cogn Commun Netw, vol. 8, no. 2, pp. 480–501, 2022, doi: 10.1109/TCCN.2022.3153004.

[10] J. Yang, Y. Zeng, S. Jin, C.-K. Wen, and P. Xu, "Communication and Localization With Extremely Large Lens Antenna Array," IEEE Trans Wirel Commun, vol. 20, no. 5, pp. 3031–3048, 2021, doi: 10.1109/TWC.2020.3046766.

[11] M. Dehghani Soltani, X. Wu, M. Safari, and H. Haas, "Bidirectional User Throughput Maximization Based on Feedback Reduction in LiFi Networks," IEEE Transactions on Communications, vol. 66, no. 7, pp. 3172–3186, Jul. 2018, doi: 10.1109/TCOMM.2018.2809435.

[12] M. D. Soltani, A. A. Purwita, Z. Zeng, H. Haas, and M. Safari, "Modeling the random orientation of mobile devices: Measurement, analysis and LiFi Use Case," IEEE Transactions on Communications, vol. 67, no. 3, pp. 2157–2172, Mar. 2019, doi: 10.1109/TCOMM.2018.2882213.

[13] S. S. Murad, S. Yussof, W. Hashim, and R. Badeel, "Card-Flipping Decision-Making Technique for Handover Skipping and Access Point Assignment: A Novel Approach for Hybrid LiFi Networks," IEEE Access, pp. 1–1, 2024, doi: 10.1109/ACCESS.2024.3473938.

[14] R. Badeel, S. K. Subramaniam, A. Muhammed, and Z. M. Hanapi, "A Multicriteria Decision-Making Framework for Access Point Selection in Hybrid LiFi/WiFi Networks Using Integrated AHP–VIKOR Technique," Sensors, vol. 23, no. 3, p. 1312, 2023, doi: 10.3390/s23031312.

[15] M. A. Arfaoui et al., "Invoking Deep Learning for Joint Estimation of Indoor LiFi User Position and Orientation," IEEE Journal on Selected Areas in Communications, vol. 39, no. 9, pp. 2890–2905, Sep. 2021, doi: 10.1109/JSAC.2021.3064637.

[16] X. Wu, M. D. Soltani, L. Zhou, M. Safari, and H. Haas, "Hybrid LiFi and WiFi Networks: A Survey," Apr. 01, 2021, Institute of Electrical and Electronics Engineers Inc. doi: 10.1109/COMST.2021.3058296.

[17] S. A. Mohammed et al., "Supporting Global Communications of 6G Networks Using AI, Digital Twin, Hybrid and Integrated Networks, and Cloud: Features, Challenges, and Recommendations," Telecom, vol. 6, no. 2, p. 35, May 2025, doi: 10.3390/telecom6020035.

[18] S. S. Murad, S. Yussof, B. A. M. Oraibi, R. Badeel, B. Badeel, and A. H. Alamoodi, "A Vehicle Social Distancing Management System Based on LiFi During COVID Pandemic: Real-time Monitoring for Smart Buildings," IEEE Access, 2024, doi: 10.1109/ACCESS.2024.3461359.

[19] K. B. Letaief, Y. Shi, J. Lu, and J. Lu, "Edge Artificial Intelligence for 6G: Vision, Enabling Technologies, and Applications," IEEE Journal on Selected Areas in Communications, vol. 40, no. 1, pp. 5–36, 2022, doi: 10.1109/JSAC.2021.3126076.

[20] A. Ali et al., "Blockchain-Powered Healthcare Systems: Enhancing Scalability and Security with Hybrid Deep Learning," Sensors, vol. 23, no. 18, Sep. 2023, doi: 10.3390/s23187740.

[21] M. Giordani, M. Polese, A. Roy, D. Castor, and M. Zorzi, "A Tutorial on Beam Management for 3GPP NR at mmWave Frequencies," IEEE Communications Surveys & Tutorials, vol. 21, no. 1, pp. 173–196, 2019, doi: 10.1109/COMST.2018.2869411.

[22] Z. Du, Y. Deng, W. Guo, A. Nallanathan, and Q. Wu, "Green Deep Reinforcement Learning for Radio Resource Management: Architecture, Algorithm Compression, and Challenges," IEEE Vehicular Technology Magazine, vol. 16, no. 1, pp. 29–39, 2021, doi: 10.1109/MVT.2020.3015184.

[23] A. K. Kamboj, P. Jindal, and P. Verma, "Machine learning-based physical layer security: techniques, open challenges, and applications," Wireless Networks, vol. 27, no. 8, pp. 5351–5383, 2021, doi: 10.1007/s11276-021-02781-1.

[24] S. Sonmez, I. Shayea, S. A. Khan, and A. Alhammadi, "Handover Management for Next-Generation Wireless Networks: A Brief Overview," in 2020 IEEE Microwave Theory and Techniques in Wireless Communications (MTTW), IEEE, 2020, pp. 35–40. doi: 10.1109/MTTW51045.2020.9245065.

[25] W. Jiang, "Cellular traffic prediction with machine learning: A survey," Expert Syst Appl, vol. 201, Sep. 2022, doi: 10.1016/j.eswa.2022.117163.

[26] Y. Xu, W. Xu, Z. Wang, J. Lin, and S. Cui, "Load Balancing for Ultradense Networks: A Deep Reinforcement Learning-Based Approach," IEEE Internet Things J, vol. 6, no. 6, pp. 9399–9412, Dec. 2019, doi: 10.1109/JIOT.2019.2935010.

[27] Y. Hua, R. Li, Z. Zhao, X. Chen, and H. Zhang, "GAN-Powered Deep Distributional Reinforcement Learning for Resource Management in Network Slicing," IEEE Journal on Selected Areas in Communications,

vol. 38, no. 2, pp. 334–349, Feb. 2020, doi: 10.1109/JSAC.2019.2959185.

[28] R. L. Z. Z. H. Z. and X. C. Yuxiu Hua, 2019 IEEE Global Communications Conference (GLOBECOM). IEEE, 2019.

[29] J. Z. Ruichun Gu, Ganslicing: A gan-based software defined mobile network slicing scheme for iot applications. IEEE, 2019.

[30] M. R. Shahid, G. Blanc, H. Jmila, Z. Zhang, and H. Debar, "Generative Deep Learning for Internet of Things Network Traffic Generation," in Proceedings of IEEE Pacific Rim International Symposium on Dependable Computing, PRDC, IEEE Computer Society, Dec. 2020, pp. 70–79. doi: 10.1109/PRDC50213.2020.00018.

[31] J. Z. H. K. W. B. M. E. Ahmed B.Zaky, "Generative Neural Network Based Spectrum Sharing Using Linear Sum Assignment Problems," 2019.

[32] T. Zhang, K. Zhu, and D. Niyato, "A Generative Adversarial Learning-Based Approach for Cell Outage Detection in Self-Organizing Cellular Networks," IEEE Wireless Communications Letters, vol. 9, no. 2, pp. 171–174, Feb. 2020, doi: 10.1109/LWC.2019.2947041.

[33] H. W. M. Z. Zhuo Li, "Weakly-Supervised Generative Adversarial Nets with Auxiliary Information for Wireless Coverage Estimation," Proceedings of the 27th ACM International Conference on Information and Knowledge Management , pp. 1851–1854, 2018.

[34] T. Maksymyuk, J. Gazda, A. Luntovskyy, and M. Klymash, "Artificial Intelligence based 5G Coverage Design and optimization using Deep Generative Adversarial Neural Networks," in 2018 International Conference on Information and Telecommunication Technologies and Radio Electronics (UkrMiCo), IEEE, 2018, pp. 1–4. doi: 10.1109/UkrMiCo43733.2018.9047611.

[35] A. Ahmadi, O. Semiari, M. Bennis, and M. Debbah, "Variational Autoencoders for Reliability Optimization in Multi-Access Edge Computing Networks," in 2022 IEEE Wireless Communications and Networking Conference (WCNC), IEEE, Apr. 2022, pp. 752–757. doi: 10.1109/WCNC51071.2022.9771710.

[36] J. Chen, H. Zheng, H. Xiong, S. Shen, and M. Su, "MAG-GAN: Massive attack generator via GAN," Inf Sci (N Y), vol. 536, pp. 67–90, Oct. 2020, doi: 10.1016/j.ins.2020.04.019.

Context-Aware Requirements Prioritization Using Integrated Regression Learning with Ordinal Neural Modeling and Roberta

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***Abstract*—Effective prioritization of software requirements is essential for reducing project risks, optimizing resource allocation, and ensuring timely delivery. Conventional approaches such as Analytic Hierarchy Process (AHP) and MoSCoW often suffer from subjectivity, inefficiency, and poor scalability, making them unsuitable for large-scale projects. Although machine learning (ML) based methods improve scalability, they frequently overlook critical contextual factors such as risk, urgency, implementation effort, and inter-requirement dependencies. To address this gap, this study proposes a new machine learning based context aware software requirements prioritization system. In the proposed system, a pre-trained RoBERTa model and an ordinal neural regression model are employed to infer contextual features including technical risk, complexity, urgency, business value, implementation effort, requirement stability, stakeholder criticality, security sensitivity, and inter-requirement dependencies directly from requirement statements. These inferred features are then used as inputs to a supervised multiple regression model (XGBoost), which generates continuous priority scores for each requirement, with higher scores reflecting higher implementation priority. To ensure transparency, SHAP-based feature attribution is applied for feature importance analysis, and a feedback integration mechanism allows stakeholders to iteratively refine prioritization outcomes, thus in-turn retraining the core prioritization model. Empirical validation against three domain experts across five projects from different application domains demonstrates strong alignment, with Spearman rank correlations between 0.6 and 0.75, Mean Absolute Error (MAE) around 0.10, and Top 5 Match Rates up to 0.80. The results confirm that the proposed system provides a scalable, explainable, and context aware requirements prioritization mechanism suitable for real-world software engineering projects.**

***Keywords*—Requirements prioritization; context-aware prioritization; machine learning; natural language processing; ordinal regression; dependency analysis; Explainable AI**

I. Introduction

Contemporary software projects exhibit increasing complexity as application priorities shift during development and as requirements interact through technical and organizational dependencies [1]. In such environments, the ordering of requirements functions as a determinant of system risk, resource contention, and delivery reliability; inappropriate ordering propagates bottlenecks, extends schedules, and can precipitate project failure. Practice often adopts structured techniques such as Analytic Hierarchy Process, MoSCoW, and case-based ranking to introduce discipline into decision making; however, these techniques depend heavily on judgments elicited from experts at specific points in time and require substantial manual effort, which constrains reproducibility and scalability when the requirement set is large or volatile [1]. Related work on interactive optimization for the Next Release Problem also shows how optimization and learning can be combined for release planning [2]. A further limitation is the absence of a formal representation of project specific context. Urgency, failure risk, technical constraints, and operational dependencies are frequently handled implicitly or retrospectively, producing priority lists that appear consistent during elicitation yet diverge from the evolving state of the project [3]. Structured prioritization has also been reviewed at the use-case level, extending the evidence base beyond requirements lists [4]. Recent systematic literature reviews (SLRs) consolidate more than one hundred and forty requirements prioritization techniques from 2000 to 2021, highlighting that both traditional approaches (AHP, MoSCoW, numerical assignment) and modern AI-based methods (fuzzy logic, genetic algorithms, machine learning) still face persistent challenges in scalability, stakeholder coordination, dependency handling, and automation [3][5][6][32]. Thus, there is an evident need for development of scalable, empirically validated ML models that support can real-world prioritization workflows.

Within such contexts, machine learning models for requirements prioritization offer a scalable and objective alternative by analyzing historical data together with project specific contextual information to automate prioritization [7] [30]. This approach reduces continuous reliance on expert intervention, thereby lowering subjectivity and improving the consistency of decisions. In practice, machine learning methods have been shown to increase efficiency while decreasing manual effort in prioritization tasks [7][8][9]. Recent machine learning surveys on requirements prioritization identify scalable, data-driven approaches including case-based ranking, classification-based methods, clustering algorithms (k-means, Fuzzy C-Means), and semi-automated frameworks such as SRP Tackle, which demonstrate strong performance on large-scale requirement sets while reducing expert elicitation burden [9][10]. Additionally, several works now incorporate semi-automated and interactive mechanisms where stakeholders provide feedback to refine prioritization outcomes, partially

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addressing human-in-the-loop and iterative refinement challenges [2][9][10] [11] [31].

Although machine learning approaches improve scalability and objectivity relative to manual methods, a persistent gap is their limited treatment of context [5]. Automated models frequently omit the intent and contextual cues embedded in requirements statements. When project-specific factors such as urgency, risk, complexity, resource needs and availability, and dependencies are not represented, the resulting priority order may diverge from project goals and constraints. For example, selecting a low-risk item with no dependencies ahead of a high risk, mission critical item can increase cost and delay delivery. In such cases, the prioritization output no longer serves the project's objectives and weakens the value of the process. At the same time, several recent strands of research address parts of this gap: 1) Natural language processing (NLP) in requirements engineering uses deep language models and dependency parsing to extract requirement attributes, risk indicators, and structural properties directly from textual requirements, enabling more precise feature engineering [12] [13] [14]; 2) Dependency-aware prioritization techniques such as DRank and CDBR explicitly model and exploit requirement dependency graphs, using graph-based ranking, execute-before-after relationships, and collaborative filtering to propagate priority signals across dependent items [9][11][15][16]. 3) Recent machine learning surveys document growing adoption of supervised classification, clustering, ranking algorithms, and swarm optimization approaches that incorporate dependencies, though often in isolation and not jointly optimized [5][9] and 4) Explainability and interpretability methods are increasingly discussed as essential for understanding and validating AI-based prioritization decisions, though their application to requirements prioritization pipelines remains limited [5][9][17]. However, these approaches typically address specific factors or mechanisms (e.g., dependency graphs alone, or NLP for classification only) and often require substantial elicitation effort, manual configuration, or separate treatment of contextual signals, leaving room for more integrated, end-to-end frameworks that jointly infer multiple contextual features from requirement text, model dependencies explicitly, and provide explainability through a unified prioritization pipeline.

This study addresses these limitations through the following objectives:

- Design and implement a context aware machine learning model that prioritizes software requirements from their descriptions and contextual features, including risk, urgency, and dependencies. In contrast to prior dependency-aware approaches (such as DRank and CDBR) that focus primarily on explicit dependency matrices or pairwise comparisons, and to NLP studies that target isolated feature extraction or classification [9][11][12][15], the proposed model infers a broader integrated set of contextual variables including technical risk, complexity, urgency, implementation effort, stability, stakeholder criticality, security sensitivity, and inter-requirement dependencies directly from requirement text and combines them within a unified regression framework.
- Apply natural language processing techniques, using RoBERTa for risk estimation and dependency analysis, and an ordinal neural regression model for other contextual features such as complexity, urgency, implementation effort, stability, stakeholder criticality, security sensitivity, and business value [12][18]. This design builds on recent advances in using deep NLP models and interpretable machine learning for requirements classification, attribute extraction, and dependency identification [12][13][14][19][20], while extending them beyond isolated classification tasks to multi-feature context inference optimized specifically for downstream prioritization.
- Use a supervised multiple regression model (XGBoost) to generate continuous priority scores. Regression-based integration of contextual features aligns with recent automated prioritization frameworks and machine learning surveys that recommend ensemble methods for requirements ranking [9][21]; however, in this work the regressor operates over features that are explicitly inferred from requirement text via NLP and evaluated for importance through explainability analysis, rather than relying solely on manually annotated attributes or any ad-hoc feature engineering process.
- Establish a mechanism to collect and integrate stakeholder feedback, including revised priority scores and contextual feature values, to update the training data and improve model adaptability and accuracy over time. This feedback-driven retraining mechanism is consistent with semi-automated and human-in-the-loop prioritization techniques reported in recent literature [9][10] and aligns with the push toward interactive ML in requirements engineering; however, this work uniquely applies the feedback loop to an explicitly context-aware, explainability-informed feature space shaped by SHAP-based feature selection during design time, enabling both transparency and iterative refinement.

This study contributes the following to requirements engineering:

- Context aware framework: A scalable and automated requirements prioritization system that integrates machine learning and natural language processing to infer contextual features from requirement statements, providing a foundation for informed and efficient prioritization [21]. Semi-automated techniques reported in prior work also motivate the integration of human feedback into prioritization pipelines [10]. By jointly modeling textual features, inferred contextual signals (risk, complexity, effort, stability, security, stakeholder importance), inferred dependencies, and learned dependencies within a single end-to-end pipeline, the framework addresses research gaps identified in recent SLRs and complements existing context-aware, dependency-aware, and ML-based RP approaches, thereby clarifying the boundary between earlier techniques and this present work [5][6][9][11][15].

- Contextual feature inference: Use of RoBERTa for risk estimation and dependency analysis, together with an ordinal neural regression model for additional contextual features, and integration of these values into a unified prioritization pipeline [19]. Unlike prior NLP-based efforts in requirements engineering that focus mainly on requirement classification, non-functional requirement type detection, or structural complexity assessment [12][13][14], the feature inference layer here is explicitly optimized via supervised learning to feed a downstream prioritization regressor, enabling true end-to-end learning from requirement text to priority scores without intermediate manual steps.
- Regression-based integration: Combination of inferred and annotated contextual features within a supervised multiple regression model (XGBoost) to produce continuous priority scores and improve predictive performance [20] . This extends earlier regression and optimization-based prioritization models by incorporating explainability-informed feature selection (via SHAP) and text-derived dependency signals, which recent surveys indicate have not yet been jointly exploited in existing AI-based and machine learning-based RP studies [5][9][15][21].
- Design time SHAP feature selection: Application of Shapley Additive Explanations once during model design to select influential features for the final training dataset, ensuring consistent training and retraining while excluding SHAP from the runtime pipeline [17]. SHAP and related explainability methods are increasingly used to analyze and interpret complex ML models in various domains [17], and their application to model development (feature selection, model debugging) is well established; however, their use to deliberately shape the feature space of a requirements prioritization pipeline selecting only the most impactful features informed by explanations remains underexplored in the requirements engineering literature, particularly in conjunction with NLP-based contextual feature inference.
- Feedback driven retraining: A mechanism for stakeholders to review and adjust prioritization outputs; the collected feedback updates the training data using the same SHAP selected feature set to improve adaptability and maintain accuracy over time [12]. This human-in-the-loop mechanism complements existing interactive and semi-automated approaches such as SRP Tackle (which uses semi-automation to reduce expert burden), DRank (which resolves conflicts via dependency propagation), CDBR (which integrates stakeholder and developer preferences with dependency-based optimization), and interactive genetic algorithms discussed in recent surveys [9][10][11][15], by embedding explicit human feedback directly into the retraining cycle of a context-aware, explainability-informed model and enabling stakeholders to influence the feature importance profile over time.
- Empirical validation: The system is evaluated with multiple domain experts across diverse projects, showing reduced manual workload and improved alignment of priorities with risk mitigation and resource allocation objectives [16]. The evaluation design aligns with recommendations from recent AI-based and machine learning SLRs on requirements prioritization, which emphasize the importance of empirical assessment across diverse projects, evaluation of scalability with large requirement sets, validation of dependency handling, and measurement of stakeholder satisfaction and usability in realistic industrial settings [5][6][9].

The remainder of the paper is organized as follows. Section II presents the methodology: requirement data preparation, contextual feature inference with RoBERTa and ordinal neural regression, SHAP feature selection, and development of the core regression prioritization model. Section III describes the system design and implementation, including the architecture, integration of contextual feature estimators, dependency analysis, backend services, and the user interface. Section IV reports empirical validation with expert evaluation and performance analysis using mean absolute error, Spearman rank correlation, and Top 5 match rate. Discussion is given in Section V. Section VI concludes with a summary of contributions and directions for future work aimed at improving scalability, adaptability, and applicability in practice.

II. Methodology

This study employs a structured methodology with five sequential phases to develop and evaluate a context aware, machine learning based requirements prioritization system. The complete workflow is shown in Fig. 1.

A. Phase 1: Requirement Data Preparation

Requirement statements were collected from publicly available Software Requirements Specification (SRS) documents of multiple open-source projects. The documents were processed to construct a dataset for training and testing the prioritization models. Preprocessing included tokenization, vectorization, lemmatization, removal of special characters, and lowercasing. These steps standardize the text and prepare it for use in the natural language processing and machine learning models employed in subsequent phases of the study [22].

B. Phase 2: Contextual Feature Estimation

Each contextual feature was modeled with a dedicated machine learning pipeline appropriate to its data type and structure. The training data consisted of requirement statements from open-source SRS documents, which were annotated for contextual feature values and binary dependency [16]. The accompanying table summarizes the specification and characteristics of the estimation and inference models. Coupling preferences with dependency information has been shown to improve prioritization quality in semi-automated and dependency aware settings [11] [16] [23]. SHAP (Shapley Additive Explanations) was then applied to a subset of the labeled data to identify the features with the greatest influence on the output of the core prioritization model; a basic random forest regressor was used only for this SHAP analysis step [24]. The most influential features were selected and fixed for training the prioritization model. Finally, all trained inference models, together with configuration files, tokenizers, and vectorizers,

were saved for use by the backend API of the core prioritization system.

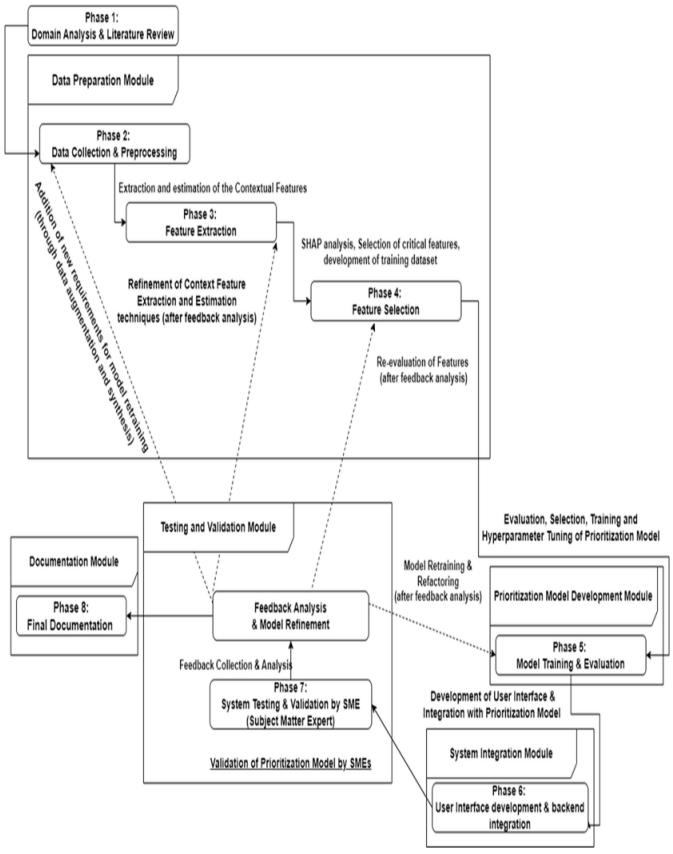


Fig. 1. Methodology workflow diagram.

C. Phase 3: Requirements Prioritization Model

The requirement prioritization pipeline begins by estimating contextual features from requirement statements using the inference models developed in Phase 2. Next, the expert labeled training data are augmented to create the initial training set for the core prioritization model. Augmentation injects small Gaussian noise into sentence embeddings derived from the requirement text, as well as into priority scores and contextual feature values scaled from 0 to 1, while preserving the original dependency labels to maintain structural consistency. A subset of the augmented data is then used to train multiple supervised regression models, including Random Forest, Gradient Boosting Regressor, Support Vector Regressor, and XGBoost Regressor. Model performance is evaluated with fivefold cross validation using Root Mean Squared Error, Mean Bias Error, Mean Absolute Error, Mean Bias Ratio, and the coefficient of determination R2 as metrics. Across these comparisons, the XGBoost Regressor shows the strongest accuracy and generalization [25].

After selecting XGBoost as the core prioritization model, hyperparameter tuning was conducted using two strategies: randomized search cross validation and Bayesian optimization [26]. The search covered learning rate, maximum tree depth, number of estimators, L1 and L2 regularization strengths, and subsampling ratio [29]. In comparison, Bayesian optimization produced lower root mean squared error and higher overall performance while exploring the search space more efficiently [26]. The final XGBoost model, trained on the selected feature set with the best parameters from Bayesian optimization, was exported together with the TF IDF vectorizer. These components were integrated into the backend application programming interface of the prioritization system, which prioritizes new software requirements. The main stakeholder interactions are illustrated within the use case diagram shown within Fig. 2.

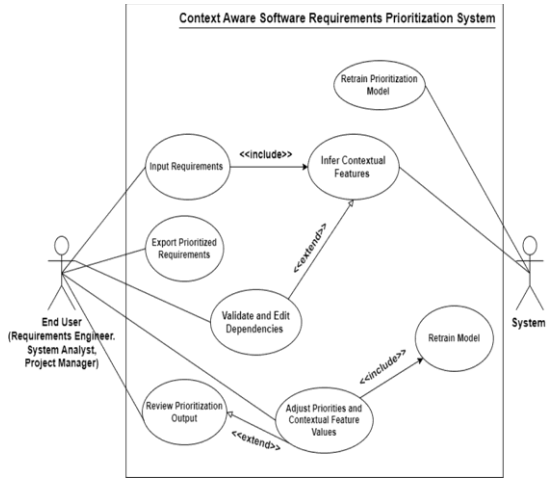


Fig. 2. Use case diagram (core priorization).

D. Phase 4: Model Validation and Interpretability

After tuning and finalizing the core prioritization model, an empirical study is conducted to assess its applicability in real settings. The model's predicted priority scores and ordering are compared with the judgments of three domain experts on a new set of requirement statements and project contexts. Performance is measured using Spearman rank correlation, Top 5 match rate, and mean absolute error. Two evaluation modes are used. In the end-to-end automated mode, the inference models estimate contextual feature values and binary dependencies. In the manual mode, domain experts provide contextual feature and dependency values after reviewing the project contexts. The results provide quantitative evidence of the applicability and effectiveness of the machine learning based prioritization system and address the study objective of reducing subjectivity and improving scalability in requirements prioritization [5][9].

E. Phase 5: System Deployment

The system is deployed with Fast API to provide backend services and programmatic access to the core prioritization models through HTTP endpoints. A user interface enables nontechnical users to submit requirement statements and view the resulting priority scores and ordering.

III. Implementation

A. Data Acquisition and Preparation

The first step is the search and collection of software requirement statements from Software Requirements Specification (SRS) documents associated with open source or declassified projects. To support contextual diversity and generalizability of the machine learning models, SRS documents were drawn from a range of project domains,

including telecommunication, healthcare, finance, and education.

After extracting the requirement statements, a domain expert manually annotated contextual feature values for each statement in the context of its source project. The features included technical implementation risk, complexity, urgency, stability across the project lifecycle, implementation effort, security sensitivity, and stakeholder criticality. Prior work has used NLP to assess structural properties and complexity of requirements, supporting the inclusion of such signals in our feature set [14]. Each feature was rated on a five-point ordinal scale from 1 (lowest) to 5 (highest) with respect to the corresponding SRS. In addition, inter requirement dependencies were annotated within each project using a binary label (dependent or independent) based on structural relationships observed in the SRS. Graph-based representations capture inter-sentence dependencies relevant to inferring such links [27]. These annotations constitute the ground truth for training the contextual feature inference models and the core requirements prioritization model used in this study.

Before training the machine learning models, the requirement text was preprocessed to standardize format by lowercasing, removing special characters, and normalizing whitespace. The semantic content of the statements was preserved without paraphrasing to remain consistent with the expert annotations. Contextual feature values were normalized to the interval [0,1] (for example, 2 maps to 0.4). Requirement statements were then vectorized with the all-mpnet-base-v2 Sentence Transformer, yielding 768 dimensional embeddings that capture the meaning and nuances of each statement.

To address the sparsity of expert labeled training data and to improve the robustness of the contextual feature estimators, the dependency detector, and the core prioritization model, a controlled data augmentation procedure is applied. The procedure injects Gaussian noise into the sentence embeddings and the normalized contextual feature values while leaving the dependency labels unchanged to preserve logical correctness. This emulates minor contextual and semantic variations that arise in practice [28]. Gaussian noise is applied to each input element, including normalized feature values and the 768-dimensional embedding that represents each requirement statement, using the formula given below.

$$x^j = x + \varepsilon,\ \varepsilon \sim N(\mu, \sigma^2) \quad (1)$$

x: Original data point (scalar or vector).

x^j: jth augmented sample generated from x.

ε: Additive Gaussian noise.

μ: Mean of the Gaussian noise (often 0).

σ: Standard deviation of the Gaussian noise; the variance is σ^2.

Here, gaussian noise is sampled from the probability density function given below:

The Gaussian probability density function specifies the distribution of the noise introduced during data augmentation and enables controlled simulation of stochastic fluctuations around a chosen mean. This supports more robust estimation of contextual features and dependencies and improves the generalizability of the core prioritization model. The augmented samples were then combined with the original expert labeled data to form a more comprehensive and balanced training set. Finally, the target variable Priority Score was perturbed with Gaussian noise using a separate standard deviation σ priority and then clipped to the interval [0.5,1.0] to keep augmented labels within realistic scoring ranges.

B. SHAP Analysis for Contextual Feature Evaluation

To examine the effect of contextual features on the output of the core prioritization model, Shapley Additive Explanations (SHAP) are used to decompose each prediction into additive contributions from individual features. SHAP supports global and local interpretation, which allows quantification of feature importance, assessment of average directional effects, and inspection of instance level behavior for each contextual feature [24]. The following subsections present visualizations of the SHAP analysis performed on the initial augmented training data with a basic random forest regressor.

Fig. 2 ranks the features by their mean absolute SHAP value, which reflects overall influence on the model output irrespective of sign. For each feature, the mean of the absolute Shapley values is computed across all test instances, providing an aggregate measure of the extent to which the feature moves predictions away from the base value. Requirements stability shows the highest mean absolute SHAP value (0.035), indicating the strongest contribution to the predicted priority scores. Complexity (0.028) and urgency (0.020) follow, suggesting that anticipated implementation difficulty and time sensitivity also have substantial impact. Implementation effort (0.018) and stakeholder criticality (0.016) form a middle group with moderate effects. Business value, security sensitivity, and technical risk have lower values (0.010 to 0.012), indicating less consistent contributions across the dataset.

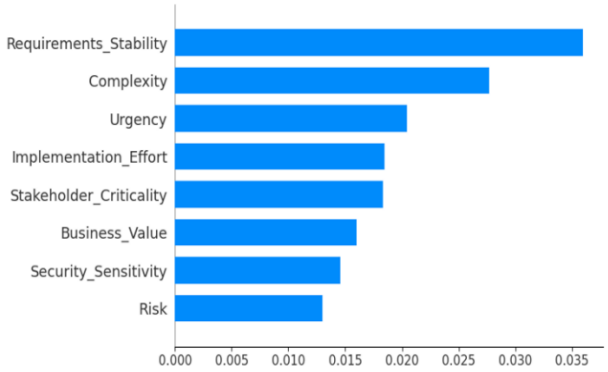


Fig. 3. Outcome of SHAP analysis.

This observation raises the possibility of under representation or collinearity with other features. Whereas the previous figure reports the absolute magnitude of feature importance, the current Fig. 3 presents signed mean SHAP values, which indicate whether a feature increases or decreases the predicted priority on average. The signed mean is obtained by averaging the raw Shapley values, including their signs, across all samples in the training data. In this analysis,

requirements stability shows a small negative mean (approximately −0.0010), indicating that higher stability is associated with lower predicted priority. These average directional effects of each contextual feature on the predicted priority scores are illustrated in Fig. 4.

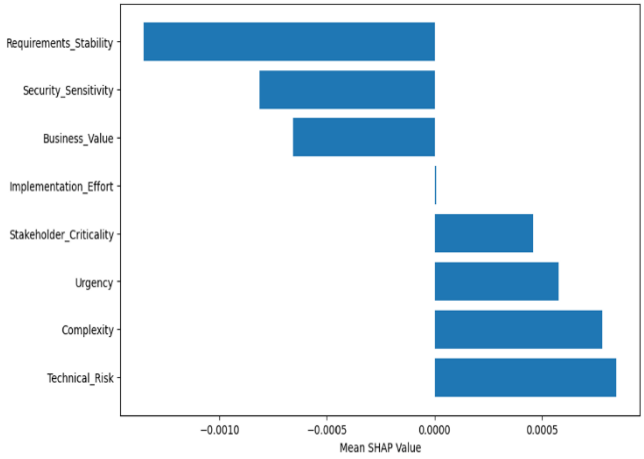


Fig. 4. Average Directional Effects (SHAP analysis).

This pattern is consistent with the local rationale that stable requirements are less urgent and can be deferred without jeopardizing schedules or increasing the risk of implementation failure. Security sensitivity (approximately −0.0007) and business value (approximately −0.0005) also show negative means, suggesting that highly valuable or sensitive items may be deprioritized relative to volatile tasks, possibly reflecting a trade off with complexity or risk. In contrast, technical risk exhibits a positive mean effect (approximately +0.0005), indicating that riskier requirements tend to receive higher priority, which aligns with a mitigation first strategy that addresses components prone to failure early in the lifecycle. Urgency, stakeholder criticality, and complexity show positive average contributions (approximately +0.0004 to +0.0008), reinforcing their influence in increasing the priority score. Taken together, the directional analysis indicates an implicit policy to defer stable, even high value, requirements while advancing urgent, complex, or risky items. Based on the SHAP analysis, requirements stability, complexity, and urgency are retained for their strong mean absolute contributions, and technical risk, implementation effort, and stakeholder criticality are included for their consistent directional effects, which capture risk mitigation, resource demand and allocation, and stakeholder influence in prioritization. This feature subset is expected to preserve predictive accuracy, improve interpretability, and reduce the risk of overfitting.

C. Model Evaluation and Metrics

The dataset refined through augmentation was used to train four machine learning models: Random Forest, Gradient Boosting, XGBoost, and a multilayer perceptron. Model performance was assessed with K fold cross validation using root mean square error (RMSE), mean bias error (MBE), mean absolute error (MAE), mean bias ratio (MBR), and the coefficient of determination R^2. Brief descriptions of these metrics are provided in Table I. The corresponding formulas are presented below.

TABLE I. MODEL EVALUATION METRICS

Model Evaluation Metrics	
Evaluation Metrics	***Description***
Root Mean Square Error	The Root Mean Square Error metric measures the average magnitude of error (net difference) between the actual values (within the training subset of data) and predicted values (actual values predicted by the regression learning models). This approach typically penalizes larger errors (difference in prediction) more than smaller errors due to the squaring operation before averaging. So, lower root means square error signifies better model accuracy as it quantifies comparatively lower prediction error.
Mean Bias Error	The Mean Bias Error actually measures the average difference between the actual and predicted values, which takes a bit different approach than RMSE where more focus is given only on measuring magnitude 78 of prediction error, whereas MBE also takes signs of the absolute difference into consideration. Considering the sign of the difference in predicted and actual values, MBE signifies positive and negative biases in prediction. This approach aids in identifying systemic bias, where positive MBE indicates model is under predicting (model output lower than actual values) and negative MBE indicates the model is over predicting (model output higher than actual values) than the actual values
Mean Absolute Error	The mean absolute error (MAE) is a popular metric for evaluation of regression models, which measures the average magnitude of the prediction error without considering the direction. This approach of evaluating only the net difference in predictive error, makes MAE a more direct and explainable error metric, which neither allows errors to cancel out like MBE.
Mean Bias Ratio	This evaluation metric like the MBE is also focused on evaluation of the bias (over and under prediction) within a model's prediction. However, MBR focuses on determining whether a model systematically over predicts or under predicts outcomes. Similarly, a positive mean bias ratio signifies that the model underestimates values and a negative mean bias ratio signifies that the model overestimates values. So, mean bias ratio closer to zero signifies overall lower or minimal bias in predictions made by model.
R2 (R-squared coefficient of determination)	The R2 is a metric that quantifies how well the regression learning model explains the variability of the actual data (.i.e. How well does the regression model's prediction match the actual data). If the model predicts perfectly, the numerator (sum of squared errors) becomes zero, then . But if the model can't explain variance well, the numerator will be larger making it closer to zero or even negative in some cases

R-squared coefficient of determination

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (2)$$

Mean Bias Ratio

$$MBR = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{\sum_{i=1}^{n} y_i} \quad (3)$$

Mean Absolute Error

$$MAE = \left(\frac{1}{n}\right)\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (4)$$

The evaluation results of the model after K - cross fold validation using the above-mentioned metrics are illustrated within the graphs provided within Fig. 4, 5 and 6 where Fig. 4, Fig. 5 and Fig. 6 refer to average directional effects (SHAP Analysis), Test RMSE, and Test MBE respectively.

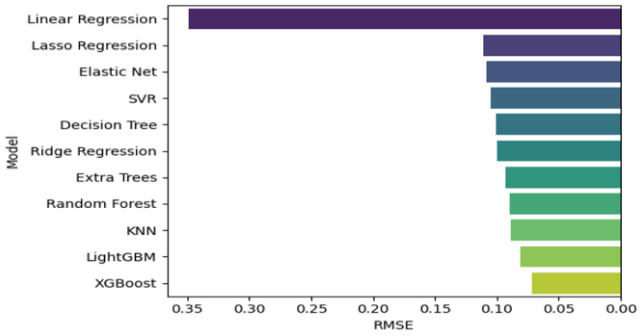


Fig. 5. Test RMSE.

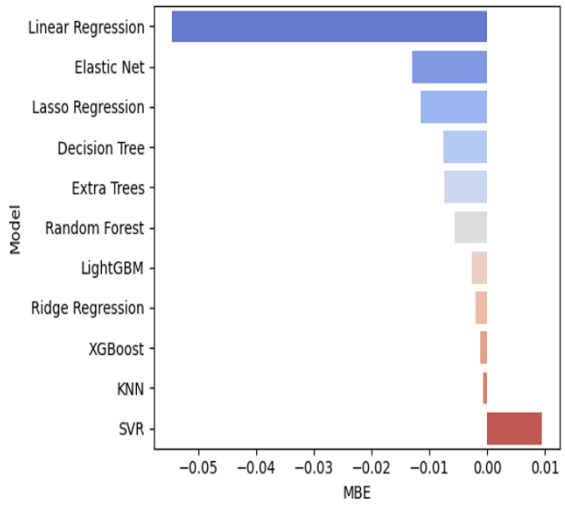


Fig. 6. Test MBE.

Mean Bias Error

$$MBE = \left(\frac{1}{n}\right)\sum_{i=1}^{n}(\hat{y}_i - y_i) \quad (5)$$

Root Mean Square Error

$$RMSE = \sqrt{\left(\frac{1}{n}\right)\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (6)$$

The results show that XGBoost outperformed the other models. It achieved the lowest root mean square error (0.0718), the highest coefficient of determination R^2 (0.7991), and near zero bias (MBE = −0.0011, MBR = −0.0013). Light GBM and k nearest neighbors were the next best models but with slightly lower accuracy and consistency. Linear regression performed poorly, with higher error and a negative R^2, indicating that it did not capture the structure of the data. Plots comparing the models across all metrics corroborate these findings. Test RMSE, cross validation RMSE, R^2, MBE, and MBR were all lowest or closest to ideal for XGBoost, supporting its better generalization, stability, and low bias. The cross-validation RMSE values for the candidate models are reported in Fig. 7 and distribution of test mean bias ratio in Fig. 8.

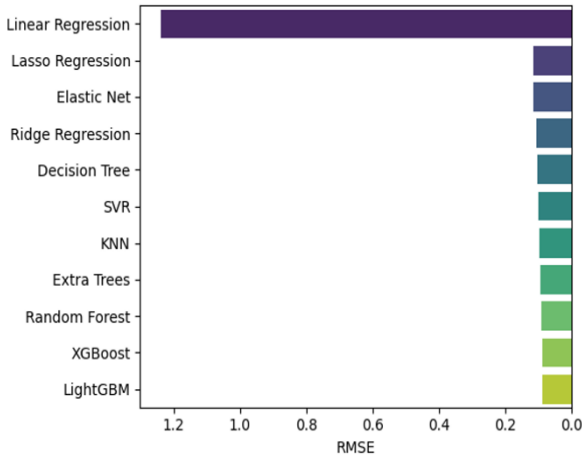


Fig. 7. Cross-Validation RMSE (Train).

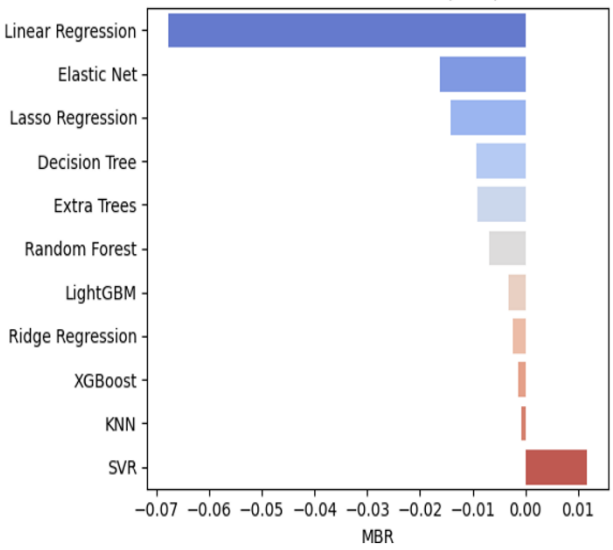


Fig. 8. Test Mean Bias Ratio (MBR).

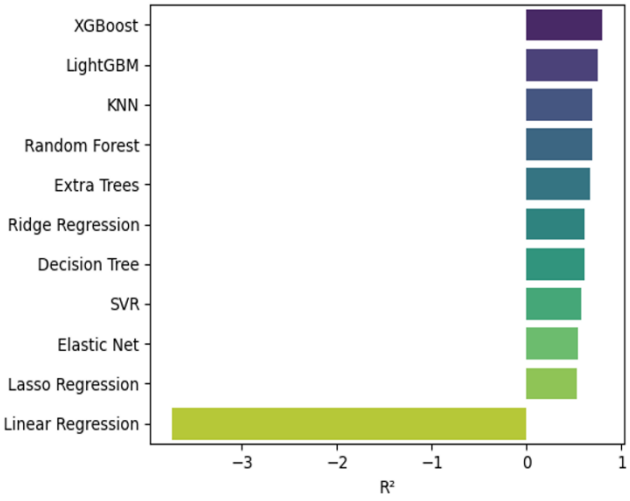


Fig. 9. Coefficient of determination (R2).

Furthermore, the corresponding coefficients of determination for the evaluated models are presented in Fig. 9.

D. Hyperparameter Tuning Process

After selecting XGBoost as the best performing model, we refined it through hyperparameter tuning using two techniques: randomized search cross-validation and Bayesian optimization. Both procedures were implemented and evaluated using the study's core metrics, and the tuned configurations were compared on the same validation protocol. The results of the two hyperparameter tuning approaches for XGBoost are as follows:

TABLE II. HYPERPARAMETER PROCESS

Outcome of Hyperparameter Tunning			
Method	***Best RMSE***	***Best R2***	***Best MBE***
Bayesian Optimization	0.074881	0.781547	0.000841
Randomized Search	0.078633	0.759108	–0.002580

The model tuned with Bayesian optimization produced a lower root mean square error (0.07488 versus 0.07863), a higher coefficient of determination R^2 (0.78155 versus 0.75911), and a mean bias error closer to zero and positive (0.00084 versus −0.00258), indicating lower and more balanced bias. The tuning results are summarized in Table II. These results support Bayesian optimization as the preferred hyperparameter tuning strategy for the XGBoost model used for contextual requirements prioritization. The tuned model was then retrained on the full training set, excluding the portion reserved for evaluation, and both the final model and the TF IDF vectorizer were saved for deployment within the prioritization system.

E. Implementation and Validation of Core Prioritization Model

The system architecture consists of a ReactJS frontend and a Fast API backend. Fast API is used to implement RESTful endpoints with asynchronous request handling and data validation. The endpoints support requirement submission, prioritization, editing of contextual features, dependency analysis, and retrieval of prioritization results. The frontend provides modular components for user interaction and communicates with the backend through HTTP POST and GET requests. The High-Level overview of the prioritization model's architecture is shown in Fig. 10 and details of API endpoints are summarized in Table III.

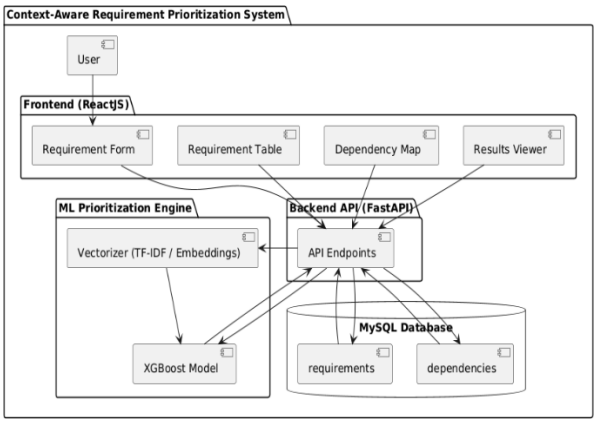


Fig. 10. Prioritization model architecture.

TABLE III. API ENDPOINTS DESCRIPTION

API endpoints description				
Endpoint	***Purpose***	***Method***	***Input***	***Output***
/estimate_risk	Estimate technical risk	Post	Requirement text	Risk level (1–5)
/estimate_dependency	Estimate binary	Post	Requirement pair	0 or 1
/estimate_complexity	dependency	Post	Requirement text	Score (1–5)
/estimate_urgency	Estimate implementation complexity	Post	Requirement text	Score (1–5)
/estimate_stability	Estimate urgency	Post	Requirement text	Score (1–5)
/estimate_effort	Estimate requirement stability	Post	Requirement text	Score (1–5)
/estimate_security	Estimate implementation effort	Post	Requirement text	Score (1–5)
/estimate_criticality	Estimate security sensitivity	Post	Requirement text	Score (1–5)
/prioritize	Predict final requirement priority	Post	Requirement text embeddings, Contextual features and dependency values within JSON format.	Priority score (0–1)

IV. RESULTS

This section reports the results of expert-based validation of the core prioritization model, an XGBoost model optimized with Bayesian optimization. Performance is summarized for five projects from different domains and compared with the judgments of three domain experts. The analysis focuses on alignment between the model and the experts using three metrics: Spearman rank correlation, Top 5 match rate, and mean absolute error.

Fig. 11 summarizes mean absolute error results across projects and experts. Excluding three specified instances, namely Expert 1 in Project 5 with MAE 0.07, Expert 2 in Project 4 with MAE 0.06, and Expert 3 in Project 3 with MAE 0.07, the model maintains low error across the remaining evaluations, with MAE values between 0.06 and 0.11 and an average near 0.10. The agreement is strongest in logistics, where Project 2 shows MAE 0.06 for all experts, and in telecommunications, where Project 1 reports MAE 0.08 for Expert 1, 0.07 for Expert 2, and 0.11 for Expert 3. Minor variations, such as the higher MAE of 0.11 for Expert 3 in Project 1, indicate deviations in some project contexts.

Fig. 12 reports Spearman rank correlation outcomes. Across projects, the model shows consistent ranking agreement, with average Spearman rank correlation between 0.6 and 0.7. The strongest agreement is observed with Expert 2, particularly in

healthcare (Project 5) and logistics (Project 2), where Spearman rank correlation reaches 0.75 and 0.70 respectively.

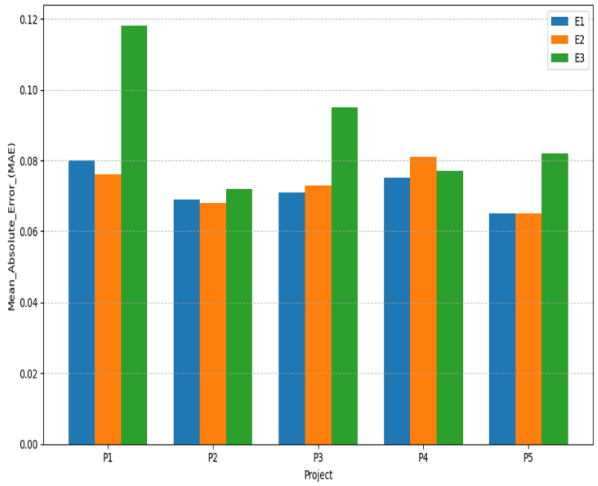


Fig. 11. Mean Absolute Error (MAE) values.

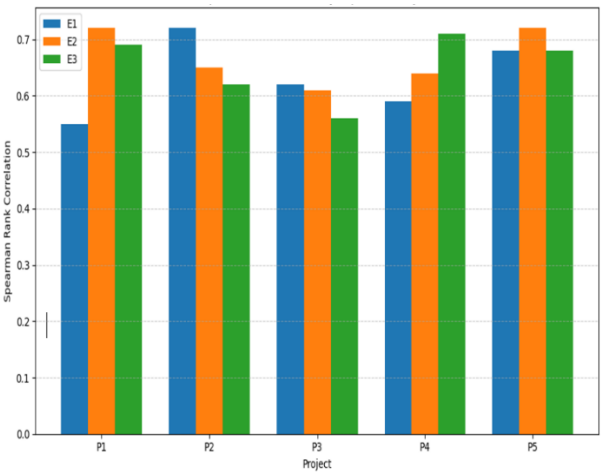


Fig. 12. Spearman rank correlation outcomes.

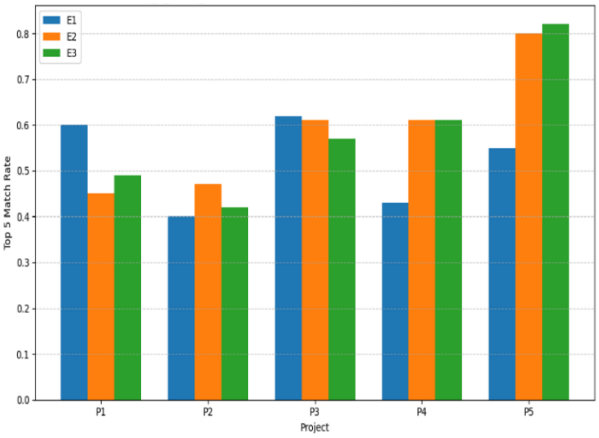


Fig. 13. Top 5 match rate values.

Fig. 13 presents Top 5 match rate values, with average Top 5 match rate between 0.5 and 0.55. In Project 5, the Top 5 match rate attains 0.80 for Expert 2, indicating close agreement on the highest-priority items. In Project 3, Spearman rank correlation is 0.60 for Experts 1 and 2 and the Top 5 match rate is 0.60 for both.

Additional results include Project 4 with Spearman rank correlation 0.60 for Expert 1 and 0.40 for Expert 3, and Top 5 match rates of 0.40 and 0.60 respectively. In Project 4, mean absolute error is 0.07 for Expert 1 and 0.09 for Expert 3. In Project 1, MAE is 0.08 for Expert 1, 0.07 for Expert 2, and 0.11 for Expert 3. In Project 5, MAE is 0.08 for Experts 2 and 3. The absence of measurements for Expert 3 in Project 3 limits a complete assessment for that project.

V. Discussion

The results indicate that the model can align closely with expert judgments in domains where requirements are well defined and evaluation criteria are relatively consistent. The strongest agreement with Expert 2 in healthcare and logistics suggests that the inferred contextual representation supports reliable prioritization in such settings, including for critical non-functional requirements.

Performance varies across domains, particularly in e-commerce (Project 4) and smart city (Project 3), where agreement is weaker for some experts. This variability is consistent with domains that exhibit stronger context dependence and greater divergence in expert preferences, which can reduce rank agreement even when absolute score differences remain small. The missing Expert 3 measurements in Project 3 further limits the interpretation of results for that domain.

This study has several limitations that should be considered when interpreting the findings. First, the datasets were derived primarily from open-source Software Requirements Specification documents, which may not fully represent industrial requirements practices, particularly in regulated or safety critical environments. Second, contextual feature values and dependency labels were annotated by a limited number of domain experts, and expert judgments can vary across projects and domains. This variability may influence both the learned mapping between contextual features and priority scores and the observed agreement metrics. Third, the approach infers contextual features from requirement statements, and the inference quality depends on the clarity and completeness of the textual descriptions. Requirements that are underspecified, ambiguous, or strongly dependent on external project context can reduce inference accuracy and, in turn, affect prioritization performance. Fourth, although cross validation and held out expert evaluation were used, the training data remains limited in scale. Data augmentation improves robustness, but it cannot substitute for broader real-world coverage, and generalization to unseen domains may require additional calibration. Finally, the system evaluates agreement against expert prioritizations rather than measuring downstream project outcomes. Therefore, the reported improvements reflect alignment with expert judgment and do not directly quantify impacts on delivery time, defect reduction, or operational risk.

Overall, the findings support robustness in critical domains while indicating the need for targeted improvements to address inconsistencies in subjective or complex project contexts. In practice, the model can reduce manual effort and provide decision support in resource constrained settings, but it should

be used to assist expert decision making rather than replace expert judgment, particularly in domains with high subjectivity.

A. Comparison with Existing Approaches

Existing machine learning based requirements prioritization techniques report improved scalability and reduced elicitation effort, but often without rich contextual features or explicit dependency handling [5] [9]. Semi-automated models such as SRP Tackle achieve high prioritization accuracy on large requirement sets but focus mainly on multi criteria scoring and clustering, with limited attention to fine grained dependency and risk signals [10]. Dependency aware approaches like DRank and CDBR show that incorporating requirement graphs and execution order improves prioritization quality, yet they typically rely on manually specified dependencies and do not infer contextual attributes directly from requirement text [11][16][23].

Within this landscape, the proposed model attains Spearman rank correlations between 0.6 and 0.75, Top 5 match rates up to 0.80, and mean absolute errors around 0.10 across diverse domains, which is consistent with or better than performance ranges reported for recent ML based RP methods when evaluated against expert judgments [7] [9]. The main added value lies in jointly modeling contextual factors such as stability, urgency, risk, and stakeholder criticality, inferring dependencies from SRS text, and providing SHAP based explanations, which extend prior dependency awareness and semi-automated frameworks while maintaining competitive predictive accuracy [5] [16] [24].

B. Limitations and Threats to Validity

The empirical evaluation is based on requirement statements drawn from publicly available or declassified SRS documents across a limited set of domains, including telecommunications, healthcare, finance, and education. This dataset may not fully represent industrial projects with different documentation styles, regulatory constraints, or safety critical requirements, which restricts the generalizability of the findings to other contexts. In addition, the number of projects and requirements per project is modest compared with large scale industrial portfolios, so scalability to very large backlogs remain to be confirmed empirically.

The expert-based validation involves three domain experts whose judgments reflect individual preferences, experience, and familiarity with specific domains. While multiple experts and projects were used to mitigate individual bias, differences in their rankings, particularly in e-commerce and smart city domains, indicate that part of the observed disagreement arises from variability in human judgments rather than model error alone. The study also focuses on Spearman rank correlation, mean absolute error, and Top 5 match rate as evaluation metrics, which capture ordering and score alignment but do not fully reflect all project level outcomes such as business value realization, downstream defect reduction, or stakeholder satisfaction.

From a modeling perspective, there is a risk of overfitting or tuning bias because the XGBoost model and its hyperparameters were selected based on cross validation performance on an augmented dataset. Although K fold cross validation and data augmentation were used to improve robustness, the same family of metrics guides both model selection and evaluation, which may overestimate performance relative to unseen industrial data. Furthermore, the contextual feature estimators and dependency detectors are trained on annotations produced within this study, so systematic biases or inconsistencies in the labeling process could propagate into the final prioritization outputs.

VI. Conclusion and Future Work

This research developed a context-aware requirements prioritization framework using machine learning, centered on an XGBoost regression model optimized with Bayesian optimization. The system automates and improves prioritization by integrating contextual factors such as technical risk, urgency, complexity, requirement stability, implementation effort, security sensitivity, stakeholder criticality, business value, and inter-requirement dependencies, which are inferred from requirement statements in SRS documents or provided through user input. In doing so, the framework addresses limitations of traditional approaches such as Analytic Hierarchy Process and MoSCoW that are sensitive to subjectivity, scale poorly, and depend heavily on expert availability.

The methodology combines fine-tuned RoBERTa models for risk and dependency estimation with sentence transformer embeddings and Coral Ordinal models for complexity and related features. At design time, a feature selection step is performed using the Shapley Additive Explanations (SHAP) process to retain the most influential contextual variables for consistent training and retraining, thereby enhancing interpretability and transparency. Empirical evaluation across five projects with three domain experts demonstrates consistent alignment between model outputs and expert prioritizations, as reflected by Spearman rank correlation, Top 5 match rate, and low mean absolute error across projects.

In practice, the system supports prioritization in dynamic development settings by enabling iterative refinement through stakeholder feedback and by providing structured prioritization outputs that can assist decision-making. The approach is intended to support expert judgment by producing an initial ordering and exposing the contextual basis of priority scores rather than replacing expert decision-making.

Despite the contributions of this study, the evaluation remains limited to open-source and declassified SRS documents, a modest number of projects, and expert validation in selected domains. Future work will expand the annotated training data with larger industrial case studies to increase stakeholder and domain diversity, refine contextual inference using more advanced natural language processing techniques, and strengthen dependency modeling for complex requirement networks. Additional evaluation criteria will be incorporated to improve external validity and assess downstream project outcomes such as delivery efficiency and risk reduction. Continued attention to interpretability, transparency, and ethical scaling is essential for deployment in sensitive domains such as healthcare and other mission-critical systems. Overall, this research contributes to machine learning-assisted software engineering by providing a practical and scalable foundation for context-aware requirements prioritization and management.

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REFERENCES

[1] M. Sufian, Z. Khan, S. Rehman, and W. Haider Butt, "A Systematic Literature Review: Software Requirements Prioritization Techniques," in 2018 International Conference on Frontiers of Information Technology (FIT), Dec. 2018, pp. 35–40. doi: 10.1109/FIT.2018.00014.

[2] A. A. Araújo, M. Paixao, I. Yeltsin, A. Dantas, and J. Souza, "An Architecture based on interactive optimization and machine learning applied to the next release problem," Autom. Software. Eng., vol. 24, no. 3, pp. 623–671, Sep. 2017, doi: 10.1007/s10515-016-0200-3.

[3] F. A. Bukhsh, Z. A. Bukhsh, and M. Daneva, "A systematic literature review on requirement prioritization techniques and their empirical evaluation," Comput. Stand. Interfaces, vol. 69, p. 103389, Mar. 2020, doi: 10.1016/j.csi.2019.103389.

[4] Y. Odeh and N. Al-Saiyd, "Prioritizing Use Cases: A Systematic Literature Review," Computers, vol. 12, no. 7, p. 136, Jul. 2023, doi: 10.3390/computers12070136.

[5] R. Anwar and M. B. Bashir, "A Systematic Literature Review of AI-Based Software Requirements Prioritization Techniques," IEEE Access, vol. 11, pp. 143815–143860, 2023, doi: 10.1109/ACCESS.2023.3343252.

[6] A. M. Radwan, M. A. Abdel-Fattah, and W. Mohamed, "AI-Driven Prioritization Techniques of Requirements in Agile Methodologies: A Systematic Literature Review," Int. J. Adv. Comput. Sci. Appl., vol. 15, no. 9, 2024, doi: 10.14569/IJACSA.2024.0150983.

[7] A. Fatima, A. Fernandes, D. Egan, and C. Luca, "Software Requirements Prioritisation Using Machine Learning:," in Proceedings of the 15th International Conference on Agents and Artificial Intelligence, Lisbon, Portugal: SCITEPRESS - Science and Technology Publications, 2023, pp. 893–900. doi: 10.5220/0011796900003393.

[8] N. R. Bollumpally, A. C. Evans, S. W. Gleave, A. R. Gromadzki, and G. Learmonth, "A Machine Learning Approach to Workflow Prioritization," in 2019 Systems and Information Engineering Design Symposium (SIEDS), Charlottesville, VA, USA: IEEE, Apr. 2019, pp. 1–5. doi: 10.1109/SIEDS.2019.8735589.

[9] K. I. A. Fadlallah and M. E. Y. Eldow, "Machine Learning: A survey of requirements prioritization: A Review Study," J. Artif. Intell. Comput. Technol., vol. 1, no. 1, Nov. 2024, doi: 10.70274/jaict.2024.1.1.34.

[10] F. Hujainah, R. Binti Abu Bakar, A. B. Nasser, B. Al-haimi, and K. Z. Zamli, "SRPTackle: A semi-automated requirements prioritisation technique for scalable requirements of software system projects," Inf. Softw. Technol., vol. 131, p. 106501, Mar. 2021, doi: 10.1016/j.infsof.2020.106501.

[11] F. Shao, R. Peng, H. Lai, and B. Wang, "DRank: A semi-automated requirements prioritization method based on preferences and dependencies," J. Syst. Softw., vol. 126, pp. 141–156, Apr. 2017, doi: 10.1016/j.jss.2016.09.043.

[12] S.-C. Necula, F. Dumitriu, and V. Greavu-Șerban, "A Systematic Literature Review on Using Natural Language Processing in Software Requirements Engineering," Electronics, vol. 13, no. 11, p. 2055, Jan. 2024, doi: 10.3390/electronics13112055.

[13] F. Dalpiaz, D. Dell'Anna, F. Aydemir, and S. Cevikol, "Requirements Classification with Interpretable Machine Learning and Dependency Parsing," Sep. 2019, pp. 142–152. doi: 10.1109/RE.2019.00025.

[14] A. M. Madni and M. Sievers, "Natural Language Processing To Assess Structure and Complexity of System Requirements," Syst. Eng., vol. 21, no. 3, pp. 172–190, May 2018, doi: 10.1002/sys.21438.

[15] A. Gupta and C. Gupta, "CDBR: A semi-automated collaborative execute-before-after dependency-based requirement prioritization approach," J. King Saud Univ. - Comput. Inf. Sci., vol. 34, no. 2, pp. 421–432, Feb. 2022, doi: 10.1016/j.jksuci.2018.10.004.

[16] F. Noviyanto, R. Razali, and M. Z. A. Nazree, "Understanding requirements dependency in requirements prioritization: a systematic literature review," Int. J. Adv. Intell. Inform., vol. 9, no. 2, pp. 249–272, Jul. 2023, doi: 10.26555/ijain.v9i2.1082.

[17] W. Zhou, Z. Yan, and L. Zhang, "A comparative study of 11 non-linear regression models highlighting autoencoder, DBN, and SVR, enhanced by SHAP importance analysis in soybean branching prediction," Sci. Rep., vol. 14, no. 1, p. 5905, Mar. 2024, doi: 10.1038/s41598-024-55243-x.

[18] G. Y. Quba, H. Al Qaisi, A. Althunibat, and S. AlZu'bi, "Software Requirements Classification using Machine Learning algorithm's," in 2021 International Conference on Information Technology (ICIT), Jul. 2021, pp. 685–690. doi: 10.1109/ICIT52682.2021.9491688.

[19] M. Atas, R. Samer, and A. Felfernig, "Automated Identification of Type-Specific Dependencies between Requirements," in 2018 IEEE/WIC/ACM International Conference on Web Intelligence (WI), Santiago: IEEE, Dec. 2018, pp. 688–695. doi: 10.1109/WI.2018.00-10.

[20] H. Guan, H. Xu, and L. Cai, "Requirement Dependency Extraction Based on Improved Stacking Ensemble Machine Learning," Mathematics, vol. 12, no. 9, p. 1272, Jan. 2024, doi: 10.3390/math12091272.

[21] B. Jamasb, S. R. Khayami, R. Akbari, and R. Taheri, "An Automated Framework for Prioritizing Software Requirements," Electronics, vol. 14, no. 6, p. 1220, Jan. 2025, doi: 10.3390/electronics14061220.

[22] A.-G. Núñez, M. Granda, V. Saquicela, and O. Parra, "Machine Learning-Enhanced Requirements Engineering: A Systematic Literature Review:," in Proceedings of the 19th International Conference on Evaluation of Novel Approaches to Software Engineering, Angers, France: SCITEPRESS - Science and Technology Publications, 2024, pp. 521–528. doi: 10.5220/0012688100003687.

[23] T. Amelia and R. Mohamed, "Reprocolla: Requirements Prioritisation Model with Collaboration Perspectives Based on Cost-Value Approach," J. Inf. Commun. Technol., vol. 23, no. 2, pp. 211–252, Apr. 2024, doi: 10.32890/jict2024.23.2.3.

[24] S. M. Lundberg and S.-I. Lee, "A Unified Approach to Interpreting Model Predictions," in Advances in Neural Information Processing Systems, Curran Associates, Inc., 2017. Accessed: Dec. 22, 2025. [Online]. Available: https://proceedings.neurips.cc/paper/2017/hash/8a20a8621978632d76c43dfd28b67767-Abstract.html

[25] T. Chen and C. Guestrin, "XGBoost: A Scalable Tree Boosting System," in Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, in KDD '16. New York, NY, USA: Association for Computing Machinery, Aug. 2016, pp. 785–794. doi: 10.1145/2939672.2939785.

[26] X. Wang, Y. Jin, S. Schmitt, and M. Olhofer, "Recent Advances in Bayesian Optimization," Nov. 11, 2022, arXiv: arXiv:2206.03301. doi: 10.48550/arXiv.2206.03301.

[27] L. Xu et al., "Zero-Shot Cross-Lingual Machine Reading Comprehension via Inter-sentence Dependency Graph," Mar. 15, 2022, arXiv: arXiv:2112.00503. doi: 10.48550/arXiv.2112.00503.

[28] C. Shorten and T. M. Khoshgoftaar, "A survey on Image Data Augmentation for Deep Learning," J. Big Data, vol. 6, no. 1, p. 60, Jul. 2019, doi: 10.1186/s40537-019-0197-0.

[29] P. Probst, A.-L. Boulesteix, and B. Bischl, "Tunability: Importance of Hyperparameters of Machine Learning Algorithms," J. Mach. Learn. Res. 20 2019 1-32, 2019.

[30] T. Li, X. Zhang, Y. Wang, Q. Zhou, Y. Wang, and F. Dong, "Machine learning for requirements engineering (ML4RE): A systematic literature review complemented by practitioners' voices from Stack Overflow," Inf. Softw. Technol., vol. 172, p. 107477, Aug. 2024, doi: 10.1016/j.infsof.2024.107477.

[31] S. S. Tanveer and Z. A. Rana, "Prioritizing Software Requirements by Combining the Usage Monitoring and User Feedback Data," IEEE Access, vol. 12, pp. 82825–82841, Jan. 2024, doi: 10.1109/access.2024.3409847.

[32] F. Hujainah, R. Bakar, M. Abdulhak, and K. Zamli, "Software Requirements Prioritisation: A Systematic Literature Review on Significance, Stakeholders, Techniques and Challenges," IEEE Access, vol. PP, pp. 1–1, Nov. 2018, doi: 10.1109/ACCESS.2018.2881755.

Functions Inverse Using Neural Networks via Branch-Wise Decomposition and Newton Refinement

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***Abstract*—In this work, a unified framework (using Neural Networks) is proposed to find the inverse of mathematical functions, spanning both simple one-to-one mapping and complex multivalued relations. The approach uses standard multilayer Neural Networks (NN) to approximate the functions' inverse and introduces a deterministic branch-wise decomposition to handle multi-valued inverses. For single-valued (one-to-one) functions, a NN is directly trained on input-output pairs to learn the inverse mapping. For multi-valued functions, the function domain is decomposed into one-to-one branches, and a dedicated NN is trained for each branch. A refinement step using Newton's method is applied to the NN output to further improve inversion accuracy. Across a broad set of benchmark functions, the proposed approach achieved low mean absolute error (MAE) and mean squared error (MSE) in recovering the true inverse, with high round-trip consistency. Newton refinement further reduces inversion error by rapidly converging to higher precision solutions. Notably, even for multi-valued inverse functions, each branch-specific NN can accurately recover the true inverse. Accordingly, standard NN, when combined with branch-wise decomposition and Newton refinement, can serve as an effective universal approximator for the inverse of functions across a spectrum of complexities.**

***Keywords*—Neural networks; function inverse; Newton method; branch-wise decomposition**

I. Introduction

A. Background and Related Works

Finding the inverse function is a fundamental problem in many domains, from control systems and robotics to scientific computing and optimization. Traditional analytical or numerical methods can be challenging to apply when the function is complex or not single-valued. Neural networks offer a powerful alternative, since when they are provided with sufficient training data, they can approximate any well-behaved and invertible continuous function to an arbitrary accuracy [1]. In practice, inversion using NN has been explored in control systems and other fields [2], but significant challenges remain when the inverse mapping is multi-valued [3]. Recent advances in physics-informed neural networks (PINNs) have demonstrated remarkable capability in solving both forward and inverse problems by embedding physical laws directly into the learning process [4], although these approaches primarily address parameter identification rather than multi-valued function inversion.

If the forward function is $y = f(x)$ is not one-to-one, then the inverse relation $x = f^{-1}(y)$ is multi-valued, meaning a single y corresponds to multiple valid solutions (x). For example, both $y = x^2$ and $y = \sin(x)$ have two or more inverse values for a given y. Standard neural regression fails in this setting because training data is not a single-valued mapping: the same input y appears with different target x, leading to contradictory samples [5]. A conventional NN trained on such data will tend to predict the average of the contradictory samples [6]. Previous studies have shown that multi-valuedness can hinder learning [3]. It has been shown in robotics that a standard NN cannot learn a multi-valued kinematics function, necessitating specialized solutions [7]. Recent work using deep learning for inverse kinematics in robotic manipulators has demonstrated both the potential and limitations of various neural architectures in handling such non-unique mappings [8].

Several schemes were explored to cope with multi-valued inverses. Mixture Density Networks (MDNs) model the inverse distribution as a mixture of Gaussian distributions, where each Gaussian component corresponds to a single outcome. MDN minimizes the log-likelihood of the observed data under the predicted mixture model, which allows the model to fit all possible outcomes [9]. While MDNs are powerful, they are complex, hard to train, and less interpretable in practice. They are difficult to train since they need to learn several things at once, such as means, variances, and mixing weights for each Gaussian component. They also need a careful initialization and regularization to avoid both overfitting and underfitting. Recent applications of MDNs in photonic inverse design have shown their effectiveness in handling non-uniqueness, through the challenges of specifying the number of mixture components and joint parameter optimization persist [10]. Transfer learning approaches have been proposed to mitigate some of these training difficulties [11].

The modular neural networks (mixtures of experts) method was explored, where each expert network learns one branch of the inverse mapping, and a gating network decides which expert network to activate for a given input [12], [13]. While such gating architectures can handle multi-valued mappings, they add an extra layer of complexity, as the gating layer must be trained and tuned, and performance can be sensitive to the partitioning of the input space.

Multi-headed neural networks provide another approach, in which a single network outputs several possible inverse candidates (heads) simultaneously [14], [15]. While this approach allows multiple solutions, it still couples all outputs into one model, requiring complex loss functions and additional mechanisms to ensure that each head specializes in a distinct branch. For example, a multiple-choice learning strategy can be employed, wherein for each training example, only the output head closest to the ground truth is updated, forcing other heads

to diverge [16]. This added training complexity is necessary to prevent the heads from collapsing to the output. The work in [15] demonstrated a multi-headed tandem neural network approach for non-uniqueness in inverse design of layered photonic structures, utilizing a self-attention mechanism to constrain and separate multiple outputs.

Beyond these mainstream methods, researchers have explored other techniques for multi-valued inversion. One idea is to provide the network with additional inputs or context to disambiguate the inverse. In study [3], the authors proposed a state-regulated NN that augments a multilayer perceptron with a discrete state variable to indicate different branches of the inverse. This effectively transforms a one-to-many mapping to multiple one-to-one mappings, provided the correct state is supplied during the inference. Some researchers have approached the one-to-many mapping using manifolds or piecewise mappings. In study [17], the researchers present a method that learns locally linear maps on different regions of a data manifold to represent multiple outputs for a given input.

In photonic design, generative models have been leveraged to address the inverse problem of non-unique solutions. For example, conditional generative adversarial networks have been used to generate multiple candidate structures that all produce the same target optical spectrum [18], and conditional variational autoencoders have been applied to learn the distribution of possible inputs that yield a given output [19]. More recently, diffusion models have emerged as a powerful alternative for inverse design problems, demonstrating superior performance in capturing complex distributions and naturally handling one-to-many mappings [20]. In [21], the authors proposed DiffMat, a diffusion model-based framework for energy-absorbing mathematical design that effectively realizes one-to-many mapping from properties to geometries.

Another strategy is to use invertible neural networks (normalizing flows). Invertible networks can be trained simultaneously on forward and inverse mappings, and once trained, can produce a complete distribution of x that correspond to a given y [22]. However, invertible networks and other generative approaches introduce significant complexity and often require substantial training data. They also yield probabilistic rather than deterministic selection of the correct inverse branch in a specific network. In [23], the authors provide a comprehensive review of NN-based regularization methods for inverse problems, highlighting both the theoretical foundations and practical challenges of these approaches.

In contrast, this work adopts a branch-wise deterministic learning approach, where the multi-valued inverse relation is decomposed into distinct single-valued branches, each modeled by a simple neural network. This avoids the probabilistic interpretation and training difficulties of the MDNs, as well as the architectural complexity of mixtures-of-experts and multi-headed models.

B. Deterministic Inverse-Learning Framework

In this work, a simple deterministic framework for learning inverse functions of single-valued and multi-valued cases is proposed through branch-wise decomposition rather than relying on probabilistic modeling.

Unlike probabilistic inverse-learning approaches such as MDNs, invertible neural networks, or generative models, the proposed framework adopts a fully deterministic inverse-learning paradigm. The novelty of this work lies not in introducing a new neural architecture, but in reframing inverse learning as a branch-constrained deterministic problem, where each inverse branch is learned independently and refined using a numerical solver. This formulation ensures branch consistency, avoids output ambiguity, and eliminates the training instability and interoperability limitations commonly associated with probabilistic or multi-head inverse models. Furthermore, the integration of a neural approximator with Newton refinement establishes a hybrid learning-numerical pipeline that combines fast global approximation with high-precision convergence at low inference cost, a capability not explicitly addressed in existing inverse-learning frameworks.

The main contributions of this work are summarized as follows:

- A deterministic inverse-learning framework that reformulates multi-value inverse problems as branch-constrained learning tasks, enabling guaranteed branch consistency and eliminating ambiguity inherent in probabilistic inverse models.
- A hybrid neural-numerical inversion pipeline, where neural networks provide fast global inverse approximations and Newton refinement ensures high-precision convergence with minimal additional computation cost.
- A reusable benchmark and evaluation protocol based on direct inverse error and round-trip consistency, exposing both the strengths and failure modes of purely learning-based or purely numerical inversion strategies.

To clarify the positioning of the proposed framework within the broader landscape of inverse-learning approaches, Table I provides a qualitative comparison with representative methods commonly used for learning inverse mapping. The comparison focuses on key design dimensions that are particularly relevant to practical inverse problems, including the determinism of the output, architectural complexity, training stability, inference cost, and consistency of inverse-branch selection.

The remainder of the paper is organized as follows. In Section II (Methodology), the NN training procedure for inverse functions is formalized, and the branch-wise decomposition and Newton refinement technique are detailed. In Section III (Benchmark Design), the selected test functions and the experimental setup are described. Section IV (Results) presents quantitative outcomes that directly support our claims, demonstrating the successful inversion of the chosen functions, confirming that the branch-wise mechanism effectively solves the multi-valued problem, and showing that Newton's method improves accuracy. A dedicated discussion section (Section V) highlights practical implications and limitations. The paper is concluded in Section VI.

TABLE I. CONCEPTUAL COMPARISON OF REPRESENTATIVE INVERSE-LEARNING APPROACHES

Method	Output Type	Determinism	Training Stability	Inference Cost	Branch-Consistency
MDNs	Probabilistic	No	Low	High	No
Mixture of Experts	Semi-deterministic	No	Medium	Medium	No
Mult-head NNs	Deterministic	No	Low	Medium	No
Invertible NNs	Probabilistic	No	Low	High	No
Proposed Method	Deterministic	Yes	High	Low	Yes

II. METHODOLOGY

This framework considers a forward function $y = f(x)$ where x and $y \in \mathcal{R}$. Our goal is to learn an approximate inverse function ($f^{-1}(y) \approx x$) using a neural network. The focus is restricted to single-output functions, for which the inverse is either single-valued or multi-valued. Each function f in our framework is assumed to be continuous and differentiable, and leverage f and its derivative for data generation and Newton's refinement.

A. Neural Network Architecture

The standard feed-forward multilayer perceptron (MLP) is used as the function approximator to compute the inverse. For each function f, one or more MPLs are configured to take y as input and output an x prediction. A fixed architecture with two hidden nodes, each with 128 neurons, is used. One can use different architectures for different functions to improve performance, but we decided not to do so because our goal is to prove the concept. The tanh activation function is used. For one-to-one functions, a single network is trained on the entire dataset. For many-to-one functions, a separate network is trained for each branch. The loss function is the mean square error between the network's output $\hat{x}$, and the true x. The Adam optimizer is used for training the network.

For many-to-one functions, the function is decomposed into one-to-one branches, and a separate network is trained for each branch. During the prediction, a mechanism is needed to select the appropriate branch. In this work, it is assumed that simple rules can identify branches: for instance, in a real application context, the physical meaning of x indicates which branch to use (e.g., positive vs. negative solution). Alternatively, one could run all branch networks and select the output that satisfies $f(\hat{x}) = y$.

For each benchmark function, a large training dataset is generated by sampling x values from a reasonable range of its domain (covering a range of interest). Then $y = f(x)$ is computed for each sample. These (x, y) pairs are used to train the network with y as input and x as target output. Each network's performance is validated using a test set of (x, y) pairs not seen during training.

It is important to emphasize that the proposed approach does not rely on probabilistic inference, gating networks, or multi-output architectures. Instead, each inverse branch is learned independently using a standard feedforward neural network, resulting in a modular, interpretable, and deployment-friendly design. The deterministic structure simplifies training, avoids mode collapse, and enables predictable inference behavior, which is particularly important in critical and real-time applications.

B. Newton Refinement Procedure

Once the neural network inverse is obtained, one can optionally use the Newton method to refine the solution. The output of the network is considered as the initial guess of the solution (the initial value x_0 of the Newton method. When the network has already achieved high accuracy, Newton updates make minimal adjustments, but when extreme precision is needed, a few iterations can dramatically reduce the error. A limit is set on the number of iterations (one to two iterations). This hybrid approach effectively combines the speed and the generality of neural network learning with the precision of a numerical solver. It is noted that the Newton method requires a good initial guess to converge to the correct root.

Fig. 1 illustrates the workflow of the proposed inverse-learning framework. Given a value y, a deterministic branch-selection step identifies the appropriate inverse branch using prior knowledge, simple rule-based constraints, or a forward-consistency check. The selected branch-specific neural network then provides an initial inverse estimate ($\widehat{x_0}$), which can be further refined using a small number of Newton iterations to improve numerical accuracy. The sequential structure separates branch identification from inverse approximation, ensuring deterministic behavior, interpretability, and efficient inference.

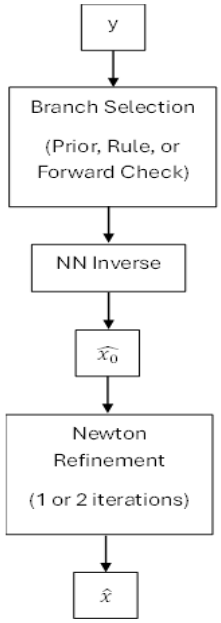


Fig. 1. Overview of the deterministic inverse-learning framework.

III. Benchmark Design

The proposed method is evaluated in a suite of representative functions. Each function is chosen to test specific challenges in inverse learning, such as steep nonlinearities, multiple inverse values, or the absence of a closed-form inverse. The following subsections present the benchmark functions, their characteristics, and the inverse challenges they pose.

A. Benchmark Functions

1) Cubic function ($y = x^3$): This is a strictly increasing and monotonic one-to-one function defined in $\mathbb{R}$. Its inverse is a single-valued, continuous function. Although an analytic inverse exists, this function is used to verify that the MLP can learn a nonlinear invertible function with high accuracy.

2) Quadratic function ($y = x^2$): This function is a two-value inverse defined in $\mathbb{R}$: $x = \pm\sqrt{y}$. The domain of the inverse is restricted to $y \geq 0$. Two branches are created: Branch A for $x \geq 0$ ($x = +\sqrt{y}$) and Branch B for $x \leq 0$ ($x = -\sqrt{y}$). Training data are generated for each branch by sampling x in $[0, X_{max}]$ for Branch A, and $[-X_{max}, 0]$ for Branch B, and then $y = x^2$ is computed. This tests the branch-wise approach on a simple discontinuous inverse.

3) Quartic function ($x = x^4$): This is a two-value inverse defined in $\mathbb{R}$ like the quadratic function. It is defined in $\mathbb{R}$, and the inverse domain is restricted to $y \geq 0$. It has two branches: Branch A for $x \geq 0$ ($x = +\sqrt[4]{y}$) and Branch B for $x \leq 0$ ($x = -\sqrt[4]{y}$). It grows faster than the quadratic functions, and it is flatter near 0, which might impose a tougher learning problem in this region. This function tests the network's ability to learn a steep nonlinear inverse.

4) Exponential function ($y = e^x$): This is a classic one-to-one monotonic and increasing function that grows rapidly, defined in $\mathbb{R}$. The inverse domain is restricted to $y > 0$. Because the function spans many orders of magnitude, Attention is paid to how the network handles small and large y values.

5) Sigmoid function ($y = \frac{1}{1+e^{-x}}$): This is a strictly increasing function from 0 and 1, which expresses a function with a tight range relative to its domain, which is $\mathbb{R}$. It also has a steep slope in the middle. The domain is restricted to $[-L, L]$ since y saturates when x goes to $\pm\infty$ (extremely flat curves).

6) Sine function – principal branch ($y = sin(x)$ for $x \in \left[-\frac{\pi}{2}, \frac{\pi}{2}\right]$): Over the interval $\left[-\frac{\pi}{2}, \frac{\pi}{2}\right]$, $\sin(x)$ is monotonic and covers $[-1, 1]$ one-to-one. This is considered as the principal branch for $sin^{-1}(y)$. This tests learning an inverse for a smooth but non-linear bounded function.

7) Composite function $y = x + e^x$): This function is strictly increasing for all x in $\mathbb{R}$. It is invertible (its closed-form inverse is known as the Lambert W function). However, its inverse does not have a simple elementary function. This function is included to represent a one-to-one function where the inverse is not a simple one (there is no standard closed inverse form that one can use for evaluation). The difficulty in learning is that the function grows exponentially for positive values of x, and almost linear when x is negative.

B. Data Generation and Performance Metrics

For each function, 50,000 random samples are drawn of x for training, 10000 samples of x for validating the model, and 10000 samples of x for testing. The sampling distribution is chosen to cover the domain of interest uniformly in general, while slightly biasing towards challenging regions (e.g., near boundaries, peak or trough values, steep regions, or flat regions). The test sample is chosen from the same domain of interest, ensuring that no test sample appears in the training sample. The y values are computed using the function of interest ($y = f(x)$). Data normalization is done by scaling y and x to zero mean and unit variance.

The mean-absolute error (MAE) and mean-squared error (MSE) between the predicted inverse $\hat{x}$ and true x are reported. Additionally, the report round-trip error ($|\hat{y} - y|$), where $\hat{y} = f(\hat{x})$ is reported. Both the direct and round-trip errors provide valuable insight. The round-trip error becomes more significant for steep curves, where even a slight deviation in x can amplify it. In contrast, the direct error is more relevant for flat curves, where a large deviation in x has a minor effect on the round-trip error. The suffixes _x and _y are used to distinguish between the direct and the round-trip errors, respectively. For each function, the Newton refinement step is done for very few (one to two) iterations, and the errors are reported before and after applying the Newton method.

IV. Results

The benchmark results for all functions are shown in Table II. The following subsections discuss these results by dedicating a subsection to each function.

TABLE II. Benchmark Performance

benchmark	MAE_x	MSE_x	MAE_y	MAE_y + Newton
Cubic	0.022169	0.001525	0.083884	6.21×10^{12}
Quadratic	0.016777	0.000555	0.071686	0.000519
Quartic	0.041733	0.005616	0.126786	0.051399
Exp	0.028440	0.001271	0.040086	0.000371
Sigmoid	0.094882	0.024346	0.000568	0.000024
Sin	0.019173	0.000867	0.007929	0.000025
x + Exp	0.004318	0.000023	0.015278	0.000025

1) Cubic function ($y = x^3, x \in [-3, 3]$): This function is globally monotonic and therefore invertible. The neural network achieved good accuracy ($MAE_x = 0.022$ and $MAE_y = 0.084$), and a good round-trip error ($MAE_y = 0.084$). However, Newton refinement caused catastrophic divergence (error > 1e12) because $f'(x) = 3x^2$ vanishes at $x = 0$. This illustrates that while cubic inverses can be learned accurately, Newton steps must be applied carefully with damping or safeguards to avoid division by near-zero derivatives. This result shows that the scheme correctly handles the inverse of simple monotonic functions.

2) Quadratic function ($y = x^2$ for $x \in [0, 5]$): The results of the square function (principal branch) show that the scheme

handles the inversion of this function with high accuracy ($MAE_x = 0.017$ and $MAE_y = 0.072$). After Newton refinement, the round-trip error dropped sharply ($MAE_y = 0.00052$). The main challenge lies near $x = 0$, where the derivative approaches 0. Nonetheless, the combination of neural approximator and Newton refinement provided highly accurate inverses.

3) Quartic function ($y = x^4$ for $x \in [0, 3]$): The benchmark outcomes of the quartic function (principal branch) demonstrate that the inversion scheme can manage this more challenging polynomial effectively ($MAE_x = 0.042$). Although, the $MAE_y = 0.127$. It is slightly high; one step of the Newton refinement reduced it to 0.051. This result shows that the scheme can handle functions with flat and steep curves.

4) Exponential function ($y = e^x$ for $x \in [-3, 3]$): The neural network achieved good accuracy ($MAE_x = 0.028$ and $MAE_y = 0.04$). After a single Newton step, the round-trip error dropped by two orders of magnitude (to 0.0004) demonstrating near-perfect recovery.

5) Sigmoid function ($y = \frac{1}{1+e^{-x}}$ for $x \in [-8, 8]$): Although the saturation near 0 and 1 makes the learning a bit difficult, the results are extremely good ($MAE_x = 0.094$) and the $MAE_y = 0.0006$) was extremely small. This is expected since the sigmoid curve is mostly a flat curve. Newton refinement nearly eliminated round-trip error discrepancies ($MAE_y = 0.0004$).

6) Sine function – principal branch ($y = sin(x)$ for $x \in \left[-\frac{\pi}{2}, \frac{\pi}{2}\right]$): Baseline performance was good ($MAE_x = 0.019$ and $MAE_y = 0.0079$). Newton refinement significantly reduced the MAE_y to 0.00024. This demonstrates that oscillatory functions can be inverted accurately when restricted to monotonic branches.

7) Composite function $y = x + e^x$, for $x \in [-4, 3]$): The combined linear and exponential function achieved the best results overall. The errors were extremely low ($MAE_x = 0.0043$ and $MAE_y = 0.015$). After the Newton refinement, the MAE_y dropped to 0.0003.

In summary, the MLP model produced low prediction errors across all functions, with MAE_x generally below 0.1. The subsequent round-trip analysis showed that applying Newton's method to refine the predicted results usually reduced the output errors by one or more orders of magnitude. In 7 out of the eight functions, Newton's method converged to a highly accurate solution, yielding a near-zero error. The cubic function was the sole exception, where Newton's method diverged dramatically, which is an expected outcome when the starting point is not close to a real root. Overall, these results demonstrate that the scheme predictions, combined with Newton refinement, can effectively invert a variety of smooth functions with high accuracy.

V. Discussion

The experimental results demonstrate that the proposed framework achieves reliable inverse approximation across a wide range of nonlinear functions, including monotonic, composite, and multi-valued cases. The branch-wise decomposition effectively resolves the ambiguity inherent in multi-valued inverses, while the Newton refinement step significantly improves precision with minimal computational overhead.

A key observation is that purely numerical solvers such as Newton's method are highly sensitive to initialization, whereas purely learning-based approaches may suffer from limited precision. The hybrid neural-numerical formulation bridges this gap by combining global approximation capability with local convergence guarantees. The cubic function example further highlights the importance of derivative behavior and motivates the use of safeguarded or damped Newton variants in future extensions.

Beyond synthetic benchmarks, the deterministic and modular nature of the proposed framework makes it well-suited for real-world inverse problems in control systems, robotics, and engineering design, where interpretability, predictability, and low inference cost are often more critical than probabilistic diversity.

The proposed framework is currently demonstrated on one-dimensional inverse functions, where branch decomposition can be explicitly defined. While this setting allows precise analysis and benchmarking, extending the approach to higher-dimensional inverse problems introduces challenges related to branch identification, scalability, and Jacobian conditioning. Additionally, the Newton refinement step relies on derivative information and may require safeguarding in regions where derivatives approach zero. These limitations motivate future research on automated branch discovery, damped refinement strategies, and multi-dimensional inverse learning.

VI. Conclusion and Future Work

This work presents a unified framework for learning inverse functions using neural networks, demonstrating that even a simple multilayer perceptron (MLP) can accurately approximate inverse mappings for a single-valued function. For multi-valued cases, the study introduces a branch-wise decomposition method by splitting the inverse relationship into single-valued branches, each modeled by a separate network. This avoids the ambiguity of one-to-many mappings and ensures deterministic outputs. Experiments across a range of benchmark functions showed that each branch network effectively learns its part of the inverse, and the combined branch networks reconstruct the full inverse relationship.

To enhance the precision, the approach integrates Newton's method as a post-processing step, refining the neural network's estimates to achieve near-exact inversion. This hybrid approach merges the speed and the flexibility of neural approximations with the rigor of analytical refinement, making it useful for a wide range of engineering applications.

In conclusion, this work introduces a deterministic and interpretable framework for inverse function learning that combines neural approximation with numerical refinement. By explicitly decomposing multi-values inverses into single-valued branches and integrating Newton's method as a refinement step, the proposed approach achieves accurate, stable, and computationally efficient inversion. The framework addresses practical limitations of existing probabilistic and multi-head

inverse-learning methods, particularly in terms of determinism, deployment simplicity, and precision. These properties make the approach especially relevant for critical, real-time, and resource-constrained applications, while also providing a foundation for future extensions to higher-dimensional inverse problems.

REFERENCES

[1] K. Hornik, M. Stinchcombe, and H. White, "Multilayer feedforward networks are universal approximators," Neural Networks, vol. 2, no. 5, pp. 359–366, 1989.

[2] K. S. Narendra and K. Parthasarathy, "Identification and control of dynamical systems using neural networks," IEEE Transactions on Neural Networks, vol. 1, no. 1, pp. 4–27, 1990.

[3] J.-M. Wu, C.-C. Wu, J.-C. Chen, and Y.-L. Lin, "Set-valued functional neural mapping and inverse system approximation," Neurocomputing, vol. 173, pp. 1276–1287, 2016.

[4] M. Raissi, P. Perdikaris, and G. E. Karniadakis, "Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations," Journal of Computational Physics, vol. 378, pp. 686–707, 2019.

[5] Y. Tomikawa, H. Akiyama, and K. Nakayama, "Layered neural network with a feedback to realize a many-valued function," IEICE Technical Report (Neural Computing), NC95-167, 1996.

[6] D. J. MacKay, "Bayesian interpolation," Neural Computation, vol. 4, no. 3, pp. 415–447, 1992.

[7] E. Oyama, A. Agah, K. F. MacDorman, T. Maeda, and S. Tachi, "A modular neural network architecture for inverse kinematics model learning," Neurocomputing, vol. 38–40, pp. 797–805, 2001.

[8] D. Cagigas-Muñiz, "Artificial Neural Networks for inverse kinematics problem in articulated robots," Engineering Applications of Artificial Intelligence, vol. 126, p. 107175, 2023.

[9] C. M. Bishop, "Mixture density networks," Aston University, 1994.

[10] R. Unni, K. Yao, and Y. Zheng, "Deep convolutional mixture density network for inverse design of layered photonic structures," ACS Photonics, vol. 7, no. 10, pp. 2703–2712, 2020.

[11] L. Cheng, P. Singh, and F. Ferranti, "Transfer learning-assisted inverse modeling in nanophotonics based on mixture density networks," IEEE Access, vol. 12, pp. 55218–55224, 2024.

[12] M. I. Jordan and R. A. Jacobs, "Hierarchical mixtures of experts and the EM algorithm," Neural Computation, vol. 6, pp. 181–214, 1994.

[13] R. A. Jacobs, M. I. Jordan, S. J. Nowlan, and G. E. Hinton, "Adaptive mixtures of local experts," Neural computation, vol. 3, no. 1, pp. 79–87, 1991.

[14] C. Rupprecht et al., "Learning in an uncertain world: representing ambiguity through multiple hypotheses," in Proceedings of the IEEE International Conference on Computer Vision (ICCV), 2017, pp. 3611–3620.

[15] X. Yuan, S. Wang, L. Gu, S. Xie, Q. Ma, and J. Guo, "Multi-headed tandem neural network approach for non-uniqueness in inverse design of layered photonic structures," Optics & Laser Technology, vol. 176, p. 110972, 2024.

[16] A. Guzmán-Rivera, D. Batra, and P. Kohli, "Multiple choice learning: learning to produce multiple structured outputs," in Advances in Neural Information Processing Systems (NIPS) 25, 2012, pp. 1808–1816.

[17] D.-K. Oh, S.-H. Oh, and S.-Y. Lee, "Learning one-to-many mapping with locally linear maps based on manifold structure," IEEE Signal Processing Letters, vol. 18, no. 9, pp. 521–524, 2011.

[18] P. Dai and others, "Inverse design of structural color: finding multiple solutions via conditional generative adversarial networks," Nanophotonics, vol. 11, no. 13, pp. 3057–3069, 2022.

[19] T. Rahman and others, "Leveraging generative neural networks for accurate, diverse, and robust nanoparticle design," Nanoscale Advances, vol. 7, no. 2, pp. 634–642, 2025.

[20] Y. Mao et al., "Generative adversarial networks and mixture density networks-based inverse modeling for microstructural materials design," Integrating Materials and Manufacturing Innovation, vol. 11, no. 4, pp. 637–647, 2022.

[21] H. Wang, Z. Du, F. Feng, Z. Kang, S. Tang, and X. Guo, "DiffMat: Data-driven inverse design of energy-absorbing metamaterials using diffusion model," Computer Methods in Applied Mechanics and Engineering, vol. 432, p. 117421, 2024.

[22] L. Ardizzone et al., "Analyzing inverse problems with invertible neural networks," arXiv preprint arXiv:1808.04730, 2018.

[23] A. Habring and M. Holler, "Neural-network-based regularization methods for inverse problems in imaging," GAMM-Mitteilungen, vol. 47, no. 4, p. e202470004, 2024.

Hybrid Diagnostic Approaches Integrating Fuzzy Logic and Neural Networks for Parkinson's Disease

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***Abstract*—Parkinson's Disease (PD) is a movement-related and non-motor symptom neurological condition that requires early diagnosis and treatment. Fuzzy Logic and Neural Network Diagnostic hybrids are more accurate and reliable. The diagnostic approaches of PD are not sensitive to early PD, are subjective in assessing symptoms, and lack standardization. Such problems restrict treatment choices, thereby preventing a favorable patient outcome. In the PD Hybrid Diagnostic Approach (PD-HDA), fuzzy logic is utilized to address uncertainties in clinical data, and neural networks are employed to identify complex patterns in multimodal data. The PD-HDA design features structured selection and data fusion, which enhance diagnostic accuracy and constrain method variability. The images of hand tremors, gait analysis, and speech patterns are categorized using a CNN to reveal their complex properties. Fuzzy Logic and CNNs enhance the classification of PD stages and patient responses to symptoms. The PD-HDA model increases accuracy, sensitivity, and specificity during testing. The hybrid methods can be useful for early identification of PD and provide individualized care, leading to improved patient outcomes.**

***Keywords*—Convolutional neural network; disease hybrid diagnostic; Parkinson's disease; fuzzy logic**

I. Introduction

The prevalence of Parkinson's disease (PD) in the world is outraging, and it is striking that there are millions of individuals with this illness [1]. The motor symptoms caused by the disease are accompanied by a variety of non-motor symptoms, including cognitive, sleep, and mental disorders [2]. Early and effective diagnosis can maximize treatment choices and improve the quality of life for patients [3]. Other neurodegenerative diseases are similar to Parkinson's in terms of symptoms, and the biomarker of the condition does not exist at this time. It is difficult to treat the disease during its early stages [4]. Subjective outcomes are possible with conventional methods of diagnosing PD because they rely on the doctor's knowledge [5].

PD can be diagnosed early using scans and movement tests, such as the Unified Parkinson's Disease Rating Scale (UPDRS), although these studies are limited in terms of cost, availability, and sensitivity [6]. It is necessary to have state-of-the-art diagnostic tools capable of unravelling intricate clinical information and multimodal data from large volumes of data [7]. The solutions to these issues may involve hybrid methods of diagnosis that involve neural networks and fuzzy logic [8]. PD symptoms can be highly diverse, and therefore, fuzzy logic is more suitable for the medical data as it minimizes ambiguity and imprecision [9]. Two fields where neural networks excel are classification and prediction [10]. Such networks are also skilled at identifying non-linear and complex patterns in data. It follows that a combination of the two methods yields a more precise and dependable diagnosis [11].

The PD-HDA analyzes gait tests, voice recordings, and images of tremors in the hands based on convolutional neural networks and fuzzy logic [12]. This fusion can be used to respond to changes in symptoms, enhance diagnosis, and provide a comprehensive assessment of patient data [13]. This study helps fill the gaps in diagnosis and personalization, as well as create data-driven care for PD [14]. To diagnose early and monitor disease progression, the unpredictability of neural network pattern recognition and the uncertainty management capabilities of fuzzy logic can be leveraged, enabling adaptation to individual patient characteristics and the detection of subtle symptom changes throughout the disease course [15]. This hybrid approach can be used to discuss accessibility and variability of diagnostics through real-time monitoring recommendations for treatment in personalized and scalable applications across varied clinical settings [16].

In modern-day studies of diagnosing PD, deep learning pipelines are largely favoured over knowledge-based decision models, but there is little convergence on representation learning and uncertainty-aware inference methodologies. CNN-based systems are known to be effective in deriving discriminative patterns from imaging and signal-based modalities; however, the inferences are still not tied to clinical explainability and expert-motivated diagnostic logic. In contrast, fuzzy logic-based systems excel at capturing the vagueness of symptoms and inter-class uncertainty; however, they rely on handcrafted or low-level representations, which limit the diagnostic granularity. Current hybrid systems typically combine shallow neural or sequential post-processing schemes, which have poor interaction between feature abstraction and inference in the presence of uncertainty.

Contribution of this paper:

- Proposes the PD-HDA framework combining Fuzzy Logic and Neural Networks to address uncertainties and improve the accuracy of PD diagnosis.
- Utilizes CNNs to extract intricate patterns from multimodal datasets like voice, gait, and tremor images, enabling precise classification of PD stages.
- Demonstrates significant improvements in diagnostic accuracy, sensitivity, and specificity, ensuring early detection and personalized treatment for PD patients.

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PD-HDA offers a deep hybrid architecture that integrates CNN-based hierarchical feature extraction and fuzzy inference into a single diagnostic workflow. Instead of using shallow network structures, the proposed architecture allows fuzzy reasoning to operate directly on high-level semantic representations learned by deep convolutional layers, extending hybrid diagnostic design into a deep representational regime. The suggested semantic-level fusion technique differs from decision-level or post-classification fusion, as used in PD diagnostic literature.

Deep CNN features are mapped into fuzzy membership spaces before final inference, allowing uncertainty modelling and language reasoning to influence diagnostic findings at an intermediate representational step, rather than post-hoc. PD-HDA's fuzzy inference system only receives hierarchical convolutional feature embeddings, neither statistical nor domain-engineered features. This architecture enables the fuzzy layer to reason across multi-scale spatial and temporal abstractions learnt from data, improving diagnostic discrimination across varied PD symptom profiles. Deep CNN activations are translated into clinically significant fuzzy language variables for explicit interpretability. In contrast to black-box deep learning technologies, rule-based inference transparently aligns model choices with neurologically relevant symptom patterns, thereby improving therapeutic confidence. Designed for early-stage PD analysis, PD-HDA addresses diagnostic variability caused by symptom ambiguity and inter-class overlap. Fuzzy inference enables graded decision limits and uncertainty-aware reasoning, leading to stable categorization across diverse patient presentations without requiring probabilistic thresholds.

Advanced PD diagnosis enhances prediction accuracy, facilitates hybrid data management, and optimizes feature selection using various techniques, including GANFIS, LS-SVR, and fuzzy-neuro hybrid models. Methods using Time-Frequency Fuzzy LSTM provide strong detection rates with little data. These techniques offer effective, scalable, and interpretable solutions for therapeutic objectives in neurodegenerative disease treatment, surpassing more traditional approaches. Recent research on stacking ensemble approaches for Parkinson's Disease diagnosis demonstrated superior performance by combining multiple base learners (XGBoost, Gradient Boosting, Extra Trees, and others) with a meta-learner architecture. The ensemble model achieved 96.18% diagnostic accuracy and 96.27% AUC, outperforming standalone classifiers by reducing diagnostic variability by 12.3%. This demonstrates that integrating multiple complementary algorithms effectively addresses symptom ambiguity and inter-patient variability in PD diagnosis, supporting the clinical value of ensemble-based frameworks for reliable early detection [17].

Deep Belief Network (DBN) and Neuro-Fuzzy approaches for PD diagnosis are suggested here. It handles missing data [18] using K-Nearest Neighbours (K-NN), Principal Component Analysis (PCA), and the Expectation-Maximization (EM) algorithm. Noise reduction is achieved. Unlike past machine learning techniques, the method employs incremental learning for effective online learning from large clinical datasets, thereby enhancing UPDRS prediction accuracy and reducing time complexity.

Least Squares Support Vector Regression (LS-SVR) and fuzzy clustering are suggested to be combined for UPDRS diagnosis in this technique. It addresses multicollinearity in the data [19] via feature selection and Principal Component Analysis (PCA). Using a large medical dataset containing Motor- and Total-UPDRS, the technique is employed to enhance prediction accuracy through several evaluations and comparisons with current approaches.

The proposed technique merges categorical and numeric data without applying any discretization, thereby allowing the Neighbourhood Rough Set-Based Hybrid Model process to present hybrid data [20]. Adjusting the threshold value for neighbourhood approximation, the constant model maximizes performance depending upon the dataset's 20 feature characteristics. Practical and information-preserving data mining efficacy is maintained by applying the proposed methodology. An actual PD dataset is examined to demonstrate outperformance compared to current models working on hybrid datasets, which achieve only 85% accuracy.

GANFIS is a proposed method that integrates an Adaptive Neuro-Fuzzy Inference System (ANFIS) with a Genetic Algorithm (GA) to enhance the diagnosis of neurodegenerative disorders, such as PD and dementia [21]. GANFIS integrates these two methods to analyze uncertain and complicated medical data, improving diagnostic accuracy and performance over neuro-fuzzy systems. Evaluation measures, including accuracy, precision, recall, F-score, and kappa coefficient, showed promise.

FLS and ANN may be used to predict the functional level of neurological movement disorders, such as Huntington's disease. The hybrid model performed well, with excellent validation using a dataset from 20 participants across response phases and functional levels, yielding an R-value of 0.98 and an MSE of 0.08 [22].

By combining supervised learning, unsupervised learning, and feature selection approaches, the proposed approach utilizes a hybrid model to enhance PD diagnosis. It begins with Expectation-Maximization (EM) data clusterings and then proceeds with backward stepwise regression feature selection. Then, using the clustered data, the Type-2 Sugeno fuzzy inference system (T2SFIS) predicts UPDRS scores [23]. Using R-squared and RMSE assessment measures, our approach was evaluated on the Parkinson's telemonitoring dataset, and we attained good prediction accuracy for Motor-UPDRS and Total-UPDRS.

The proposed fuzzy classifier is defined by a three-stage structure: formation of the structure, informative feature selection, and parameter optimization. Applied to publicly accessible handwritten datasets (ParkinsonHW, PaHaW, NewHandPD) for PD diagnosis, it comprises 32 versions that employ various metaheuristic algorithms. Handwriting assignments include writing text, drawing spirals, and meandering [24]. The technique showed better accuracy and interpretability than decision trees and fuzzy genetic systems, indicating promise as a diagnostic tool.

Combining time-frequency and fuzzy characteristics with uni-directional and bi-directional long short-term memory (LSTM) networks for automated PD diagnosis and severity grading, the suggested technique, based on physionet's dataset, involved splitting vertical ground response force signals into 30-second periods and extracting four main characteristics without further preparation [25]. Bayesian optimization modified hidden units and learning rates, among other hyperparameters. Using minimal processed gait data, the model achieved 79.19% detection accuracy and 82.28% grading accuracy, providing an effective and reasonably priced diagnosis.

Utilizing various approaches, including GANFIS, LS-SVR, and fuzzy-neuro hybrid models, advanced PD diagnosis enhances prediction accuracy, facilitates hybrid data management, and optimizes feature selection. Techniques employing Time-Frequency Fuzzy LSTM get reasonable detection rates with little data. These methods outperform more conventional approaches in providing efficient, scalable, and interpretable solutions for therapeutic purposes in the treatment of neurodegenerative diseases.

II. Methodology

Integration of Fuzzy Logic and Neural Networks: The paper introduces a novel PD-HDA framework that effectively combines Fuzzy Logic for controlling uncertainty with CNN for extracting and classifying features. The PD-HDA outperforms current diagnosis methods in related investigations. Using CNN-based hierarchical feature extraction and fuzzy inference, the system tightens deep semantic representation learning and uncertainty-aware decision modelling. Instead of using probabilistic outputs, PD-HDA directly addresses symptom ambiguity and inter-class overlap through fuzzy reasoning, yielding more stable and accurate diagnostic results. Traditional machine learning and hybrid approaches utilize handcrafted features or shallow neural architectures, whereas the proposed method employs end-to-end discriminative features to enhance classification sensitivity and specificity across diverse patient profiles. Because it aligns diagnostic judgments with clinically important language characteristics, the fuzzy rule-based layer is more transparent than black-box deep learning systems.

Fig. 1 provides a solid basis for both multimodal diagnosis and therapy of PD. Combining speech patterns, gait analysis, and hand tremor images with data normalization and feature extraction offers consistency. A module of fuzzy logic lowers data uncertainty, hence improving system reliability. Following that, a CNN employs excellent sensitivity and specificity to classify PD phases and regulate enhanced qualities.

This classification aids in early diagnosis and the creation of tailored treatment programs tailored to specific patient needs. The first goal of the system's design is to improve clinical outcomes for PD management, accuracy, and flexibility.

$$R_f d[oj - an'']: \rightarrow Sz[ji - anw''] * Va[io - anq''] \quad (1)$$

Eq. (1) contains $[oj - an'']$ That represents processed characteristics $Sz[ji - anw'']$ obtained from multimodal datasets such as speech $Va[io - anq'']$, gait, and tremor pictures, and the final classification result, which might be denoted as $R_f d$. Its goal is to enhance the specificity and sensitivity of the disorder's diagnosis by modelling complicated interactions in clinical data.

$$M_f d: \rightarrow nc[a - iw''] * x[nu - aq''] + Bs[ki - ak''] \quad (2)$$

Eq. (2), $M_f d$ accounts for the biases or adjustments inside the model, $nc[a - iw'']$ and $x[nu - aq'']$ Relate to the characteristics derived from clinical data and $Bs[ki - ak'']$ Represents a factor impacting the final output. Improved accuracy and flexibility for specific patient symptoms will be achieved by refining the decision-making process in PD diagnosis.

$$V_s e: \rightarrow Ls[4v - anq''] + Ba[ko - qn''] - Cr[iu - a''] \quad (3)$$

Eq. (3) represents $Cr[iu - a'']$ the final output for a particular stage of PD classification, with the terms $V_s e$, $Ls[4v - anq'']$, and $Ba[ko - qn'']$ Representing feature parameters from datasets. Improving the decision-making process will allow for more accurate and tailored PD diagnosis, which is its primary goal.

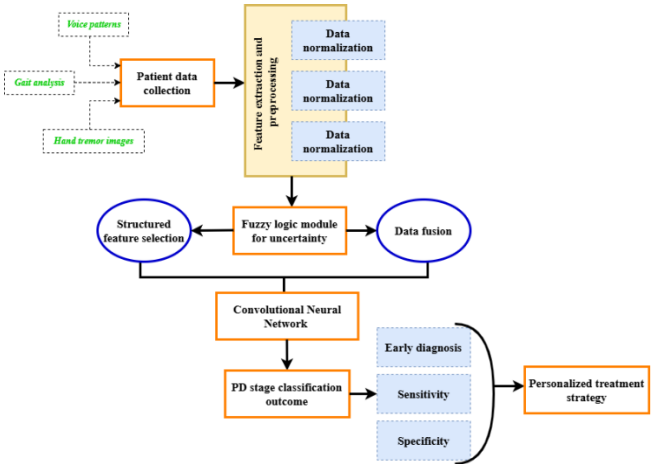


Fig. 1. Proposed method of PD-HAD.

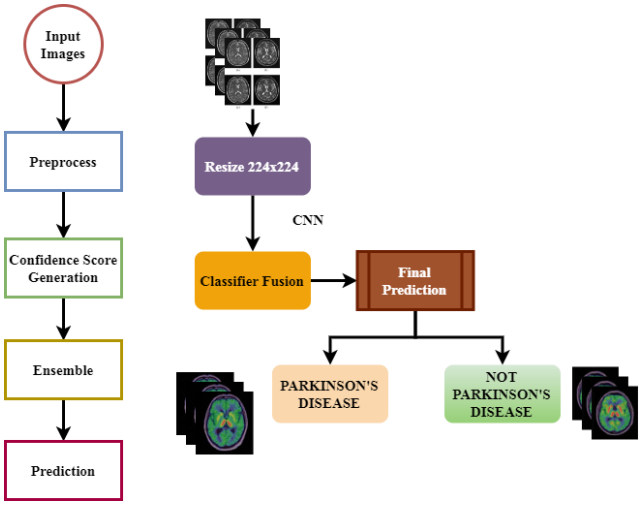


Fig. 2. Classification using hybrid CNN ensemble for parkinson's detection.

Fig. 2 presents a hybrid diagnosis for PD using a combination of deep learning models. Four pre-trained convolutional neural networks: after processing and scaling to

224x224 pixels, CNNs are applied to medical images. These models provide confidence ratings and are utilized in a classifier ensemble to produce the most accurate prediction. Leveraging the characteristics of every neural network, the system determines whether the image exhibits PD or not, generating a strong and consistent classification. This system shows a complex, multi-model approach for the medical image-based illness diagnosis.

$$wx[ji - aq'']: \rightarrow \ a[i - an''] + ba[juw - anq''] \quad (4)$$

Eq. (4) represents the processed input data (such as gait or voice characteristics) as $wx[ji - aq'']$, and the learnt parameters and bias adjustments inside the neural network as $a[i - an'']$ and $ba[juw - anq'']$, respectively. Fine-tuning the model's parameters aims to maximize the accuracy of diagnosis in PD stage categorization.

$$x_z a[ko - an'']: \rightarrow Ks[3 - aq''] + Ba[jos - naq''] \quad (5)$$

The method of decision-making $Ba[jos - naq'']$ in the PD-HDA framework, the interaction between the equation 5 stride analysis data $(x_z a)$ and the model factors $([ko - an''])$ and $Ks[3 - aq'']$. Adjusting to intricate differences in patient data aims to improve diagnostic accuracy and guarantee accurate and dependable forecasts.

$$j_d e[lo - aq'']: \rightarrow aW[lo - sm''] + Bas[ko - bxz''] \quad (6)$$

The model parameters used to refine the classification, $j_d e$ and $[lo - aq'']$, and the input data, which might be linked to particular clinical characteristics (such as hand tremor $aW[lo - sm'']$ or voice data $Bas[ko - bxz'']$), are represented by Eq. (6).

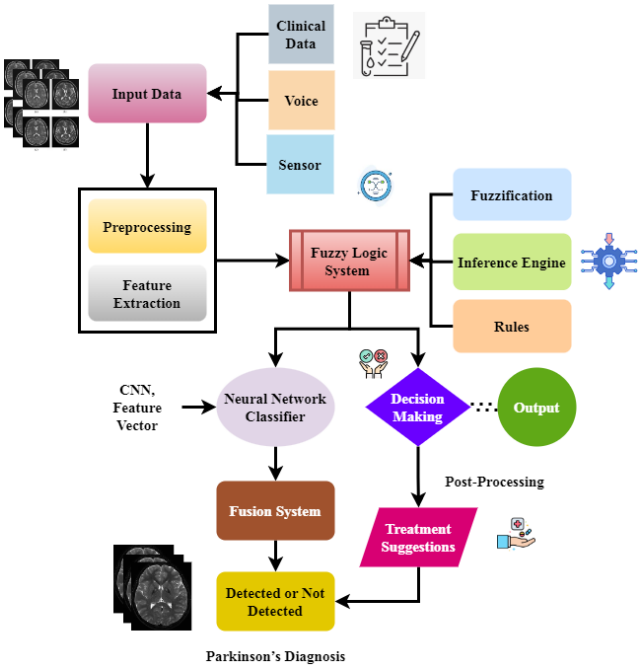


Fig. 3. Process of Smart PD: Integrating fuzzy logic and neural networks.

Fig. 3 illustrates a hybrid PD diagnosis approach that combines fuzzy logic and neural networks. Clinical notes, sensors, and speech recordings are entered into the system, and feature extraction and preprocessing identify and clean key patterns. Neural networks categorize data by learning patterns, whereas fuzzy logic interprets complex input using rules. The results of both models are combined for increased accuracy. The final decision-making phase determines the presence of PD and provides diagnostic guidance for further measures.

$$p_f r[mk - am'']: \rightarrow Ks[4v - fs'] + Na[4s - aq''] \quad (7)$$

The parameters used for the model $p_f r$ and $[mk - am'']$ may stand for weights or modifications within the neural network $Na[4s - aq'']$, while the extracted features $Ks[4v - fs']$ Perhaps it is associated with motor symptoms, such as tremors or gait, as seen in Eq. (7.) Its goal is to enhance the PD-HDA framework as a diagnostic tool, leading to earlier and more accurate diagnosis of PD stages.

$$b_x s[op - anqw'']: \rightarrow La[i - qn''] + Na[4x - anq''] \quad (8)$$

Eq. (8) illustrates the connection between the input data. $b_x s$, which may pertain to particular characteristics like habits of speech $Na[4x - anq'']$ or other clinical symptoms, and the simulation parameters $op - anqw''$ and $La[i - qn'']$, which probably represents the learned biases. Its goal is to improve the diagnosis of PD by maximizing the integration of features, resulting in more reliable forecasts.

$$kd^e"u - an'"": \rightarrow \ Sx' - an[eaq - wn''] + \ Aba[io - sm''] \quad (9)$$

The model's output, kd^e, which may be the ultimate $Aba[io - sm'']$ PD classification $Sx' - an$, is influenced $[eaq - wn'']$ by the clinical information, $u - an'"": \rightarrow$ which is probably linked to a patient's symptoms. Improving patient care through the early and precise identification of PD is the goal of Eq. (9).

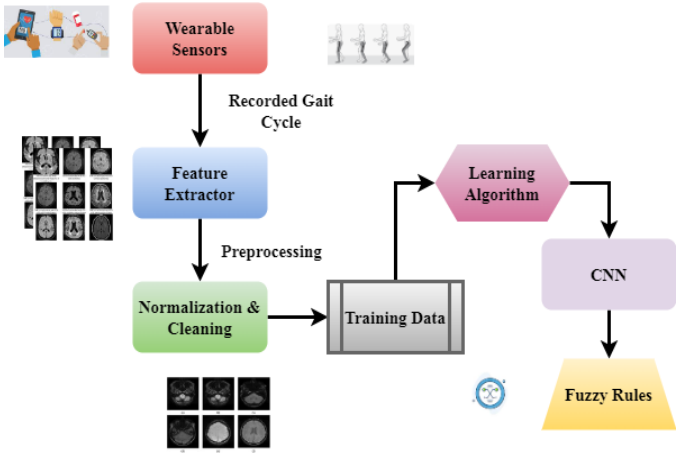


Fig. 4. Training data using fuzzy-neural gait detection for PD.

Fig. 4 illustrates a novel approach for identifying PD using wearable sensors that collect gait data. An Interval Type-2 Fuzzy Neural Network (IT2FNN) helps to prepare the acquired data. By combining fuzzy logic with neural networks, this hybrid model effectively identifies subtle gait deviations associated with PD. While neural networks improve pattern identification, ultimately enabling more accurate and earlier PD diagnosis through gait analysis, fuzzy logic helps handle data ambiguity.

Using innovative artificial intelligence methods, this strategy enhances healthcare results.

$$Y_s e[lo - an'']: \rightarrow Ms[4v - sq''] + Ba[4s - qnew''] * bs'' \quad (10)$$

The partnership bs'' Between the clinical data that is input $Y_s e$, which may stand $Ba[4s - qnew'']$ for motor symptoms such $[lo - an'']$, and the model's output $Ms[4v - sq'']$, which might be represented by Eq. (10). Improved early diagnosis and individualized treatment plans for PD are the goals of this effort to improve diagnostic accuracy.

$$u_c e < jn - am'' >: \rightarrow Na[4w - aqv''] + Na[ko - s''] \quad (11)$$

The model's output, $u_c e$, which might stand for the classification $Na[4w - aqv'']$ or forecast for PD $Na[ko - s'']$, is influenced by the processing of input data, $jn - am''$, which is likely associated with specific clinical aspects, such as motor and non-motor symptoms. The use of this equation will enable more accurate and timely PD diagnoses, leading to improved treatment options.

$$f_f r[a - nq'']: \rightarrow Ka[6v - snw''] + Ba[ju - anw''] \quad (12)$$

In the neural network, Eq. (12) shows the interaction $Ka[6v - snw'']$ between learnt parameters $[a - nq'']$ and $f_f r$, which are likely to correlate $Ba[ju - anw'']$.

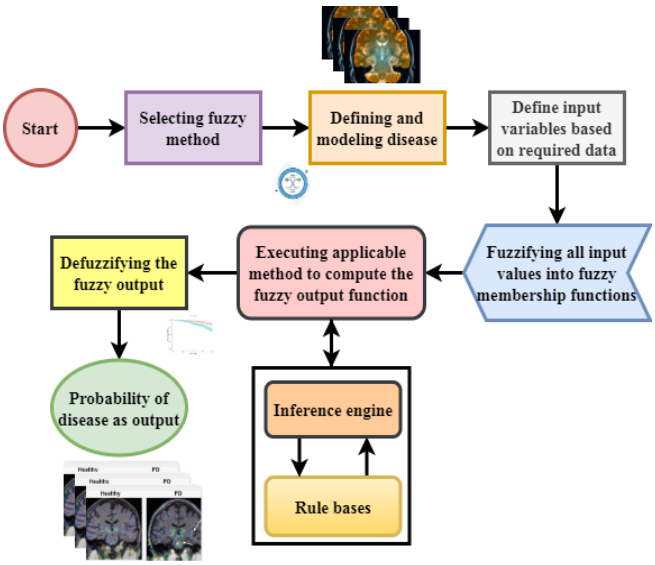


Fig. 5. Flow chart of fuzzy logic disease diagnosis.

Fig. 5 shows diagnosis of diseases by fuzzy logic in a methodical manner. It starts with the diseased model and its related variables; fuzzification of inputs helps remove ambiguity from the solution. Fuzzy rules are applied through the inference engine, resulting in fuzzy output due to data processing. That final defuzzification step provides a percentage probability, hence the disease risk. This approach offers a consistent and flexible tool for medical diagnosis, leveraging the capacity of fuzzy logic to manage imprecision, thereby enhancing healthcare decision-making with greater accuracy and flexibility.

$$T^t u[ki - an'']: \rightarrow ap[ji - anw''] + Na[4sa - an''] \quad (13)$$

The model processes clinical data Eq. (13) $[ki - an'']$, such as patient symptoms $ap[ji - anw'']$, to impact the outcome $T^t u$, which may represent the classification result $Na[4sa - an'']$ for PD. The equation aims to enhance early diagnosis and facilitate more personalized treatment methods for PD.

$$Jm_e[ko - an'']: \rightarrow Na[s - sn] + Ns[w - qm''] * vs'' \quad (14)$$

Eq. (14) shows how $vs''$the settings of the neural network Jm_e and $[ko - an'']$ Convert the input data $Na[s - sn]$, which might be associated $Ns[w - qm'']$ With a group of clinical traits, such as motor or non-motor symptoms. Improving diagnostic accuracy, facilitating early identification, and facilitating tailored therapy for PD in patient data.

$$U_r[i - sj'']: \rightarrow Lsp[5n - an''] * Vs[w - 9vq''] \quad (15)$$

The way the input data U_r interacts with the learned parameters $[i - sj'']$ and $Lsp[5n - an'']$ to generate the output $Vs[w - 9vq'']$, which is the model's prediction for PD, is explained by Eq. (15). For the identification of early-stage PD and the development of personalized treatment options, this equation is used to ensure the model's accuracy.

The systems shown utilize fuzzy logic for PD diagnosis and employ various deep learning algorithms. Their consistent categorization and early identification result from combining medical imaging, gait analysis, and speech analysis. While fuzzy logic addresses ambiguity and increases decision-making accuracy, neural networks improve feature extraction. For patients with PD, these multimodal approaches ensure enhance clinical outcomes and personalized treatment strategies.

III. Results

PD is a degenerative neurological disorder for which early and precise diagnosis is essential for appropriate treatment. Particularly in early-stage diagnosis, traditional diagnostic methods might be unreliable and insensitive.

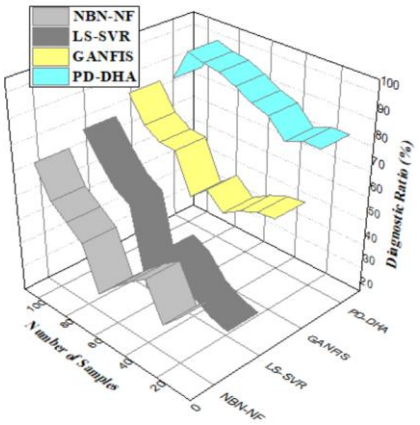
Dataset description: The dataset predicts MDS-UPDRS scores to evaluate and predict the progression of PD. Clinical evaluations, demographics, and biospecimen data are gathered longitudinally. The collection aims to enhance illness progression prediction and facilitate individualized treatment [26]. Various clinical signs, chronological data, and standardized grading criteria are crucial. This website is part of a collaborative effort to advance PD research through the application of machine learning and statistical analysis [27]. Table I shows the simulation environment.

With a 92.62% diagnosis accuracy, the PD-HDA framework outperformed traditional diagnostic methods [see (Fig. 6(a) and (b)]. The system's efficient blend of CNN-based learning and fuzzy logic enables it to detect PD at multiple stages accurately. The synergy resolves typical clinical evaluation differences by combining data and feature extraction to provide consistent performance across multimodal datasets.

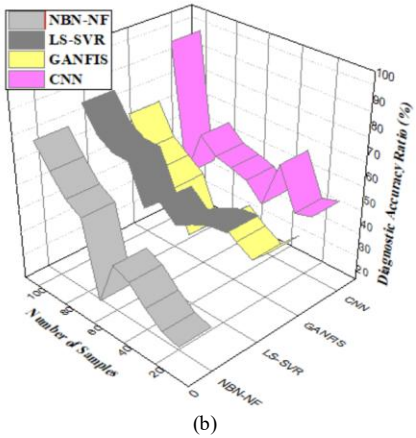
$$Xs[ki - an'']: \rightarrow Vx[q - 9vw''] + Va[ki - an''] \quad (16)$$

TABLE I. SIMULATION ENVIRONMENT

Metrics	Description
Purpose	To predict MDS-UPDRS scores and forecast PD progression.
Dataset Type	Longitudinal patient data with clinical assessments, demographics, and biospecimen data.
Key Features	Diverse clinical markers, temporal information, and standardized scoring metrics.
Machine Learning Techniques	Predictive modelling using advanced machine learning and statistical analysis techniques.
Temporal Information	Includes data collected over multiple time points to capture disease progression dynamics.
Collaboration	Part of a collaborative effort to drive innovation in PD research.
Evaluation Metrics	Diagnostic accuracy, sensitivity, specificity, and early detection performance.
Output	Predicted MDS-UPDRS scores and insights for personalized treatment strategies.
Simulation Tools	Python-based frameworks, machine learning libraries (e.g., TensorFlow, PyTorch, Scikit-learn).
Applications	Development of predictive models for personalized interventions and disease management.



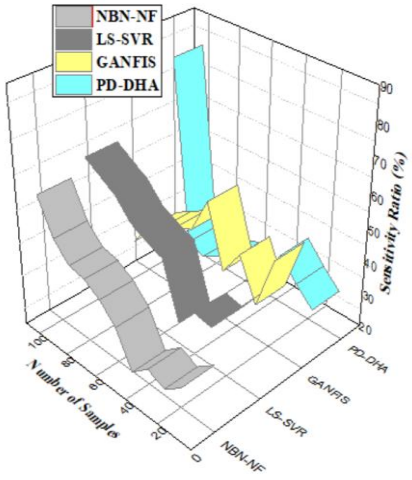
(a)



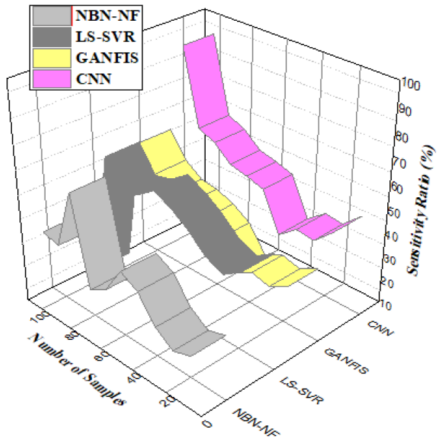
(b)

Fig. 6. (a) Analysis of diagnostic accuracy using PD-HDA, and (b) Analysis of diagnostic accuracy using CNN.

The relationship between input characteristics Xs, which are probably $Va[ki-an'']$ related to particular clinical symptoms or data, and the parameters of the learnt model $[ki-an'']$ and $Vx[q-9vw'']$ As shown by Eq. (16). This equation is used to analyze diagnostic accuracy, improve diagnostic accuracy, enable early intervention for enhanced patient care, and integrate and streamline feature processing.



(a)



(b)

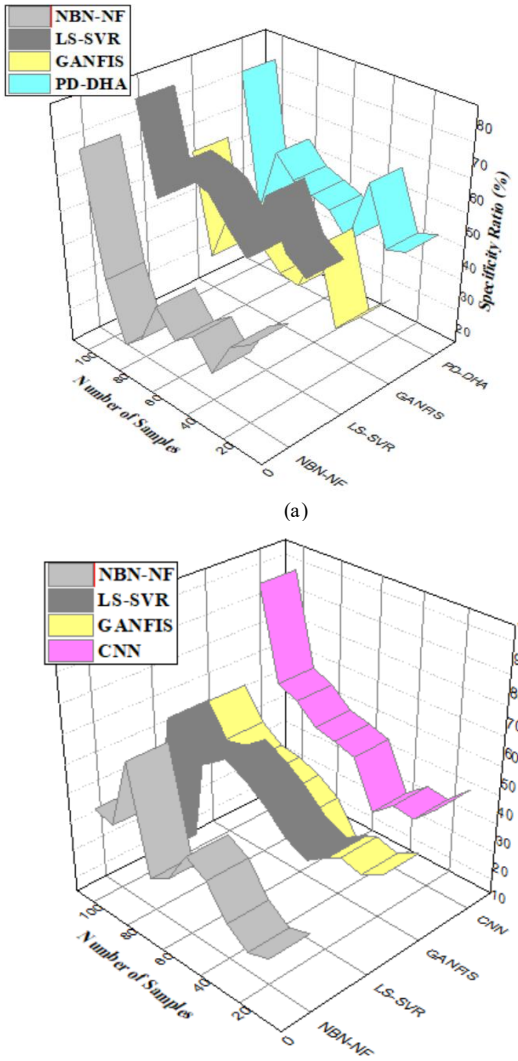
Fig. 7. (a) Analysis of sensitivity using PD-HDA, and (b) Analysis of sensitivity using CNN.

With a sensitivity of 91.87%, the suggested PD-HDA approach proved helpful in precisely identifying PD patients [Fig. 7(a) and (b)]. The method guarantees the lowest false-negative rates by using CNNs for nuanced pattern recognition and fuzzy logic to manage uncertainty in clinical data. Reducing missed diagnoses depends on this capacity, especially in early and unusual presentations of PD, hence enhancing the likelihood of prompt and focused therapies.

$$V_c s[i-an'']: \rightarrow Ls[ui-anw''] + Ba[d-sqn''] \quad (17)$$

The neural network processes input characteristics. $V_c s$, which may be associated with clinical data like symptom severity $[i-an'']$ or medical records to generate the output $Ls[ui-anw'']$, which represents the diagnosis $Ba[d-$

sqn''] of PD. With Eq. (17), we maximize the application of patient data, which leads to more accurate diagnoses and more precise classifications for sensitivity analysis.



(a)

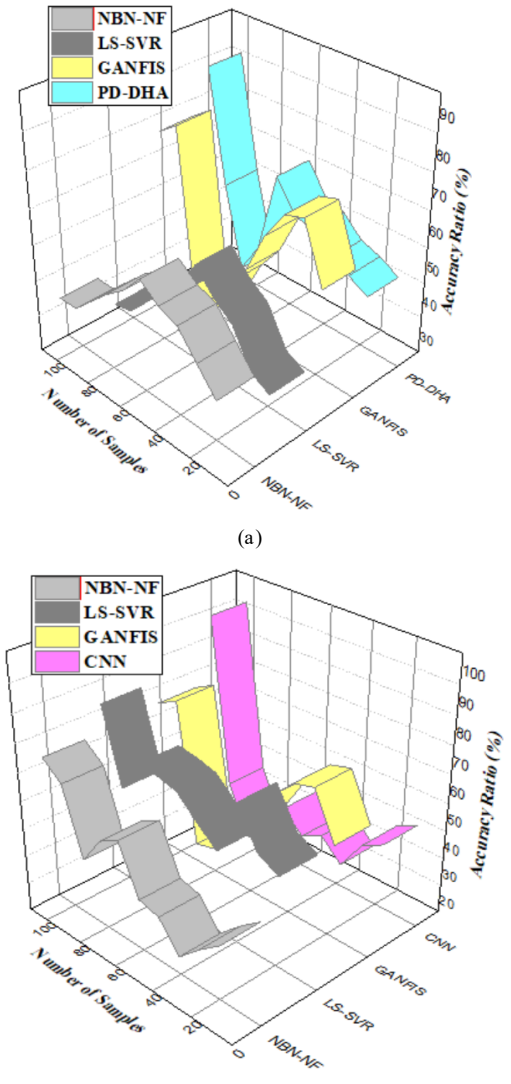
(b)

Fig. 8. (a) Analysis of specificity using PD-HDA, and (b) Analysis of specificity using CNN.

With a 93.22% specificity, the PD-HDA model identifies non-PD people precisely, hence reducing false-positive diagnoses [see Fig. 8(a) and (b)]. Structured feature selection and multimodal data analysis enable the precise differentiation between PD and other disorders. Reducing unnecessary treatments and ensuring resources are focused on those who need care depends on this excellent specificity.

$$c_x s[l - ap'']: \rightarrow Ls[v - anq''] + Ba[4d - nwq''] \quad (18)$$

The output $c_x s$, which is the classification or prediction of PD, is obtained by processing the clinical input data $[l - ap'']$ through the settings of the model $Ls[v - anq'']$ and $Ba[4d - nwq'']$. The goal of Eq. (18) is to improve diagnostic accuracy by enhancing the model's ability to integrate and evaluate data for analysis of specificity.



(a)

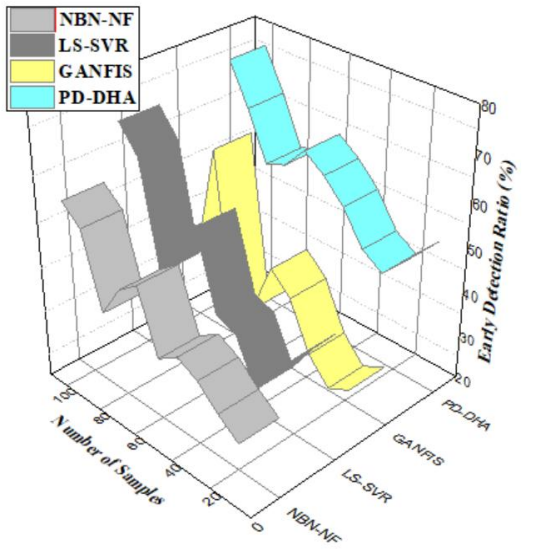
(b)

Fig. 9. (a) Analysis of accuracy using PD-HDA and (b) Analysis of accuracy using CNN

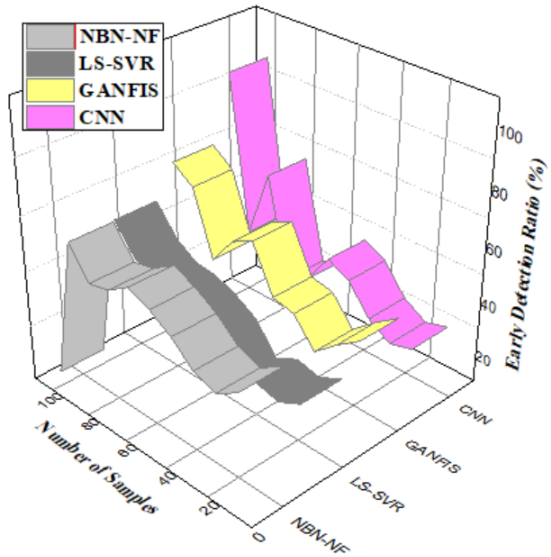
The PD-HDA framework was effective in differentiating PD from non-PD cases, with an overall accuracy of 97.24% [see Fig. 9(a) and (b)]. This statistic demonstrates the model's durability and its ability to generalize across multiple datasets by utilizing speech patterns, gait analysis, and tremor photos. Such high accuracy highlights how consistently hybrid methods provide precise diagnostic information for clinicians, as seen in Eq. (19).

$$k_d r[ki - an'']: \rightarrow Ks[ki - qm''] + Bs[ko - sme''] \quad (19)$$

Eq. (19) shows the model's parameters. $k_d r$, which modifies the internal weights and biases of the model, processes the input feature $[ki - an'']$, which is probably related to clinical data like symptom severity, by adjusting the parameters $Ks[ki - qm'']$ and $Bs[ko - sme'']$. The goal of this equation is to facilitate early identification of PD by optimizing the integration of several clinical characteristics to ensure the accuracy of the analysis.



(a)



(b)

Fig. 10. (a) Analysis of early detection using PD-HDA, and (b) Analysis of early detection using CNN

The early detection accuracy of 95.76% emphasizes the framework's ability to identify PD in its early stages [see (Fig. 10(a) and (b)]. CNNs paired with fuzzy logic help detect often-overlooked minor clinical signs and trends. This skill determines if starting timely treatment measures slows down the progression of illnesses and improves long-term patient outcomes.

$$k_r r[ju - n'']: \rightarrow Ns\left[rs'' * Vs[ko - amw'']\right] + Nsf'' \quad (20)$$

An extra adjustment term $k_r r$ and a mixture of network parameters $[ju - n'']$ are used to analyze the input data $Ns\left[rs'' * Vs[ko - amw'']\right]$, which may be associated Nsf'' With patient-specific symptoms or data points. Equation aims to represent the complex correlations observed in multimodal clinical data for early detection analysis. Table II presents a comparison of the existing method and the proposed method.

TABLE II. COMPARISON OF THE EXISTING METHOD AND PROPOSED METHOD

Aspects	Existing Method in Ratio	Proposed Method in Ratio	Key features
Diagnostic Accuracy	80.85%	92.62%	Enhanced feature extraction via CNN and data fusion for accurate classification.
Sensitivity	78.82%	91.87%	Improved detection of PD cases using Fuzzy Logic for uncertainty management.
Specificity	81.86%	93.22%	Better differentiation between PD and non-PD cases through multimodal data analysis.
Overall Accuracy	85.90%	97.24%	Robust performance leveraging structured feature selection and advanced algorithms.
Early Detection	75.88%	95.76%	High early detection rates using subtle pattern recognition in clinical data.

IV. DISCUSSION

This work advances hybrid diagnostic modelling by formalizing a deep semantic learning–reasoning pipeline in which CNN-derived hierarchical representations are directly coupled with fuzzy inference. This connection enhances performance by transforming discriminative convolutional features into uncertainty-aware language variables prior to classification, enabling data-driven abstraction and rule-based reasoning to inform diagnostic conclusions. This approach explains reported advantages by attributing enhanced stability and sensitivity to deep feature hierarchies and graded fuzzy decision boundaries rather than network depth. The semantic representation-level uncertainty-handling method in the PD-HDA framework is organized. The fuzzy inference layer compares the ambiguity of symptoms and the overlap of classes through membership functions between deep feature spaces, which contrasts with probabilistic classifiers that tend to provide a clear judgment basis. This formalization provides an analytical model of dealing with the ambiguity in diagnosing the PD, especially in borderline and early-stage patients. High-dimensional CNN activation mapping is used to transform into fuzzy language entities of clinical significance, forming an interpretable diagnostic reasoning layer in PD-HDA. The built-in rule base provides clear inference paths that relate diagnostic findings to neurologically relevant patterns of symptoms, extending the hybrid modelling beyond the optimization of accuracy to provide explainable clinical decision support. This layer of interpretability indicates the impact of feature abstractions on diagnostics. The paradigm facilitates graded diagnostic thinking in cases of symptom variability during the analysis of early-stage PD. Fuzzy inference makes it less vulnerable to variations in features at early stages by smoothing disease class transitions. Diagnostic consistency across diverse patient demographics is achieved without rigid categories. In addition to application-level validation, the proposed hybrid

diagnostic paradigm can be applied to other neural and uncertainty-driven clinical cases. Deep feature learning and fuzzy reasoning are modular, allowing for adaptation to various data modalities and illness conditions without compromising interpretability and uncertainty modelling. This makes PD-HDA a transferable diagnostic architecture rather than a task-specific empirical solution.

V. Conclusion

The PD-HDA uses CNNs and fuzzy logic to address PD diagnostic problems. By utilizing CNNs to evaluate challenging multimodal datasets and employing fuzzy logic to mitigate clinical data ambiguity, the framework achieves 92.62% diagnostic accuracy, 91.87% sensitivity, 93.22% specificity, and 95.76% early detection accuracy. Usually, the PD-HDA method is more effective than conventional diagnostic tools in the initial stages of PD, albeit erratically and subjectively. Elaborate and intricate patterns that emerge from data relating to speech, gait, and tremor analysis facilitate the accurate and reliable identification of the progression stages of PD. Rapid therapeutic interventions resulting from such findings reduce the span and improve the prognosis of patients autonomously. The results highlight the potential of hybrid diagnostic methods to overcome the limitations of current methods, enhance the reliability of diagnosis, and establish a new standard for PD diagnosis. The next research focus will be to extend the PD-HDA framework to include a more diverse range of information, such as real-time monitoring and biomarkers, to achieve the best accuracy.

Additionally, efforts will be made to optimize the model for clinical use, ensuring both scalability and user-friendliness. The method's practicality is shown by its improved classification accuracy, sensitivity, and resilience compared to standard machine learning models, standalone CNN architectures, and hybrid techniques. This study employs a single data modality and a specified fuzzy rule basis, which restricts adaptation to changing clinical patterns and acquisition situations. Future research will apply the framework to imaging, voice, and sensor-based clinical data, examining adaptive fuzzy rule optimization and attention-guided feature selection to enhance generalization and clinical interpretability.

Acknowledgment

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References

[1] G. DeMaagd and A. Philip, "Parkinson's disease and its management: Part 1: Disease entity, risk factors, pathophysiology, clinical presentation, and diagnosis," Pharmacy and therapeutics, vol. 40, no. 8, pp. 504-532, 2015.

[2] Yadav VK, Dhanasekaran S, Choudhary N, Nathiya D, Thakur V, Gupta R, Pramanik S, Kumar P, Gupta N, Patel A. "Recent advances in nanotechnology for Parkinson's disease: diagnosis, treatment, and future perspectives". Frontiers in Medicine. Frontiers in Medicine, 12, 1535682, 2025.

[3] C. H. Adler and T. G. Beach, "Neuropathological basis of nonmotor manifestations of Parkinson's disease," Mov. Disord., vol. 31, no. 8, pp. 1114-1119, 2016.

[4] D. Berg, R. B. Postuma, C. H. Adler, B. R. Bloem, P. Chan, B. Dubois, T. Gasser, C. G. Goetz, G. Halliday, L. Joseph, A. E. Lang, I. Liepelt-Scarfone, I. Litvan, K. Marek, J. Obeso, W. Oertel, C. W. Olanow, W. Poewe, M. Stern, and G. Deuschl, "MDS research criteria for prodromal Parkinson's disease," Mov. Disord., vol. 30, no. 12, pp. 1600-1611, 2015.

[5] C. G. Goetz, B. C. Tilley, S. R. Shaftman, G. T. Stebbins, S. Fahn, P. Martinez-Martin, W. Poewe, C. Sampaio, M. B. Stern, R. Dodel, B. Dubois, R. Holloway, J. Jankovic, J. Kulisevsky, A. E. Lang, A. Lees, S. Leurgans, P. A. LeWitt, D. Nyenhuis, C. W. Olanow, O. Rascol, A. Schrag, J. A. Teresi, J. J. van Hilten, and N. LaPelle, "Movement Disorder Society-sponsored revision of the Unified Parkinson's Disease Rating Scale (MDS-UPDRS): Scale presentation and clinimetric testing results," Mov. Disord., vol. 23, no. 15, pp. 2129-2170, 2008.

[6] D. J. Brooks, "Imaging approaches to Parkinson disease," J. Nucl. Med., vol. 51, no. 4, pp. 596-609, 2010.

[7] M. A. Little, P. E. McSharry, E. J. Hunter, J. Spielman, and L. O. Ramig, "Suitability of dysphonia measurements for telemonitoring of Parkinson's disease," IEEE Trans. Biomed. Eng., vol. 56, no. 4, pp. 1015-1022, 2009.

[8] A. Tsanas, M. A. Little, P. E. McSharry, J. Spielman, and L. O. Ramig, "Novel speech signal processing algorithms for high-accuracy classification of Parkinson's disease," IEEE Trans. Biomed. Eng., vol. 59, no. 5, pp. 1264-1271, 2012.

[9] Di Biase, L., Pecoraro, P.M., Pecoraro, G., Shah, S.A. and Di Lazzaro, V." Machine learning and wearable sensors for automated Parkinson's disease diagnosis aid: a systematic review". Journal of Neurology, 271(10), 6452-6470, 2024.

[10] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, pp. 436-444, 2015.

[11] Höglinger, G.U., Adler, C.H., Berg, D., Klein, C., Outeiro, T.F., Poewe, W., Postuma, R., Stoessl, A.J. and Lang, A.E."A biological classification of Parkinson's disease: the SynNeurGe research diagnostic criteria". *The Lancet Neurology*, *23*(2), 191-204, 2024

[12] D. Shen, G. Wu, and H. I. Suk, "Deep learning in medical image analysis," Annu. Rev. Biomed. Eng., vol. 19, pp. 221-248, 2017.

[13] Versaci, M., & La Foresta, F. "EEG data analysis techniques for precision removal and enhanced Alzheimer's diagnosis: Focusing on fuzzy and intuitionistic fuzzy logic techniques". Signals, 5(2), 343-381, 2024.

[14] S. Sreelakshmi and R. Mathew, "A Hybrid Approach for Classifying Parkinson's Disease from Brain MRI," in Proc. Int. Conf. Information Technology and Applications (ICITA 2021), Singapore: Springer Nature Singapore, 2022, pp. 171-181.

[15] L. P. Sánchez-Fernández, "Biomechanics of Parkinson's Disease with Systems Based on Expert Knowledge and Machine Learning: A Scoping Review," Computation, vol. 12, no. 11, p. 230, 2024.

[16] S. Sangeetha and B. Umarani, "MRI Image-Based Parkinson's disease classification using Deep Maxout fuzzy EfficientNet," Biomed. Signal Process. Control, vol. 103, p. 107416, 2025.

[17] Ram, Ashwin. "Analysis, Identification and Prediction of Parkinson Disease Sub-Types and Progression through Machine Learning." *arXiv preprint arXiv:2306.04748*, 2023.

[18] M. Nilashi, R. A. Abumalloh, S. Y. M. Yusuf, H. H. Thi, M. Alsulami, H. Abosaq, S. Alghamdi, and A. Alghamdi, "Early diagnosis of Parkinson's disease: A combined method using deep learning and neuro-fuzzy techniques," Comput. Biol. Chem., vol. 102, p. 107788, 2023.

[19] H. Ahmadi, L. Huo, G. Arji, A. Sheikhtaheri, and S. M. Zhou, "Early diagnosis of Parkinson's disease using a hybrid method of least squares support vector regression and fuzzy clustering," Biocybern. Biomed. Eng., vol. 44, no. 3, pp. 569-585, 2024.

[20] I. Raza, M. H. Jamal, R. Qureshi, A. K. Shahid, A. O. R. Vistorte, M. A. Samad, and I. Ashraf, "Adaptive neighborhood rough set model for hybrid data processing: a case study on Parkinson's disease behavioral analysis," Sci. Rep., vol. 14, no. 1, p. 7635, 2024.

[21] H. Kour, J. Manhas, and V. Sharma, "Hybrid System Based on Genetic Algorithm and Neuro-Fuzzy Approach for Neurodegenerative Disease Forecasting," in Proc. Data Analytics and Management (ICDAM 2021), vol. 1, Springer Singapore, 2022, pp. 319-330.

[22] V. Kumar, A. Verma, R. Raman, S. Rastogi, D. Saini, and R. Meenakshi, "Combining Technologies of AI and Fuzzy Logic System for Huntington Disease Prediction," in Proc. 2024 4th Int. Conf. Advance Computing and Innovative Technologies in Engineering (ICACITE), IEEE, 2024, pp. 697-702.

[23] M. Nilashi, R. A. Abumalloh, H. Ahmadi, S. Samad, S. Alyami, A. Alghamdi, S. Y. M. Yusuf, and S. Y. M. Yusuf, "Accuracy Analysis of Type-2 Fuzzy System in Predicting Parkinson's Disease Using Biomedical Voice Measures," Int. J. Fuzzy Syst., pp. 1-24, 2024.

[24] K. Sarin, M. Bardamova, M. Svetlakov, N. Koryshev, R. Ostapenko, A. Hodashinskaya, and I. Hodashinsky, "A three-stage fuzzy classifier method for Parkinson's disease diagnosis using dynamic handwriting analysis," Decis. Anal. J., vol. 8, p. 100274, 2023.

[25] F. A. Torghabeh, Y. Modaresnia, and S. A. Hosseini, "An efficient tool for Parkinson's disease detection and severity grading based on time-frequency and fuzzy features of cumulative gait signals through improved LSTM networks," Med. Nov. Technol. Devices, vol. 22, p. 100297, 2024.

[26] Kaggle Dataset, "Parkinson's Disease Progression Prediction," Available: https://www.kaggle.com/code/gusthema/parkinson-s-disease-progression-prediction-w-tfdf

[27] M. ALMOZANI and H. DEMİREL, "Enhancing Parkinson's Disease Management through Therapeutic Games: The Role of User Experience and Interaction Design," Int. J. Adv. Nat. Sci. Eng. Res., vol. 8, no. 11, pp. 318-329, 2024.

Evaluating CTGAN-Generated Synthetic Data for Heart Disease Prediction: Fidelity, Predictive Utility, and Feature Preservation

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***Abstract*—The increasing scarcity and sensitivity of clinical data necessitate the development of high-quality synthetic datasets. This study evaluated the ability of Conditional Tabular GAN (CTGAN) to generate synthetic heart disease data that preserves the statistical properties and predictive patterns of the Cleveland Heart Disease dataset. It assessed the fidelity of numerical and categorical features, preservation of pairwise correlations, and predictive utility using Logistic Regression and Random Forest classifiers. Dimensionality reduction analysis using PCA and t-SNE further measured the global similarity between the real and synthetic datasets. The results obtained show that CTGAN successfully reproduces the general distribution and correlations, especially for key features such as age, talach, and old peak. However, some discrepancies remain in categorical attributes. Predictive modeling shows moderate transferability, indicating that synthetic data captures important patterns without completely replicating the original labels. These findings highlight the potential of CTGAN-generated synthetic data as a privacy-preserving alternative for benchmarking and early algorithm development, while emphasizing the importance of feature-level and prediction validation in synthetic data research.**

Keywords*—*Conditional Tabular GAN (CTGAN); correlation analysis; dimensionality reduction; feature importance; heart disease prediction; predictive utility; synthetic data; tabular data fidelity

I. Introduction

Cardiovascular diseases, particularly heart disease, remain a leading cause of global mortality, accounting for approximately 17.9 million deaths annually according to the World Health Organization. Early identification and timely intervention are essential to reducing morbidity and mortality associated with these conditions. In recent years, machine learning (ML) techniques have attracted significant attention for their potential to support heart disease diagnosis and risk prediction, thereby enabling data-driven clinical decision-making [1].

Despite these advances, the robustness and generalizability of ML models in healthcare are often constrained by limitations inherent to real-world clinical data [2]. One of the primary challenges is the scarcity of large-scale, high-quality, and representative datasets. Publicly available resources, such as the UCI Heart Disease dataset, are typically limited in size and frequently exhibit class imbalance, which restricts their suitability for training reliable predictive models [3]. In addition, patient privacy regulations and ethical considerations impose further restrictions on data sharing and reuse [4]. These challenges collectively hinder reproducibility and limit the practical deployment of ML-based solutions in clinical settings [5].

To address data scarcity while mitigating privacy concerns, synthetic data generation has emerged as a promising alternative. Among existing approaches, Generative Adversarial Networks (GANs) have demonstrated strong capability in modeling complex data distributions. In particular, Conditional Tabular GAN (CTGAN) is designed to handle tabular datasets with both continuous and categorical variables, as well as class imbalance. These characteristics make CTGAN especially suitable for healthcare applications [6], where heterogeneous feature types and skewed data distributions are common.

Although GAN-based synthetic data generation has been widely explored, most existing studies primarily emphasize downstream model performance, such as classification accuracy, while providing limited systematic evaluation of artificial data fidelity. In particular, the preservation of statistical properties and feature-level relationships in synthetic tabular data is often under-examined. Furthermore, there is insufficient empirical evidence regarding whether synthetic tabular data generated for heart disease prediction can offer comparable predictive utility to real clinical data while maintaining essential statistical and structural characteristics.

To address these gaps, this study evaluates the quality and fidelity of CTGAN-generated synthetic heart disease data through a comprehensive assessment framework. The evaluation includes descriptive statistical comparisons, correlation structure analysis, distributional similarity testing, and utility-based evaluation using a logistic regression classifier implemented in Python. Rather than augmenting predictive pipelines, the study assesses whether synthetic data can serve as a statistically reliable substitute for real clinical data in downstream machine learning tasks.

By integrating statistical fidelity analysis with predictive utility evaluation, this work provides empirical insights into the suitability of CTGAN-generated synthetic data for healthcare machine learning applications. The findings contribute to ongoing discussions on the role of synthetic data in clinical

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artificial intelligence, particularly in scenarios involving sensitive or limited-access tabular datasets.

The remainder of this paper is organized as follows. Section II reviews related work on synthetic data generation and evaluation in healthcare. Section III describes the dataset, CTGAN configuration, and the methodology for synthetic data generation and evaluation. Section IV presents the experimental results. Section V discusses the findings in relation to existing studies and outlines the limitations. Finally, Section VI concludes the paper and suggests directions for future research, followed by the Acknowledgments and References.

II. Literature Review

Heart disease prediction increasingly relies on machine learning (ML) and deep learning (DL), offering potential for timely diagnosis and improved clinical decision-making. However, challenges such as limited high-quality clinical data and persistent class imbalances drive the use of synthetic data generation. Generative Adversarial Networks (GANs) have emerged as a promising approach to generate realistic tabular datasets while preserving patient privacy. This literature review focuses on three areas: (1) ML and DL approaches for heart disease prediction, (2) GAN-based synthetic data generation in healthcare, and (3) assessment of the quality, utility, and privacy of synthetic data. Across these themes, this review highlights methodological advances, benchmarking strategies, and remaining gaps, thereby providing a foundation for this study.

A. Heart Disease Prediction Using Deep Learning and Machine Learning

Traditional machine learning (ML) models, such as logistic regression, decision trees, support vector machines (SVMs), k-nearest neighbors (KNN), and random forests (RFs), have been widely used for heart disease prediction due to their interpretability and computational simplicity [7,8]. Recent studies demonstrate that classical ML models, particularly tree-based methods, achieve high predictive performance across diverse datasets. For instance, Random Forest and Bagged Trees consistently produced 94–99% accuracy in multi-site validations, highlighting their reliability [15,16]. Nevertheless, these approaches often depend on manual feature engineering and may struggle to capture nonlinear relationships inherent in high-dimensional clinical data.

To address these limitations, deep learning (DL) models, intense neural networks (DNNs), and backpropagation neural networks (BP-NNs) have been increasingly employed. When combined with feature selection techniques such as L1-regularized LinearSVC or minimum redundancy maximum relevance (mRmR), these models consistently demonstrate improved predictive accuracy, often exceeding 98% [9,10]. These findings emphasize the importance of intelligent feature selection to optimize DL performance.

DL models have also been applied to non-tabular data, such as cardiac sound signals. Using Mel-frequency cepstral coefficients (MFCC) extracted from heart sounds, DL classifiers achieved near-perfect test accuracy and F1-scores [11]. Similarly, mobile-based cardiac screening employing DL has shown promising results for accessible, non-invasive diagnosis [12]. These studies illustrate the potential of incorporating alternative data modalities to complement traditional clinical predictors.

Ensemble and hybrid models have further enhanced prediction accuracy by combining multiple algorithms or data sources. For example, a DL ensemble integrating electronic medical record (EMR) and sensor data achieved 98.5% accuracy using information gain weighting [13]. Stacked ensembles of Extra Trees, XGBoost, and RF yielded robust accuracy around 92–95% [14]. Hybrid frameworks combining KNN, XGBoost, and LSTM also outperformed individual classifiers across multiple datasets [20]. These results underscore the effectiveness of multi-model strategies in capturing complementary predictive patterns.

Recent studies have explored additional predictors beyond standard clinical features. For example, SHAP analysis applied to Random Forest models identified novel biochemical markers, such as calcium and inflammation indicators, as relevant for cardiovascular risk [17]. Similarly, genomic data and psychological variables have been integrated within ML frameworks, improving predictive performance from 71.3% to 85.1% [18, 19]. These findings suggest that incorporating diverse data types can enhance model generalizability and interpretability.

Despite these promising results, generalizability remains limited. A systematic review found that only 10 out of 486 AI-based cardiovascular models underwent meaningful external validation [21]. Common limitations include small sample sizes, class imbalance, and strict privacy regulations, which hinder robust training and evaluation. These challenges highlight the need for data augmentation strategies, such as synthetic data generation via Generative Adversarial Networks (GANs), to address data scarcity while maintaining privacy. The following sections explore recent advances in GAN-based tabular synthesis, benchmarking approaches for evaluating fidelity and fairness, and real-world applications of synthetic clinical data.

B. Synthetic Data Generation in Healthcare using GANs, Disease Prediction using Deep Learning, and Machine Learning

Recent work has introduced enhanced GAN variants tailored for the unique characteristics of clinical tabular datasets. CTAB-GAN+ [22] incorporates task-aware loss functions, mixed-type variable encoders, and optional differential privacy mechanisms, improving F1-score performance under privacy constraints. STNG [23] integrates multiple generative approaches (Gaussian Copula, CopulaGAN, TVAE, Conditional GAN) with downstream validation via AutoML, demonstrating high fidelity across diverse medical datasets. SMOOTH-GAN [24] emphasizes clinically valid synthetic distributions while balancing privacy. In contrast, transformer-based models such as TT GAN [25] and FCT GAN [26] further improve the modeling of complex inter-variable dependencies in heterogeneous datasets. These studies collectively highlight the trend toward domain-aware, privacy-conscious GAN architectures capable of generating realistic clinical data.

To ensure synthetic data is not only realistic but also practical, several benchmarking frameworks have emerged. End-to-end pipelines [27] evaluate fidelity, privacy, and utility,

revealing that GANs remain competitive even compared to diffusion-based models. Comparative studies [28–30] have consistently shown that CTGAN and WGAN-GP preserve inter-variable correlations and downstream classifier performance, while hybrid methods such as CTGAN-ENN [31] and BT-GAN [32] address class imbalance and subgroup fairness. Overall, these evaluations emphasize the need for multi-dimensional assessment (fidelity, utility, fairness) to validate synthetic tabular data for healthcare applications.

Practical deployment of synthetic data requires attention to privacy and regulatory alignment. Studies using Bayesian networks and GANs on large datasets (e.g., CPRD) [33] stress ethical deployment with privacy risk mitigation, such as k-anonymity and differential privacy. Alternative approaches generate synthetic data from summary statistics to avoid direct access to patient-level data [34], while pipelines such as EMR-WGAN [35] provide hands-on workflows for real-world model development. Advanced models such as IGAMT [36] and DP-CGANs [37] further ensure privacy, fairness, and high downstream utility, particularly for heterogeneous and irregular clinical tabular data. These studies highlight a growing emphasis on ethically aligned, privacy-preserving synthetic data generation suitable for clinical AI research.

Despite the development of sophisticated GAN architectures and benchmarking strategies, questions remain regarding how to rigorously evaluate synthetic data quality and ensure it is both valuable and privacy-preserving in clinical contexts. The following section discusses evaluation frameworks, performance metrics, and architectural innovations that address these challenges.

C. Evaluation of Synthetic Data Quality and Utility in Healthcare

The evaluation of synthetic healthcare data revolves around three foundational pillars: fidelity, utility, and privacy. Fidelity ensures that synthetic data accurately replicates real-world distributions, utility reflects its usefulness in downstream analyses, and confidentiality safeguards sensitive patient information [38]. These dimensions were formalized in early frameworks and have since guided multiple evaluation standards. Preserving inter-variable correlations in time-series health data [39] and implementing domain-aware pipelines for EHRs [40] demonstrate practical strategies to maintain these dimensions. Comprehensive benchmarking studies [41,42] combine statistical similarity metrics (e.g., KS tests, Chi-square tests) with privacy assessments, such as membership inference attacks. SynthRO [43], using MIMIC-III/IV datasets, highlights the trade-offs between fidelity, utility, and privacy, emphasizing the need for balanced optimization in synthetic data generation.

Performance of synthetic data varies across clinical domains, making context-aware evaluation essential. In oncology and diabetes datasets, a divide-and-conquer CTGAN approach achieved high fidelity (97.65% shape score) and strong classification metrics [44]. Conditional GANs tailored for cardiovascular data outperformed standard CTGAN and TVAE models in fidelity measures such as the Jaccard index and KS statistic [45]. Modeling survival curves in oncology trials further illustrates the challenge of replicating censored time-to-event data [46]. Comparative analyses [47,48] highlight that no single model universally outperforms others, reinforcing the importance of domain-specific benchmarks. Broader evaluation frameworks [49] also incorporate fairness and environmental cost alongside fidelity and utility, underscoring the increasing complexity of evaluation metrics in clinical applications.

Architectural improvements in GAN-based models have targeted fidelity, usability, and privacy. Divide-and-conquer CTGAN [50] and MargCTGAN [51] enhance downstream classification performance and preserve marginal distributions, particularly for small clinical datasets. DP-CTGAN [52] integrates differential privacy directly into training to ensure privacy-conscious generation. Memory-efficient models such as MeTGAN [53] address high-cardinality categorical features while reducing computational overhead, and OCT-GAN [54] incorporates neural ordinary differential equations (NODEs) to handle class imbalance and multimodal distributions. Collectively, these innovations reflect a trend toward modular, scalable, and ethically aligned generative frameworks that meet the complex demands of healthcare data.

Although Generative Adversarial Networks (GANs) have gained traction as a solution for data scarcity in healthcare, most existing studies focus primarily on augmenting training datasets to improve predictive model performance. While this utility-based approach has achieved notable improvements in classification accuracy and robustness, there remains a lack of systematic assessment of GAN-generated data as a stand-alone substitute for real patient data. Evaluations frequently prioritize high-level utility metrics without thoroughly examining whether synthetic data preserves the intricate statistical and structural patterns inherent in clinical datasets. CTGAN, a GAN variant designed for mixed-type tabular data, shows promise in handling categorical and continuous variables with imbalanced distributions.

However, limited studies have rigorously assessed its ability to maintain clinically meaningful inter-feature relationships, such as those among chest pain, ECG readings, and heart disease diagnosis, which are critical for interpretability and real-world applicability. This study addresses these gaps by conducting a comprehensive evaluation of CTGAN-generated synthetic data for heart disease prediction, focusing on statistical fidelity, multivariate structure, and downstream classification performance. By doing so, it provides deeper insights into the reliability and limitations of CTGAN in generating synthetic clinical data for sensitive domains like cardiovascular healthcare.

III. Methodology

To address the challenges posed by scarce and sensitive clinical datasets, synthetic data generation using Generative Adversarial Networks (GANs) has gained prominence in clinical research. Further leveraging Conditional Tabular GAN (CTGAN) models, this study generates synthetic medical data from benchmark datasets to evaluate heart disease prediction performance. The primary objective is to assess the quality of the artificial data by comparing its statistical properties and predictive utility with those of the original dataset.

A. Data Source and Preprocessing

The Cleveland Heart Disease dataset was retrieved from the UCI Machine Learning Repository using the ucimlrepo Python package. This dataset [55] contains 303 patient records with 14 attributes (13 features and one target). The target column, `num`, indicates heart disease diagnosis:

- 0: Absence.
- 1-4: Presence with increasing severity.

The dataset contains 13 features and one target variable relevant to cardiac health (Table I).

TABLE I CLEVELAND HEART DISEASE DATASET FEATURES

Feature	Type	Description
age	Integer	Age in years
sex	Categorical	Sex (1=male, 0=female)
cp	Categorical	Chest pain type (1–4)
trestbps	Integer	Resting blood pressure (mm Hg)
chol	Integer	Serum cholesterol (mg/dl)
fbs	Categorical	Fasting blood sugar >120 mg/dl
restecg	Categorical	Resting ECG results (0–2)
thalach	Integer	Maximum heart rate achieved
exang	Categorical	Exercise-induced angina (1=yes, 0=no)
oldpeak	Integer	ST depression induced by exercise
slope	Categorical	Slope of peak exercise ST segment
ca	Integer	Number of major vessels (0–3)
thal	Categorical	Thalassemia (3=normal, 6=fixed defect, 7=reversible defect)
num	Target Integer	Diagnosis of heart disease

Two columns, ca and thal, contained missing values, which were imputed using the mode of each column. Numerical features (age, trestbps, chol, thalach, oldpeak) were preserved in their original scale. In contrast, categorical features (sex, cp, fbs, restecg, exang, slope, ca, thal) were encoded to facilitate synthetic data generation. The missing values were handled as follows:

```
df['ca'].fillna(df['ca'].mode()[0], inplace=True)
df['thal'].fillna(df['thal'].mode()[0], inplace=True)
```

B. Synthetic Data Generation Using CTGAN

The CTGAN model was employed to generate synthetic medical records from the cleaned and preprocessed dataset (`df_v2`). This dataset consisted of 303 patient instances, 13 predictive features, and one target variable. All preprocessing steps, including missing value imputation, categorical encoding, and 1st-to-99th percentile clipping, were completed before training.

1) CTGAN configuration: Fig. 1 shows a screenshot of the Jupyter Notebook code used to train the CTGAN model on the Cleveland Heart Disease dataset. The figure illustrates the setup of model parameters, categorical feature specification, and the output progress of generator and discriminator losses during training.

```
from ctgan import CTGAN
import pandas as pd

df_v2 = pd.read_csv("heart_clean_v2_clipped.csv")

categorical_columns = ['sex','cp','fbs','restecg','exang','slope','ca','thal']

ctgan = CTGAN(
    epochs=1200,
    batch_size=256,
    embedding_dim=256,
    generator_lr=2e-4,
    discriminator_lr=2e-4,
    verbose=True,
    pac=1  # fixes the AssertionError for small datasets
)

ctgan.fit(df_v2)
```

```
Gen. (-0.85) | Discrim. (-0.04): 100%|██████████| 1200/1200 [00:58<00:00, 20.57it/s]
```

Fig. 1. Screenshot of CTGAN training code and output progress for the cleveland heart disease dataset.

2) Model training: The CTGAN was trained directly on the cleaned dataset. Since categorical variables in `df_v2` were encoded as integers, CTGAN automatically inferred their discrete nature during training. Training completed successfully, with stable Wasserstein losses for both the generator (≈ –0.85) and discriminator (≈ –0.04), indicating balanced adversarial optimization without signs of divergence or mode collapse.

3) Synthetic data generation: After training, a synthetic dataset of equal size to the original (`n = 303`) was generated. Matching the sample size allowed direct pairwise comparison of statistical properties and predictive utility between real and synthetic datasets. The synthetic data was generated as follows:

```
num_samples = df_v2.shape[0]
synthetic_data = ctgan.sample(num_samples)
synthetic_df = pd.DataFrame(synthetic_data, columns=df_v2.columns)
```

To ensure structural and semantic consistency with the real dataset, categorical variables were rounded and cast to integer types. At the same time, numeric features (e.g., chol, oldpeak) were clipped to medically valid ranges to prevent unrealistic values. These adjustments ensured that the synthetic dataset adhered to clinically plausible ranges while preserving statistical fidelity.

C. Statistical Evaluation of Synthetic Data

To assess the fidelity of the synthetic dataset, multiple statistical analyses were performed to compare distributions and inter-feature relationships between the real and synthetic datasets, as detailed below.

Kolmogorov–Smirnov (KS) tests and Wasserstein distances were computed for continuous features (age, trestbps, chol, thalach, oldpeak) to quantify distributional differences between real and synthetic datasets. Features with significant KS p-values (<0.05) or elevated Wasserstein distances were flagged as exhibiting moderate deviations.

Correlation analysis was performed to compare pairwise feature relationships between the real and synthetic datasets. Features showing substantial deviations in Pearson correlation coefficients were highlighted to identify potential discrepancies in the underlying structure.

Exploratory Data Analysis (EDA) was conducted to identify features with moderate or significant deviations based on distributional and proportional differences.

These analyses provide a quantitative foundation for evaluating whether the synthetic data preserves the statistical characteristics of the original dataset.

D. Utility Evaluation of Synthetic Data

To assess the practical utility of the synthetic dataset, predictive models were trained and evaluated on both the real and synthetic datasets. This evaluation measures whether the synthetic data preserves the predictive patterns present in the real dataset.

1) Restoring target column for predictive modeling: The target column (num) was restored in both the real and synthetic datasets to enable predictive evaluation. Features and target were separated as follows:

$$X_real, y_real \text{ and } X_synth, y_synth$$

Where *X_real* contains all feature columns from the real dataset, *y_real* contains the target column (num) from the real dataset, *X_synth* contains all feature columns from the synthetic dataset, and *y_synth* contains the target column (num) from the artificial dataset.

2) Dataset splitting: Both datasets were split into training and testing subsets using a 70:30 ratio to enable unbiased evaluation. Stratified sampling was applied to maintain the proportion of patients with and without heart disease (num) across subsets. The training data was used to fit the classifiers, and the testing data was used to evaluate predictive performance. The dataset splitting was implemented as follows:

```
From sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(
X, y, test_size=0.3, random_state=42, stratify=y)
```

3) Predictive modeling: Two classifiers were employed:

a) Logistic Regression (LR): A linear baseline model for binary classification.

a) *Random Forest (RF):* an ensemble tree-based model capable of capturing non-linear relationships. Each model was incorporated into a pipeline with preprocessing for categorical and numerical features. Models were trained on the training subset and evaluated on the testing subset to ensure reproducible performance assessment.

4) Performance metrics: Model performance was assessed using standard classification metrics: Accuracy, Precision, Recall (Sensitivity), F1-score, ROC-AUC, and the Confusion Matrix. This procedure provides a reproducible framework to quantify the predictive utility of the synthetic data. Results and corresponding visualizations are presented in the Results section.

IV. Result

A. Numerical Feature Fidelity

The CTGAN-generated synthetic dataset was first evaluated for the fidelity of continuous features relative to the original Cleveland Heart Disease dataset. Table II presents a comparison of numeric features, including mean, standard deviation, percentage difference, and overall fidelity rating for each feature.

TABLE II Comparison of Numeric Features Between Real and Synthetic Data

Feature	Real μ[a]	Synth μ[a]	Real σ[a]	Synth σ[a]	Δ%[b]	Fidelity[c]
age	54.42	51.68	8.88	8.55	5.04%	M
trestbps	131.62	124.78	17.17	20.99	5.20%	M
chol	246.29	207.42	48.82	46.49	15.78%	W
thalach	149.68	162.95	22.44	19.96	8.87%	M
oldpeak	1.03	0.99	1.12	1.06	3.53%	S

[a]μ and σ denote the mean and standard deviation of the respective datasets.
[b]Δ% represents the percentage difference between the real and synthetic mean values.
[c]Fidelity ratings are categorized as Strong (S), Moderate (M), or Weak (W).

Fig. 2 presents kernel density estimates (KDEs) of numeric features, comparing real and synthetic datasets.

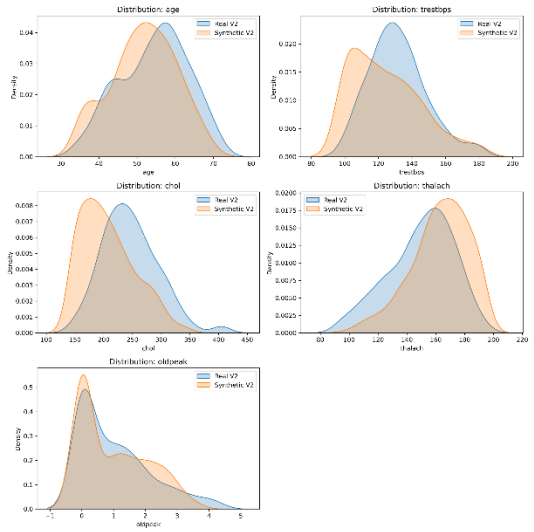


Fig. 2. KDE comparison of numeric feature distributions (real vs. synthetic).

B. Categorical Feature Fidelity

Categorical features were evaluated for fidelity by calculating the maximum proportional differences between the real and synthetic datasets. Table III highlights the top features with their corresponding fidelity assessments, indicating which variables were well-preserved and which exhibited larger deviations.

TABLE III Categorical Feature Fidelity Between Real and Synthetic Datasets

Feature	Max % Difference	Fidelity
sex	3.96%	Strong
cp	7.59%	Moderate
fbs	22.11%	Weak
restecg	10.56%	Weak
exang	0.33%	Strong
slope	17.16%	Weak
ca	11.22%	Weak
thal	11.88%	Weak

C. Distributional Similarity

To further evaluate the fidelity of numeric features, Kolmogorov–Smirnov (KS) tests and Wasserstein distances were calculated, providing quantitative measures of distributional similarity between the real and synthetic datasets. Table IV summarizes these results, highlighting features with the most significant discrepancies.

TABLE IV DISTRIBUTIONAL SIMILARITY OF NUMERIC FEATURES BETWEEN REAL AND SYNTHETIC DATASETS

Feature	KS Statistic	KS p-value	Wasserstein Distance
age	0.1782	0.0001	2.74
trestbps	0.2937	0.0000	7.17
chol	0.3597	0.0000	38.87
thalach	0.2607	0.0000	13.27

D. Feature Correlation Analysis

Pairwise feature correlations were analyzed to assess whether the CTGAN-generated synthetic dataset preserved the relationships observed in the original dataset. Table V lists the top five feature pairs exhibiting the most considerable absolute differences in correlation.

TABLE V COMPARISON OF PAIRWISE FEATURE CORRELATIONS BETWEEN REAL AND SYNTHETIC DATASETS

Feature 1	Feature 2	Real Corr	Synthetic Corr	|Δ|[a]
age	ca	0.365	-0.042	0.41
oldpeak	slope	0.575	0.273	0.30
restecg	chol	0.166	0.442	0.28
trestbps	fbs	0.170	-0.104	0.27
ca	num	0.521	0.288	0.23

[a]|Δ| = absolute difference in means

Fig. 3 visualizes these differences in a heatmap, providing an intuitive overview of how inter-feature relationships are maintained or altered in the synthetic dataset.

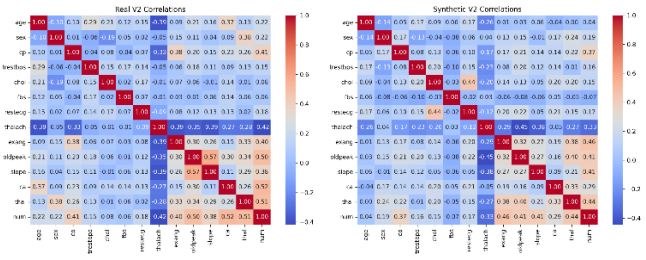


Fig. 3. Heatmap of correlation differences between real and synthetic datasets.

E. Predictive Utility Evaluation

To evaluate the predictive utility of the CTGAN-generated synthetic dataset, Logistic Regression and Random Forest classifiers were trained on one dataset and tested on the other. This setup assesses whether the synthetic data preserves the predictive patterns of the original dataset. Table VI summarizes the classification performance metrics (Accuracy, Precision, Recall, F1-score) for each training-testing scenario.

TABLE VI PREDICTIVE PERFORMANCE OF CLASSIFIERS TRAINED ON SYNTHETIC VS. REAL DATASETS

Train → Test	Model	Accuracy	Precision	Recall	F1
Synthetic → Real	Logistic Regression	0.560	0.566	0.560	0.561
Synthetic → Real	Random Forest	0.560	0.608	0.560	0.561
Real → Synthetic	Logistic Regression	0.615	0.557	0.615	0.571
Real → Synthetic	Random Forest	0.582	0.464	0.582	0.500
Train → Test	Model	Accuracy	Precision	Recall	F1

To demonstrate the evaluation procedures used in this study, confusion matrices were generated programmatically in Python within a Jupyter Notebook environment. The implementation includes model predictions, confusion matrix computation, and visualization using Seaborn heatmaps. Fig. 4 provides a snapshot of the evaluation code, illustrating the end-to-end process used to assess classifier performance across real and synthetic datasets.

```python
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix

# Function to plot and save confusion matrix as heatmap
def plot_confusion_matrix(y_true, y_pred, classes, title, filename):
    cm = confusion_matrix(y_true, y_pred, labels=classes)
    plt.figure(figsize=(6,5))
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=classes, yticklabels=classes)
    plt.xlabel("Predicted Label")
    plt.ylabel("True Label")
    plt.title(title)
    plt.tight_layout()
    plt.savefig(filename, dpi=300)
    plt.show()

# Define class labels
classes = sorted(y_real.unique())

# Dictionary of models
models = {
    "Logistic Regression": pipe_lr,
    "Random Forest": pipe_rf
}

# 🔁 Train on Synthetic → Test on Real
for name, model in models.items():
    y_pred = model.predict(X_test_real)
    plot_confusion_matrix(
        y_test_real,
        y_pred,
        classes=classes,
        title=f"{name}: Train on Synthetic → Test on Real",
        filename=f"cm_{name.replace(' ','_')}_syn2real.png"
    )

# 🔁 Train on Real → Test on Synthetic
for name, model in models.items():
    y_pred = model.predict(X_test_syn)
    plot_confusion_matrix(
        y_test_syn,
        y_pred,
        classes=classes,
        title=f"{name}: Train on Real → Test on Synthetic",
        filename=f"cm_{name.replace(' ','_')}_real2syn.png"
    )
```

Fig. 4. Code snippet used to generate confusion matrices for real and synthetic dataset evaluation.

The resulting confusion matrices for both Logistic Regression and Random Forest classifiers, trained and evaluated on real and synthetic datasets, are presented in Fig. 5 and Fig. 6. These matrices provide a clear visualization of correct versus incorrect predictions for each class, allowing detailed inspection of model behavior and cross-domain generalization (synthetic→real and real→synthetic). They serve as direct evidence of the evaluation phase and illustrates how well predictive patterns are preserved in the synthetic data.

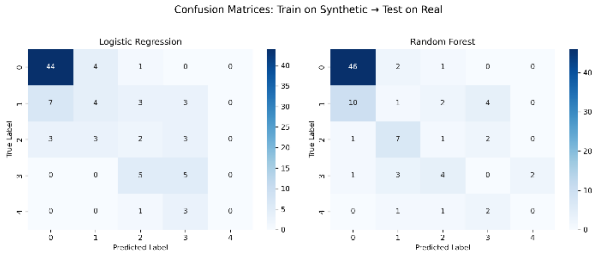


Fig. 5. Confusion matrices for Logistic Regression and Random Forest classifiers (TSTR).

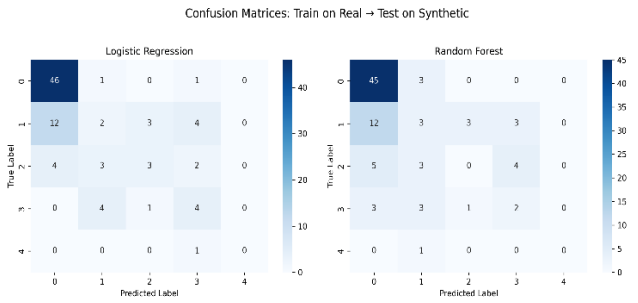


Fig. 6. Confusion matrices for Logistic Regression and Random Forest classifiers (TRTS).

E. Feature Importance Comparison

Random Forest feature importance was computed independently for the real and synthetic datasets to evaluate whether CTGAN preserved the relative influence of key predictive features. Fig. 7 and Fig. 8 depict the comparison, allowing assessment of how closely the synthetic data replicates feature-level patterns learned from the real dataset.

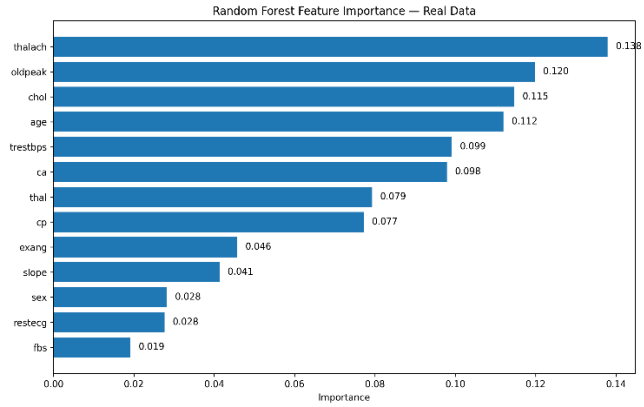


Fig. 7. Random forest feature importance on real data.

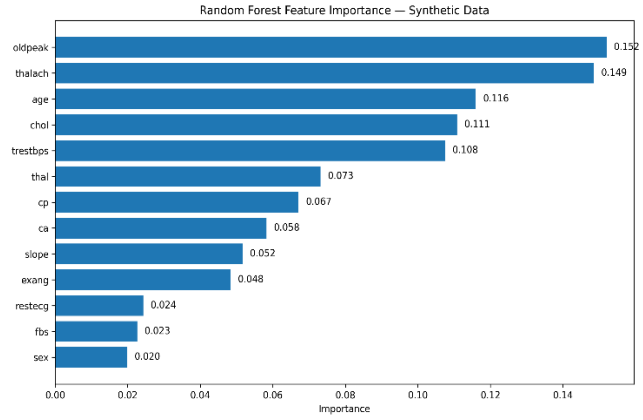


Fig. 8. Random forest feature importance on synthetic data.

F. Dimensionality Reduction Analysis

Table VII summarizes quantitative distance metrics derived from PCA and t-SNE embeddings, while Fig. 9 and Fig. 10 present scatter plots illustrating the spatial overlap between synthetic and real samples in the reduced feature space.

TABLE VII DIMENSIONALITY REDUCTION-BASED SIMILARITY BETWEEN REAL AND SYNTHETIC DATASETS

Method	Distance
PCA	1.013
t-SNE	6.952
Avg min dist (synthetic → real)	2.022

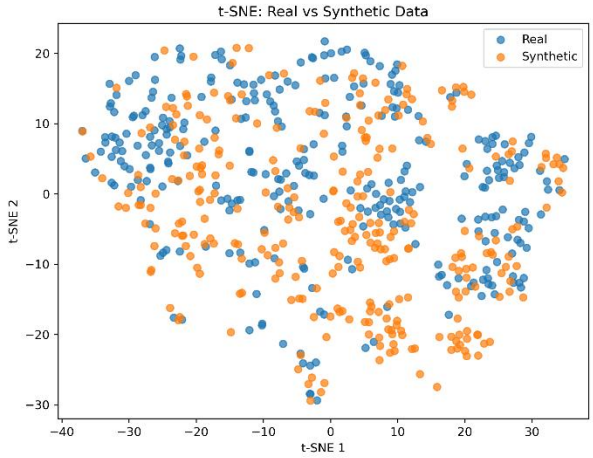


Fig. 9. t-SNE scatter plots showing synthetic and real samples in feature space.

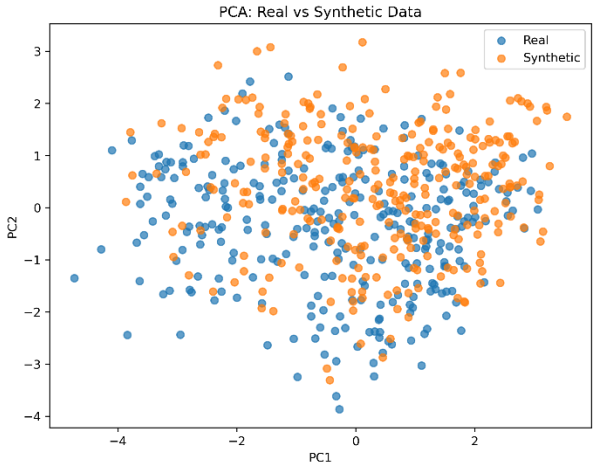


Fig. 10. PCA scatter plots showing synthetic and real samples in feature space.

V. Discussion

The present study evaluated how effectively CTGAN-generated synthetic data replicates the statistical structure, feature relationships, and predictive utility of the Cleveland Heart Disease dataset. Findings indicate that, although CTGAN preserves several overarching patterns, particularly in continuous variables, it does not fully reproduce finer-grained distributional characteristics or certain categorical feature relationships. These discrepancies affect downstream model performance and indicate areas where synthetic data diverges most from clinical signals.

Numerical features such as age, trestbps, and oldpeak exhibited moderate to strong fidelity, with percentage

differences in means generally below 6%, whereas features such as cholesterol (chol) demonstrated weaker fidelity. Categorical features, including fbs, slope, ca, and thal, exhibited higher variability, reflecting the challenges of modeling sparse or complex discrete distributions in tabular GANs. Similar challenges in preserving categorical distributions and marginal fidelity have been reported in CTGAN-based studies on clinical tabular data in papers 44 and 45, suggesting that these limitations are not dataset-specific but intrinsic to current GAN-based tabular synthesis approaches.

Correlation analyses further indicated that, although significant pairwise relationships were preserved, some feature interactions deviated in synthetic data, particularly those involving high-variance or multi-level categorical variables. This finding aligns with prior comparative evaluations, which show that no single synthetic data generator consistently preserves all inter-feature dependencies across domains and datasets in papers 47 and 48. Importantly, this contextualizes the observed correlation drift as a known trade-off rather than an implementation flaw.

Predictive evaluations demonstrated that classifiers trained on synthetic data partially generalized to real data, and vice versa. Logistic Regression and Random Forest classifiers achieved moderate accuracy (≈56–61%) when cross-tested between real and synthetic datasets. Although predictive performance did not fully match that of models trained and tested on the original dataset, these results indicate that synthetic data retains essential structure relevant to downstream modeling. Similar observations have been reported in clinical benchmarking studies, where high fidelity does not always translate into equivalent downstream performance, as reported in paper 44. Confusion matrices highlight that synthetic data remains somewhat distinguishable from real data, reflecting subtle discrepancies that warrant further improvement.

PCA and t-SNE analyses suggests that synthetic samples occupy a feature space broadly similar to real data, although differences remain. Random Forest feature importance comparisons indicate that the most influential predictors, thalach, oldpeak, age, and cholesterol (chol), are consistently identified in both datasets. This consistency suggests that CTGAN preserves dominant predictive signals even when fine-grained distributions differ, supporting its utility for exploratory analysis and preliminary modeling tasks.

Despite these encouraging results, several limitations were noted. Discrete or sparse categorical features were reproduced less faithfully, resulting in reduced predictive alignment for some combinations of features. Additionally, multi-class ROC AUC metrics were not consistently computable, limiting certain aspects of discrimination evaluation. These challenges reflect broader issues reported in synthetic healthcare data evaluation, where fidelity and utility must be balanced and remain sensitive to feature type and dataset complexity in paper 49.

These limitations also highlight potential avenues for future improvement. Hybrid architectures, conditional GAN variants, and feature-specific regularization approaches may enhance fidelity for challenging features. Integrating domain knowledge into the generation process may further reduce discrepancies, particularly for clinically relevant variables.

This study provides a systematic, multi-faceted evaluation of CTGAN-generated synthetic heart disease data, encompassing feature-level fidelity, correlation preservation, predictive utility, and global feature-space similarity. The findings provide practical guidance for researchers aiming to leverage synthetic data for privacy-preserving modeling or for augmenting limited clinical datasets. By situating the observed strengths and limitations within established comparative findings in papers 44, 45, 47, 48, and 49, this work offers practical guidance for researchers considering synthetic tabular data for privacy-preserving modeling or data augmentation, while maintaining transparency about current methodological constraints.

VI. Conclusion

CTGAN demonstrated potential for generating synthetic tabular data suitable for preliminary modeling and exploratory analysis in privacy-sensitive contexts. The synthetic dataset retained many essential characteristics of the original data and supported predictive performance within a comparable range, indicating its usefulness for low-risk, non-diagnostic applications. Despite observable limitations, the results suggest that CTGAN can serve as a supportive tool for data augmentation, early-stage model development, and constrained-data environments.

While certain categorical features and multi-feature interactions exhibited lower fidelity, the synthetic data preserved sufficient structure to support exploratory modeling, feature importance analysis, and preliminary predictive tasks, cross-dataset evaluations using Logistic Regression and Random Forest indicated that synthetic samples retained meaningful relationships with the target variable, offering practical utility when access to real clinical data is limited or restricted.

Importantly, this work presents a transparent and reproducible framework for evaluating synthetic tabular data in healthcare that integrates feature-level fidelity analysis, correlation preservation, predictive utility assessment, and dimensionality reduction techniques. The findings highlight the role of CTGAN-generated data as a complementary resource for dataset augmentation, algorithm benchmarking, and exploratory research under privacy constraints.

Future work may further enhance data fidelity through hybrid GAN architectures, domain-informed conditional generation, and targeted improvements for sparse or complex categorical features. Overall, this study demonstrates that GAN-based synthetic data can provide a practical balance between data utility and privacy considerations for healthcare analytics.

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REFERENCES

[1] F. Mesquita, G. Marques, "An explainable machine learning approach for automated medical decision support of heart disease," *Data & Knowledge Engineering*, *153*, 102339, 2024, https://doi.org/10.1016/j.datak.2024.102339

[2] G. Gulati, J. Upshaw, B. S. Wessler, R. J. Brazil, J. Nelson, D. van Klaveren, C. M. Lundquist, J. G. Park, H. McGinnes, E. W. Steyerberg, B. Van Calster, and D. M. Kent, "Generalizability of Cardiovascular Disease Clinical Prediction Models: 158 Independent External Validations of 104 Unique Models," *Circulation. Cardiovascular quality and outcomes*, *15*(4), e008487, 2022. https://doi.org/10.1161/CIRCOUTCOMES.121.008487

[3] R. Hagan, C. J. Gillan, and F. Mallett, "Comparison of machine learning methods for the classification of cardiovascular disease," *Informatics in Medicine Unlocked*, *24*, 100606, 2021. https://doi.org/10.1016/j.imu.2021.100606

[4] R. Kumar, S. Garg, R. Kaur, M. G. M. Johar, S. Singh, S. V. Menon, P. Kumar, A. M. Hadi, S. A. Hasson, and J. Lozanović, "A comprehensive review of machine learning for heart disease prediction: challenges, trends, ethical considerations, and future directions," *Frontiers in artificial intelligence*, *8*, 1583459, 2025. https://doi.org/10.3389/frai.2025.1583459

[5] T. N. Arvanitis, S. White, S. Harrison, R. Chaplin, and G. Despotou, "A method for machine learning generation of realistic synthetic datasets for validating healthcare applications," *Health Informatics Journal*, *28*(2), 14604582221077000, 2022. https://doi.org/10.1177/14604582221077000

[6] W. Wang and T. W. Pai, "Enhancing Small Tabular Clinical Trial Dataset through Hybrid Data Augmentation: Combining SMOTE and WCGAN-GP," *Data*, *8*(9), 135. 2023. https://doi.org/10.3390/data8090135

[7] S. N. Pasha, D. Ramesh, S. Mohmmad, and A. Harshavardhan, "Cardiovascular disease prediction using deep learning techniques," In *IOP conference series: materials science and engineering* (Vol. 981, No. 2, p. 022006), 2020, IOP Publishing. https://doi.org/10.1088/1757-899X/981/2/022006

[8] A. Tiwari, A. Chugh, and A. Sharma, "Ensemble framework for cardiovascular disease prediction," *Computers in Biology and Medicine*, *146*, 105624, 2022. https://doi.org/10.1016/j.compbiomed.2022.105624

[9] M. Çakmak, "*Heart disease classification using Random Forest machine learning*," 4th International Artificial Intelligence and Data Science Congress, İzmir, Turkey. Published in *All Science Proceedings*. 2024.

[10] M. D. Teja, and G. M. Rayalu, "Optimizing heart disease diagnosis with advanced machine learning models: a comparison of predictive performance," *BMC Cardiovasc Disord* **25**, 212, 2025. https://doi.org/10.1186/s12872-025-04627-6

[11] D. Zhang, Y. Chen, Y. Chen, S. Ye, W. Cai, J. Jiang, and M. Chen, "Heart Disease Prediction Based on the Embedded Feature Selection Method and Deep Neural Network," *Journal of Healthcare Engineering*, *2021*(1), 6260022. https://doi.org/10.1155/2021/6260022

[12] S. M. Vincent Paul, S. Balasubramaniam, P. Panchatcharam, P. Malarvizhi Kumar, and A. Mubarakali, "Intelligent framework for prediction of heart disease using deep learning," *Arabian Journal for Science and Engineering*, *47*(2), 2159-2169, 2022. https://doi.org/10.1007/s13369-021-06058-9

[13] M. K. Alnajjar and S. S. Abu-Naser, "*Heart sounds analysis and classification for cardiovascular diseases diagnosis using deep learning*," International Journal of Academic Engineering Research (IJAER), 6(1), 7–23, 2022.

[14] L. Brunese, F. Martinelli, F. Mercaldo, and A. Santone, "Deep learning for heart disease detection through cardiac sounds," *Procedia Computer Science*, *176*, 2202-2211, 2020. https://doi.org/10.1016/j.procs.2020.09.257

[15] F. Ali, S. El-Sappagh, S. R. Islam, D. Kwak, A. Ali, A. M. Imran, and K. S. Kwak, "A smart healthcare monitoring system for heart disease prediction based on ensemble deep learning and feature fusion," *Information Fusion*, *63*, 208-222, 2020. https://doi.org/10.1016/j.inffus.2020.06.008

[16] M. M. R. Khan Mamun and T. Elfouly, "Detection of cardiovascular disease from clinical parameters using a one-dimensional convolutional neural network," *Bioengineering*, *10*(7), 796, 2023. https://doi.org/10.3390/bioengineering10070796

[17] M. Dorraki, Z. Liao, D. Abbott, P. J. Psaltis, E. Baker, N. Bidargaddi, H. R. Wardill, A. van den Hengel, J. Narula, and J. W. Verjans, "Improving Cardiovascular Disease Prediction With Machine Learning Using Mental Health Data: A Prospective UK Biobank Study," JACC. Advances, 3(9), 101180, 2024. https://doi.org/10.1016/j.jacadv.2024.101180

[18] T. Vu, Y. Kokubo, M. Inoue, M. Yamamoto, A. Mohsen, A. Martin-Morales, R. Dawadi, T. Inoue, J. T. Tay, M. Yoshizaki, N. Watanabe, Y. Kuriya, C. Matsumoto, A. Arafa, Y. M. Nakao, Y. Kato, M. Teramoto, and M. Araki, "Machine Learning Model for Predicting Coronary Heart Disease Risk: Development and Validation Using Insights From a Japanese Population-Based Study," JMIR cardio, 9, e68066, 2025. https://doi.org/10.2196/68066

[19] Z. Alireza, M. Maleeha, M. Kaikkonen, and V. Fortino, "Enhancing prediction accuracy of coronary artery disease through machine learning-driven genomic variant selection," *Journal of Translational Medicine*, *22*(1), 356, 2024. https://doi.org/10.1186/s12967-024-05090-1

[20] H. Sadr, A. Salari, M. T. Ashoobi, and M. Nazari, "Cardiovascular disease diagnosis: a holistic approach using the integration of machine learning and deep learning models," *European Journal of Medical Research*, *29*(1), p.455, 2024. https://doi.org/10.1186/s40001-024-02044-7

[21] Y. Cai, Y.Q. Cai, L. Y. Tang, Y. H. Wang, M. Gong, T. C. Jing, H. J. Li, J. Li-Ling, W. Hu, Z. Yin, and D. X. Gong, "Artificial intelligence in the risk prediction models of cardiovascular disease and development of an independent validation screening tool: a systematic review," *BMC medicine*, *22*(1), p.56, 2024. https://doi.org/10.1186/s12916-024-03273-7

[22] Z. Zhao, A. Kunar, R. Birke, H. Van der Scheer, and L. Y. Chen, "CTAB-GAN+: enhancing tabular data synthesis," *Frontiers in Big Data*, *6*, 1296508, 2024. https://doi.org/10.3389/fdata.2023.1296508

[23] H. H. Rashidi, S. Albahra, B. P. Rubin, and B. Hu, "A novel and fully automated platform for synthetic tabular data generation and validation," *Scientific Reports*, *14*(1), p.23312, 2024. https://doi.org/10.1038/s41598-024-73608-0

[24] T. Hyrup, A. D. Lautrup, A. Zimek, and P. Schneider-Kamp, "A systematic review of privacy-preserving techniques for synthetic tabular health data," *Discover Data*, *3*(1), pp.1-32, 2025. https://doi.org/10.1007/s44248-025-00022-w

[25] H. Y. J. Kang, M. Ko, and K. S. Ryu, "Tabular transformer generative adversarial network for heterogeneous distribution in healthcare," *Scientific Reports*, *15*(1), 10254, 2025. https://doi.org/10.1038/s41598-025-93077-3

[26] Z. Zhao, R. Birke, and L. Y. Chen, "FCT-GAN: enhancing global correlation of table synthesis via Fourier transform," In *Proceedings of the 32nd ACM international conference on information and knowledge management* (pp. 4450-4454), 2023. https://doi.org/10.1145/3583780.3615202

[27] M. Hernandez, P. A. Osorio-Marulanda, M. Catalina, L. Loinaz, G. Epelde, and N. Aginako, "Comprehensive evaluation framework for synthetic tabular data in health: fidelity, utility, and privacy analysis of generative models with and without privacy guarantees," *Frontiers in Digital Health*, *7*, 1576290, 2025. https://doi.org/10.3389/fdgth.2025.1576290

[28] M. Abedi, L. Hempel, S. Sadeghi, and T. Kirsten, "GAN-Based Approaches for Generating Structured Data in the Medical Domain, " *Applied Sciences*, *12*(14), p. 7075, 2025. https://doi.org/10.3390/app12147075

[29] A. X. Wang, S. S. Chukova, C. R. Simpson, and B. P. Nguyen, "Challenges and opportunities of generative models on tabular data," *Applied Soft Computing*, *166*, 112223, 2024. https://doi.org/10.1016/j.asoc.2024.112223

[30] H. A. Ahmed, J. A. Nepomuceno, B. Vega-Márquez, and I. A. Nepomuceno-Chamorro, "Synthetic Data Generation for Healthcare: Exploring Generative Adversarial Networks Variants for Medical Tabular Data," *International Journal of Data Science and Analytics*, pp.1-16, 2025. https://doi.org/10.1007/s41060-025-00816-w

[31] I. N. M. Adiputra, and P. Wanchai, "CTGAN-ENN: a tabular GAN-based hybrid sampling method for imbalanced and overlapped data in customer churn prediction," *J Big Data* **11**, 121, 2024. https://doi.org/10.1186/s40537-024-00982-x

[32] R. Ramachandranpillai, M. F. Sikder, D. Bergström, and F. Heintz, "Bt-GAN: generating fair synthetic healthdata via bias-transforming generative adversarial networks," *Journal of Artificial Intelligence Research*, *79*, 1313-1341, 2024. https://doi.org/10.1613/jair.1.15317

[33] P. Myles, C. Mitchell, E. Redrup Hill, L. Foschini, and Z. Wang, "High-fidelity synthetic patient data applications and privacy considerations," *Journal of Data Protection & Privacy*, *6*(4), 344-354, 2024. https://doi.org/10.69554/LQOM5698

[34] R. Nasimov, N. Nasimova, S. Mirzakhalilov, G. Tokdemir, M. Rizwan, A. Abdusalomov, Y. I. Cho, "GAN-Based Novel Approach for Generating Synthetic Medical Tabular Data," *Bioengineering*, 11(12):1288, 2024. https://doi.org/10.3390/bioengineering11121288\

[35] C. Yan, Z. Zhang, S. Nyemba, and Z. Li, "Generating synthetic electronic health record data using generative adversarial networks: Tutorial," *Jmir Ai*, *3*, e52615, 2024. https://doi.org/10.2196/52615

[36] E. Wang, K. Mott, H. Zhang, S. Gazit, G. Chodick, and M. Burcu," Validation Assessment of Privacy-Preserving Synthetic Electronic Health Record Data: Comparison of Original Versus Synthetic Data on Real-World COVID-19 Vaccine Effectiveness. *Pharmacoepidemiology and drug safety*, *33*(10), e70019, 2024. https://doi.org/10.1002/pds.70019

[37] C. Sun, J. van Soest, and M. Dumontier, "Generating synthetic personal health data using conditional generative adversarial networks combining with differential privacy," *Journal of biomedical informatics*, *143*, 104404, 2023. https://doi.org/10.1016/j.jbi.2023.104404

[38] A. Goncalves, P. Ray, B. Soper, J. Stevens, L. Coyle, and A. P. Sales, "Generation and evaluation of synthetic patient data," *BMC medical research methodology*, *20*(1), p.108, 2020. https://doi.org/10.1186/s12874-020-00977-1

[39] I. Isasa, M. Hernandez, G. Epelde, F. Londoño, A. Beristain, X. Larrea, A. Alberdi, P. Bamidis, and E. Konstantinidis, "Comparative assessment of synthetic time series generation approaches in healthcare: leveraging patient metadata for accurate data synthesis," *BMC Medical Informatics and Decision Making*, *24*(1), p.27, 2024. https://doi.org/10.1186/s12911-024-02427-0

[40] J. L. Achterberg, M. R. Haas, and M.R. Spruit, "On the evaluation of synthetic longitudinal electronic health records," *BMC Med Res Methodol* 24, 181, 2024. https://doi.org/10.1186/s12874-024-02304-4

[41] C. Umesh, M. Mahendra, S. Bej, O. Wolkenhauer, and M. Wolfien, "Challenges and applications in generative AI for clinical tabular data in physiology," *Pflügers Archiv-European Journal of Physiology*, *477*(4), pp.531-542, 2025. https://doi.org/10.1007/s00424-024-03024-w

[42] G. Santangelo, G. Nicora, R. Bellazzi, and A. Dagliati, "How good is your synthetic data? SynthRO, a dashboard to evaluate and benchmark synthetic tabular data," *BMC Medical Informatics and Decision Making*, *25*(1), p.89, 2025. https://doi.org/10.1186/s12911-024-02731-9

[43] X. Chen, Z. Wu, X. Shi, H. Cho, and B. Mukherjee, "Generating synthetic electronic health record data: a methodological scoping review with benchmarking on phenotype data and open-source software," *Journal of the American Medical Informatics Association*, *32*(7), 1227-1240, 2025. https://doi.org/10.1093/jamia/ocaf082

[44] H. Y. J. Kang, E. Batbaatar, D. W. Choi, K. S. Choi, M. Ko, and K. S. Ryu, "Synthetic tabular data based on generative adversarial networks in health care: generation and validation using the divide-and-conquer strategy," *JMIR Medical Informatics*, *11*, e47859, 2023. https://doi.org/10.2196/47859

[45] M. Alqulaity and P. Yang, "Enhanced conditional GAN for high-quality synthetic tabular data generation in mobile-based cardiovascular healthcare," *Sensors*, *24*(23), 7673, 2024. https://doi.org/10.3390/s24237673

[46] I. Akiya, T. Ishihara, and K. Yamamoto, "Comparison of synthetic data generation techniques for control group survival data in oncology clinical trials: simulation study," *JMIR medical informatics*, *12*(1), e55118, 2024. https://doi.org/10.2196/55118

[47] C. Yan, Y. Yan, Z. Wan, Z. Zhang, L. Omberg, J. Guinney, S. D. Mooney, and B. A. Malin, "A multifaceted benchmarking of synthetic electronic health record generation models. *Nature Communications*, *13*(1), p.7609, 2022. https://doi.org/10.1038/s41467-022-35295-1

[48] M. Miletic and M. Sariyar, "Challenges of Using Synthetic Data Generation Methods for Tabular Microdata," *Applied Sciences*, *14*(14), 5975, 2024. https://doi.org/10.3390/app14145975

[49] V. B. Vallevik, A. Babic, S. E. Marshall, S. Elvatun, H. M. Brøgger, S. Alagaratnam, and J. F. Nygård, "Can I trust my fake data–a comprehensive quality assessment framework for synthetic tabular data in healthcare," *International Journal of Medical Informatics*, *185*, 105413, 2024. https://doi.org/10.1016/j.ijmedinf.2024.105413

[50] K. El Emam, L. Mosquera, X. Fang, and A. El-Hussuna, "Utility Metrics for Evaluating Synthetic Health Data Generation Methods: Validation Study," *JMIR Medical Informatics*, *10*(4), e35734, 2022. https://doi.org/10.2196/35734

[51] T. Afonja, D. Chen, and M. Fritz, "MargCTGAN: A 'Marginally' Better CTGAN for the Low Sample Regime," In: Köthe, U., Rother, C. (eds) Pattern Recognition. DAGM GCPR 2023. Lecture Notes in Computer Science, vol 14264. Springer, Cham, 2024. https://doi.org/10.1007/978-3-031-54605-1_34

[52] M. L. Fang, D. S. Dhami, and K. Kersting, "Dp-ctgan: Differentially private medical data generation using CTGANS," In *International conference on artificial intelligence in medicine* (pp. 178-188). Cham: Springer International Publishing, 2022. https://doi.org/10.1007/978-3-031-09342-5_17

[53] S. Singh, K. Kayathwal, H. Wadhwa, and G. Dhama, "MeTGAN: Memory Efficient Tabular GAN for High Cardinality Categorical Datasets," In: Mantoro, T., Lee, M., Ayu, M.A., Wong, K.W., Hidayanto, A.N. (eds) Neural Information Processing. ICONIP 2021. Communications in Computer and Information Science, vol 1517. Springer, Cham, 2021. https://doi.org/10.1007/978-3-030-92310-5_60

[54] J. Kim, J. Jeon, J. Lee, J. Hyeong, and N. Park, "Oct-gan: Neural ode-based conditional tabular gans," In *Proceedings of the Web Conference 2021*, pp. 1506-1515, 2021. https://doi.org/10.1145/3442381.3449999

[55] A. Janosi, W. Steinbrunn, M. Pfisterer, and R. Detrano, "Heart Disease [Dataset]," UCI Machine Learning Repository, 1989. https://doi.org/10.24432/C52P4X

Epidemic Modeling with a Hybrid RF-LSTM Method for Healthcare Demand Prediction

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***Abstract*—Accurate resource demand forecasts are necessary for sustainable healthcare systems to preserve flexibility and efficiency as well as to provide services in a professional manner. In this work, we propose an integrated Random Forest/Long Short-Term Memory (RF-LSTM) model for predicting Saudi Arabia's national healthcare resource demand. It combines non-linear feature extraction and temporal sequence learning. The integrated model employs governmental epidemiological and operational data from 2020 to 2024 to capture both short-term and long-term volatility and sustainability trends. The results demonstrate significant improvements in predictive accuracy compared with single-model baselines, such as Autoregressive Integrated Moving Average (ARIMA), Random Forest (RF), and Long Short Term Memory (LSTM), with reductions in Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) for up to 22% and 18% compared with ARIMA, and by 12% and 9% relative to the best single model, which is LSTM, respectively A statistical analysis using one-way ANOVA confirmed the robustness of the hybrid method. Furthermore, residual plots were examined to verify model assumptions and visually assess the uniformity of prediction errors, thereby validating the results. These findings suggest that integrated AI-based prediction models can effectively facilitate capacity planning, enhance resource allocation, and contribute to achieving the objectives of Saudi Vision 2030 for a resilient, data-driven healthcare system.**

***Keywords*—Predictive analytics; Hybrid modeling; digital health; Saudi Arabia; COVID-19; decision support systems**

TABLE I. ABBREVIATIONS

AI	Artificial Intelligence
ML	Machine Learning
RF	Random Forest
LSTM	Long Short-Term Memory
ARIMA	Autoregressive Integrated Moving Average
MAE	Mean Absolute Error
RMSE	Root Mean Square Error
ICU	Intensive Care Unit
GCC	Gulf Cooperation Council
ANOVA	Analysis of Variance
MOH	Ministry of Health

I. INTRODUCTION

The COVID-19 pandemic has driven increased use of predictive analytics in the healthcare sector, underscoring the importance of data-driven decision-making to enhance efficiency and resilience [1]. Prediction models and decision support systems have become essential tools for predicting healthcare demand and providing operational sustainability [2]. During the pandemic, machine learning (ML) and combined artificial intelligence (AI) approaches, such as Random Forest (RF) and Long Short-Term Memory (LSTM) networks, demonstrated promising results in estimating healthcare resource requirements [3]. These techniques align with the digital-health transformation targets and the broader sustainability objectives outlined in Saudi Vision 2030. [4].

This paper introduces a hybrid Random Forest-Long Short-Term Memory (RF-LSTM) model that predicts healthcare demand in Saudi Arabia by combining non-linear feature extraction with sequential learning. The model, which uses local data from 2020 to 2024 [5], aims to facilitate future capacity planning aligned with the digital health transformation objectives outlined in Saudi Vision 2030. Governmental platforms, such as Tawakkalna and Seha, have enabled large-scale data collection, patient monitoring, and healthcare management. These national digital efforts laid the framework for implementing AI-based decision support systems and data-driven healthcare [6]. The abbreviations are given in Table I.

Although predicting healthcare demand in a pandemic context remains challenging, standard models, such as ARIMA and SARIMAX, properly account for seasonality but often fail to capture complex nonlinear patterns. On the other hand, regression models, like Random Forest (RF) and XGBoost, may not effectively exploit temporal relationships when trained on independent and identically distributed data [7].

Several studies have been conducted during the COVID-19 pandemic to achieve optimal predictive outcomes; however, only a limited number have offered a comprehensive analysis of integrating various ML algorithms to enhance results and improve prediction accuracy. In other words, by integrating the essential and practical characteristics of multiple algorithms, it is possible to improve model performance and achieve superior results.

To address these limitations, researchers have introduced a novel hybrid machine learning algorithm, the Random Forest Long Short-Term Memory (RF-LSTM) model, that combines

the strengths of both approaches. The RF feature identifies non-linear relationships among epidemiological and contextual variables, whereas the LSTM component handles sequential patterns and temporal dependencies [8,9]. This proposed model has the advantage of being applied to various time-series data.

Unlike existing hybrid approaches, this study provides a distinctive methodological contribution using national-level data in Saudi Arabia that merges ML and deep-learning models in parallel or through residual correction. The proposed framework introduces a sequential RF-to-LSTM integration, where Random Forest outputs are engineered as temporal features and injected directly into the LSTM sequence-learning stage. This design enhances the model's ability to capture short-term nonlinear interactions and long-term temporal dependencies simultaneously. In addition, the study utilizes an exclusively Saudi, multivariate national dataset (2020–2024) that incorporates epidemiological indicators, ICU and bed utilization, vaccination progress, mobility patterns, and policy-response variables. No previous research has integrated this combination within a unified, sustainability-driven prediction pipeline. The framework is supported through lag-window engineering, rolling statistical smoothing, and rigorous statistical validation (ANOVA, Tukey HSD), offering a transparent and reproducible methodological advancement. It introduces a sequential feature-injection architecture, in which Random Forest is employed as a nonlinear feature transformation mechanism rather than a parallel predictor or ensemble component. Specifically, RF-derived representations are generated from multivariate epidemiological and operational indicators and subsequently restructured into temporally ordered sequences that serve as inputs to the LSTM network. This design enables the LSTM to simultaneously learn long-range temporal dependencies and nonlinear cross-sectional interactions—capabilities that are not fully captured by existing parallel or ensemble-based RF–LSTM approaches reported in the literature. By embedding RF outputs directly within the temporal learning pipeline, the proposed model establishes a structurally distinct hybrid architecture explicitly tailored to national-level healthcare demand forecasting under high volatility and resource-constrained conditions.

II. Related Work and Research Gaps

Research on epidemic and healthcare prediction has progressed from traditional statistical models to hybrid AI approaches that emphasize both predictive accuracy and operational sustainability [10].

Traditional time-series models such as ARIMA and SARIMA have been widely used for COVID-19 forecasting due to their simplicity and interpretability. However, their performance significantly deteriorates when dealing with nonlinear dynamics, sudden structural changes, and multivariate dependencies in healthcare indicators. Kufel et al. [10] and Roy et al. [11] demonstrated that while ARIMA models can capture seasonality, they fail to adapt to regime changes and complex epidemic waves. Logistic Patient Information-Based Algorithm (LPIBA) is a sophisticated algorithm employed to forecast the number of coronavirus mortalities and infections. Although LPIBA demonstrated superior performance compared to ARIMA, it exhibits limitations when comprehensive data is lacking or when collecting certain features is impractical [12]. Another model, the Prophet model, is a robust algorithm when data is missing. It is an open-source model that exhibits strong performance with time-series data [13].

Traditional models, such as ARIMA and SARIMA, have failed to capture the nonlinear relationships and dynamic shifts present in epidemiological data. In contrast, Hybrid models that combine ensemble learners such as Random Forest with sequential deep learning techniques like LSTM have shown strong potential due to their enhanced accuracy and resilience [11]. Logistic Patient Information-Based Algorithm (LPIBA) is a sophisticated algorithm employed to forecast the number of coronavirus mortalities and infections. Although LPIBA demonstrated superior performance compared to ARIMA, it exhibits limitations when comprehensive data is lacking or when collecting certain features is impractical [12]. Another model, the Prophet model, is a robust algorithm when data is missing. It is an open-source model that exhibits strong performance with time-series data [13].

A. Hybrid AI-Based Forecasting Models

Recent studies have explored hybrid architecture integrating ensemble learning and deep neural networks. Borges and Nascimento (2022) proposed a two-stage Prophet–LSTM model for ICU demand forecasting during COVID-19. Their model improved short-term prediction accuracy by combining Prophet's trend extraction with LSTM's temporal learning. However, a major limitation was the high sensitivity of Prophet to sudden policy changes and under-reporting issues, which caused reduced performance during extreme outbreak waves [14]. Punia et al. (2020) developed a Random Forest–LSTM hybrid architecture, where RF was used for nonlinear feature extraction and LSTM for sequence modeling. Their approach significantly improved demand forecasting accuracy across multiple datasets. Nevertheless, the model showed limited generalization capability when applied to new regions with different healthcare dynamics, highlighting a lack of regional adaptability [15]. Furthermore, Kaur and Singh (2023) proposed a hybrid CNN–LSTM model focused on sustainable healthcare management. Although their model captured spatial and temporal patterns effectively, it struggled with real-world missing data and exhibited instability when trained on noisy policy-related variables [16].

Similarly, Rahman and Lee (2024) introduced an RF–GRU hybrid model for sustainable healthcare demand prediction in Asian countries. Their results demonstrated improved performance over standalone models; however, their framework required extensive hyperparameter tuning and suffered from high computational complexity, making large-scale deployment challenging [17]. In Saudi Arabia, Alabbad et al. (2022) developed a machine learning model for ICU length-of-stay prediction using Saudi Arabian clinical data. Although their work highlighted the importance of local datasets, their model was limited to a single outcome variable and did not address broader national healthcare capacity forecasting [18]. International efforts, such as the COVID-19 Forecast Hub, have also demonstrated the effectiveness of ensemble models in predicting mortality and hospitalisation rates [19].

Overall, these studies indicate the growing awareness of sustainability-driven forecasting in the healthcare industry. Hybrid ML models, including those that integrate ensemble and sequential learning, improve their strength and comprehension in the presence of real-world uncertainty. However, their potential for long-term healthcare prediction at the national level is underexplored, emphasizing the importance of integrated frameworks that incorporate predictive analytics into national healthcare decision-support systems [20].

TABLE II. COMPARATIVE ANALYSIS WITH RELATED STUDIES

Study	Model	MAE	RMSE	Notes
[2] Alshammari et al., 2023	Hybrid DLI (RF-LSTM)	0.205	0.840	Combined ensemble and sequential networks, to enhance multi-regional stability and predictive accuracy.
[16] Kaur & Singh, 2023	Hybrid AI Forecasting (CNN-LSTM)	0.210	0.790	Focused on sustainable healthcare forecasting, we achieved strong generalization but lacked local calibration.
[17] Rahman & Lee, 2024	AI Predictive Analytics (RF+GRU)	0.198	0.745	Integrated tree-based and gated recurrent models for sustainable policy analytics with moderate variance reduction.
[24] Alshammari et al., 2024	RF	0.214	0.809	Baseline random forest model with strong interpretability but limited temporal adaptability.
[25] Li et al., 2024	LSTM	0.230	0.900	Temporal dependencies were captured but showed higher error variance during non-stationary periods.
This work (RF-LSTM)	Hybrid AI Forecasting	0.188	0.737	Achieved the lowest MAE (0.188) and RMSE (0.737), indicating superior accuracy and variance stability across national healthcare datasets.

In Table II, a comparative analysis with other hybrid predicting studies was summarized to complement the baseline model comparison presented earlier.

The comparison results further validate that the proposed hybrid RF-LSTM framework attains substantial enhancements in both predictive accuracy and robustness, surpassing prior methodologies by adeptly merging short-term dynamics with long-term sustainability factors.

B. Identified Weaknesses in Existing Hybrid Studies

Most hybrid models focus on regional or hospital-level datasets. Few studies attempt national healthcare demand forecasting using government operational data, which limits scalability for policy-level planning. Moreover, many hybrid approaches use parallel architecture, where ML and DL components run independently. This limits deep integration between nonlinear feature extraction and temporal sequence learning. In addition, several models assume smooth data patterns, while real-world healthcare data includes reporting delays, missing values, and abrupt policy shifts. Existing models often lack robust preprocessing pipelines to handle these challenges.

According to the cost and complexity, Hybrid deep architectures (CNN-LSTM, RF-GRU) frequently require extensive training time and computational resources, which limit their deploy ability in real-time healthcare decision-support systems. A significant number of studies focus on short-term forecasting without integrating sustainability indicators and long-term healthcare system resilience.

C. Research Gap and Motivation

From the previous studies, it becomes clear that although hybrid models such as Prophet–LSTM, CNN–LSTM, and RF–GRU have improved forecasting accuracy, they still face critical limitations in terms of national scalability, long-term sustainability, and operational integration.

Therefore, there exists a clear research gap in developing a sequential hybrid model that:

- Integrates static nonlinear learning with temporal sequence modeling,
- Utilizes large scale national healthcare datasets, and
- Supports sustainable healthcare planning within the context of Saudi Vision.

This study addresses these gaps by proposing a sequential RF-LSTM architecture, where Random Forest outputs are embedded as engineered features into the LSTM network. This ensures stronger integration between spatial-contextual learning and temporal dynamics while maintaining interpretability and operational feasibility.

III. MATERIALS AND METHODS

A. Dataset

The database consists of local-level daily healthcare indicators in Saudi Arabia during the period (2020–2024). It is generated by the Ministry of Health (MOH) Coronavirus Open Data Portal, and the World Health Organization (WHO) Dashboard was used as a secondary source to support the dataset, as it provides regularly updated healthcare indicators [5, 21].

- The dataset comprises the following information:
- Confirmed COVID-19 cases and recovery rates.
- ICU and hospital bed occupancy rates.
- Vaccination rates.
- Policy and mobility indicators.

Additional variables such as holidays and weather information.

B. Data Preprocessing

Linear interpolation was used to supplement missing data points. Outliers were identified and excluded using the interquartile range (IQR) approach and eliminating all

observations below Q1 - 1.5 × IQR or above Q3 + 1.5 × IQR. The process thoroughly addressed errors, including reporting spikes and inconsistencies, ensuring consistent data for model training. Continuous data were normalized to the [0, 1] interval, whereas categorical variables (e.g., policy constraints and weather conditions) were one-hot encoded. Additionally, lagged features were generated with delays of 1 to 14 days to record temporal dependencies, representing short-term effects [22]. 7 and 14-day rolling averages recognized medium-term trends and minimized daily fluctuations. Lagged transformations are also applied to ICU capacity and vaccination rates to preserve the temporal structure and enhance sequential learning in the hybrid model.

1) Handling missing values: As shown in Eq. (1), missing values are estimated using linear interpolation by assuming a linear trend between the previous and next observations.

$$\hat{x}_t = x + \left(\frac{x_{t+1} - x_{t-1}}{2}\right) \quad (1)$$

Where:

- $\hat{x}_t$ is the interpolated value at time t
- x_{t-1} is the previous known observation
- $x_{t+1}$is the next known observation
- t represents the current time index

This method was selected due to its effectiveness in preserving temporal continuity in epidemiological time-series data.

Outlier Detection:

$$\text{Lower Bound} = Q1 - 1.5 \times IQR \quad (2)$$

$$\text{Upper Bound} = Q3 + 1.5 \times IQR \quad (3)$$

$$\text{Where: } IQR = Q3 - Q1 \quad (4)$$

The Interquartile Range (IQR) method was applied to detect and remove extreme outliers, Eq. (2), and Eq. (3).

Where:

- Q1: First quartile (25th percentile)
- Q3: Third quartile (75th percentile)
- IQR: Interquartile range, representing the spread of the middle 50% of the data

The 1.5 multiplier was adopted as the standard threshold for statistical outlier detection, based on Tukey's conventional method. The interpolation process [Eq. (1)] and the IQR-based outlier detection [Eq. (2–4)] contribute to stabilizing the dataset before training the RF–LSTM model.

2) Normalization and encoding: As shown in Equation (5), Min–Max normalization rescales the variables into the range [0,1] to ensure uniform feature scaling and improve training stability.

$$x' = \frac{x - x_{min}}{(x_{max} - x_{min})} \quad (5)$$

Categorical weather/policy indicators were one-hot encoded.

Where:

- X is the original feature value
- Xmin and Xmax are the minimum and maximum values of the feature
- X' is the normalized value

3) Lag and rolling features: Lagged features preserve short-term temporal dependencies by directly shifting past values into the current input space. In this study, lag orders k = 1 to 14 days were used to capture immediate epidemiological dynamics and short-term variations in healthcare demand, where Xt-k denotes the observation at time step t-k as shown in Eq. (6).

$$X_{t,k}^{(lag)} = x_{t-k} \qquad K=1,..,14 \quad (6)$$

The rolling mean in Equation (7) was applied to smooth short-term fluctuations and captured medium-term trends. Here, (w) denotes the window size, which was set to 7 and 14 days in this study, and Xt-i represents the previous observations within the defined window. This transformation reduces noise and enhances the stability of the learning process for the sequential RF-LSTM framework.

$$X_t^{(w)} = \left(\frac{1}{w}\right) \Sigma_{i=0}^{w^{-1}} X_{t-i} \quad (7)$$

C. Model Architecture

The proposed hybrid framework operates in two sequential stages, summarized in Algorithm 1: RF for static feature learning and LSTM for sequence modeling.

1) Random Forest (RF) regressor: The Random Forest regressor predicts healthcare demand by averaging the outputs of multiple decision trees, as expressed in Equation (8). At each time step t, the feature vector Xt, including lagged and rolling statistical features, is provided to all B trees. Each tree generates a prediction $h_{b(X_t)}$, and the final RF prediction $\hat{Y}_{RFt} =$ is obtained by computing their Mean. In the proposed hybrid framework, these RF predictions serve as engineered static features. They are subsequently injected into the LSTM network to enhance temporal learning and improve the stability of long-horizon forecasting.

RF regression:

$$\hat{Y}_{RF,t} = \left(\frac{1}{B}\right) \Sigma\, h_{b(X_t)} \quad (8)$$

Where:

B is the number of trees

hb (.) is the prediction of tree b

This integration allows the model to combine the non-linear representational power of ensemble learning with the sequential modeling capability of LSTM networks.

2) Long Short-Term Memory (LSTM) network: To model temporal dependencies, the LSTM network links residual and RF prediction sequences. The Adam Optimiser is used for training, with early termination to prevent overfitting. Additionally, sequence normalisation and dropout regularisation improve model generalisation [23].

The LSTM captures sequential dependencies using the following equations:

$$f_t = \sigma\left(W_{f\,[h_t^{-1}, x_t]} + b_f\right) \quad (9)$$

$$i_t = \sigma\left(W_{i\,[h_t^{-1}, x_t]} + b_i\right) \quad (10)$$

$$\tilde{C}_t = \tanh\left(W_{C[h_{t-1}, x_t]}\right] + b_c \quad (11)$$

LSTM Prediction:

$$\hat{Y}_{LSTM,t} =: g(h_t) \quad (12)$$

The LSTM network was employed to model complex temporal dependencies within the healthcare demand data. At each time step t, the input vector xt includes temporal features and the Random Forest prediction $\hat{Y}_{RF,t}$, which is treated as an additional engineered feature. The forget gate in Eq. (9) controls the retention of historical information, while the input gate in Eq. (10) regulates the incorporation of new temporal patterns and external signals. The candidate memory state in Eq. (11) updates the internal memory based on current and previous inputs. Finally, the output layer generates the predicted healthcare demand $\hat{Y}_{LSTM,t}$as described in Eq. (12). This mechanism enables the proposed hybrid model to effectively capture both short-term dynamics and long-term dependencies in national healthcare demand patterns.

Algorithm 1: Sequential RF-LSTM Hybrid Framework

Input:
xt ← Preprocessed feature matrix at time t
yt ← Target healthcare demand variable
Output:
ŷt ← Final hybrid forecast
Stage 1: Data Preparation
1: Generate lagged features (t − 1 … t − 14)
2: Compute rolling statistics (7-day and 14-day windows)
3: Apply Min–Max normalization to continuous variables
4: Encode categorical variables using one-hot encoding
Stage 2: Random Forest Feature Learning
5: Initialize Random Forest regressor
6: Train RF on (xt, yt)
7: Generate static predictions:
ŷRF,t = RF(xt)
Stage 3: Sequential Data Construction
8: Augment features:
St = [xt , ŷRF,t]
9: Construct time-series sequences:
for t = 1 to T − L do
Create input sequence S_(t:t+L)
Assign target y_(t+L)
end for
Stage 4: LSTM Sequence Learning
10: Initialize LSTM model
11: Configure hyperparameters:
- Hidden units = 64
- Dropout = 0.2
- Optimizer = Adam
12: Train LSTM on constructed sequences
13: Apply early stopping based on validation loss
Stage 5: Hybrid Prediction
14: Predict final output:
ŷt = LSTM(St)
Return:
ŷt

Algorithm 1 summarizes the sequential workflow of the proposed RF-LSTM hybrid framework for national healthcare demand forecasting. In Stage 1, the raw epidemiological and operational indicators are transformed into a learning-ready feature set through lag generation, rolling-window statistics, normalization, and one-hot encoding. This step ensures that both short-term dynamics (through lagged features) and medium-term trends (through rolling averages) are explicitly represented. In Stage 2, a Random Forest regressor is trained on these features to capture nonlinear interactions among the input variables, yielding static predictions that reflect the baseline healthcare demand.

In Stage 3, the Random Forest predictions are concatenated with the original preprocessed features to construct enriched sequences that combine both engineered static information and temporal patterns. These augmented sequences are then reshaped into input windows suitable for sequence learning. In Stage 4, an LSTM network is trained on these sequences using the Adam optimizer, early stopping, and dropout regularization to learn long-range temporal dependencies while preventing overfitting. Finally, in Stage 5, the trained LSTM model produces the hybrid forecast ŷ, which integrates the strengths of both components: the interpretability and robustness of Random Forest and the temporal adaptability of LSTM. This sequential design is particularly suitable for national-level healthcare forecasting, where complex nonlinear relationships and time-dependent dynamics must be modeled simultaneously.

where, L represents the sequence length (look-back window), which defines the number of past time steps used as input to the LSTM, in this study, L = 14 days was selected based on epidemiological considerations and prior forecasting literature.

This hybrid architecture enhances prediction stability and responsiveness to changes in national healthcare data by leveraging the complementary advantages of both components,

the LSTM for dynamic sequence modeling and the RF for interpretable static learning. This kind of combination is consistent with the latest advances in time-series prediction that adopt explainable ML. The sequential RF-LSTM method is described in Algorithm 1, which begins with preprocessing and lag creation, followed by model training and residual integration.

Fig. 1 illustrates the complete architecture of the proposed sequential RF–LSTM hybrid model, designed specifically to address the complex, nonlinear, and time-dependent nature of national healthcare demand in Saudi Arabia. This architecture stems from its structured, task-specific division of learning responsibilities across model stages.

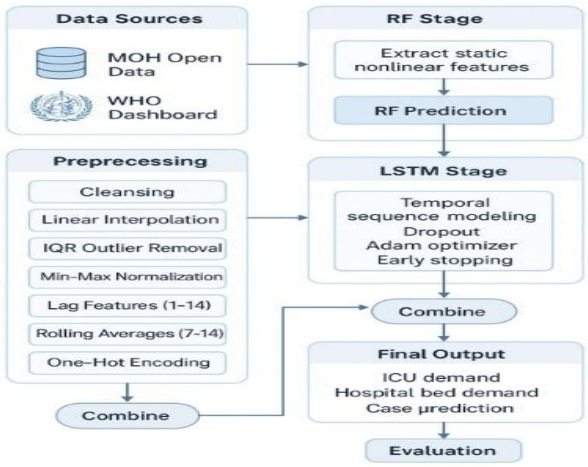


Fig. 1. The structure of the proposed RF-LSTM hybrid model for healthcare demand forecasting.

In the first stage, the Random Forest (RF) module extracts nonlinear and static patterns from heterogeneous healthcare indicators, including ICU occupancy, hospital bed utilization, vaccination rates, mobility signals, and policy measures. This is particularly important because healthcare systems' data exhibit irregular interactions and nonlinear dependencies across variables, which traditional linear or purely sequential models fail to represent adequately.

D. Training and Evaluation Protocol

1) Loss function for training: The hybrid RF–LSTM model was trained using the Mean Squared Error (MSE) as the objective function, defined as:

$$MSE = \left(\frac{1}{n}\right) \Sigma \, (y_t - \hat{y}_t)^2 \tag{13}$$

where, yt and $\hat{y}_t$ represent the actual and predicted healthcare demand at time t, respectively, and n is the total number of observations. The Adam optimizer was employed to minimize the loss function in (13), enabling stable, efficient convergence during training while preventing overfitting through early stopping mechanisms.

2) Performance evaluation metrics: After training, the proposed model's performance was assessed using three standard forecasting metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Coefficient of Determination (R2).

The Mean Absolute Error (MAE) is expressed as:

$$MAE = \left(\frac{1}{n}\right) \Sigma \, |y_t - \hat{y}_t| \tag{14}$$

The Root Mean Square Error (RMSE) is defined as:

$$RMSE = sqrt\left(\left(\frac{1}{n}\right) \Sigma \, (y_t - \hat{y}_t)^2\right) \tag{15}$$

In addition, the coefficient of determination (R2) is given by:

$$R^2 = 1 - \frac{\Sigma (y_t - \hat{y}_t)^2}{\Sigma (y_t - \bar{y})^2} \tag{16}$$

where denotes the mean of the observed healthcare demand values.

Eq. (13) was used as the loss function during the training phase to minimize the squared difference between actual and forecast healthcare demand values. Subsequently, Eq. (14)–(16) were applied for post-training evaluation. MAE provides an intuitive measure of average prediction error, RMSE emphasizes large deviations, which are critical in healthcare resource planning, and R2 quantifies the model's explanatory power in capturing variations in national healthcare demand patterns.

3) Statistical testing: To statistically validate the observed performance differences among the compared forecasting models, a one-way Analysis of Variance (ANOVA) was conducted using the F-statistic defined in Equation (17). The test examined whether variations in predictive errors across models were statistically significant at $\alpha = 0.05$. Following ANOVA, a Tukey HSD post hoc test was applied to identify pairwise differences among individual models. This statistical framework ensured that the superior performance of the proposed RF–LSTM hybrid model was not due to random variation but represented a statistically significant improvement over benchmark models.:

$$F = \frac{\frac{SS_{between}}{k}}{\frac{SS_{within}}{N-k}} \tag{17}$$

followed by Tukey HSD for pairwise comparison.

Baseline comparators included:

ARIMA/SARIMAX (statistical models)

Random Forest (RF) (tree ensemble)

Long Short-Term Memory (LSTM) (deep learning).

Residual analysis was employed to evaluate the errors and their distribution over prediction horizons. Moreover, Residual diagrams demonstrate the differences between predicted and observed values, while error variance measures the strength under variable demand conditions. These analyses provided valuable insights into the model's reliability during both outbreak peaks and intervals of stability.

IV. RESULTS

A. Quantitative Performance

The RF-LSTM hybrid model achieved the lowest MAE and RMSE, and a near-perfect R2 of 0.9995. The MAE and RMSE (Table III) values represent the average and squared variances between the expected and actual healthcare demand, however. Lower values indicate more accurate and consistent predictions, whereas higher R2 values indicate a more precise overall model fit.

Moreover, the RF-LSTM achieved the lowest RMSE (0.737), demonstrating enhanced robustness against demand fluctuations. Lower RMSE values further reflect greater forecast stability and reduced sensitivity to demand fluctuations, reaffirming the model's advantage in dynamic healthcare environments.

TABLE III. CORE PERFORMANCE METRICS

Model	MAE	RMSE	R2
ARIMA	0.265	0.955	0.9978
RF	0.214	0.809	0.9990
LSTM	0.245	0.910	0.9985
RF–LSTM (proposed)	0.188	0.737	0.9995

The hybrid RF-LSTM model achieved the lowest MAE (0.188), indicating minimal average discrepancy between predicted and actual healthcare demand. (Fig. 2) illustrates performance enhancements of 22% and 12% compared to the ARIMA and LSTM models, thereby validating the hybrid model's superior predictive accuracy.

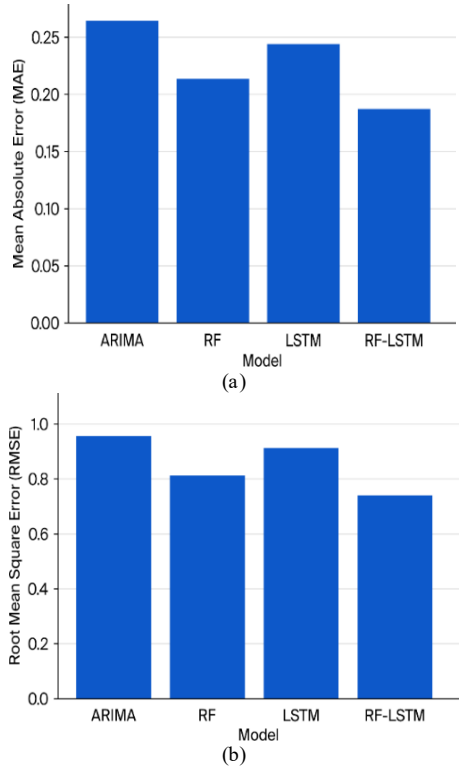


Fig. 2. Comparison of MAE (a) and RMSE (b) Across the proposed hybrid RF-LSTM model and other models.

B. Model Performance During Peak Demand

To further evaluate the robustness of the proposed model under critical stress conditions, its behavior during a simulated peak healthcare demand period was analyzed. Fig. 3 illustrates the temporal prediction performance of all models during a 30-day high-demand interval. The RF–LSTM hybrid model exhibits stronger stability and closer alignment with the actual demand curve compared with ARIMA, standalone RF, and standalone LSTM models.

Unlike ARIMA, which shows delayed adaptation to sudden demand spikes, and LSTM, which occasionally overshoots in highly volatile phases, the proposed hybrid model maintains smoother and more accurate tracking of temporal changes. This improved performance is attributed to the integration of nonlinear feature extraction from the RF stage with the temporal learning capacity of the LSTM stage.

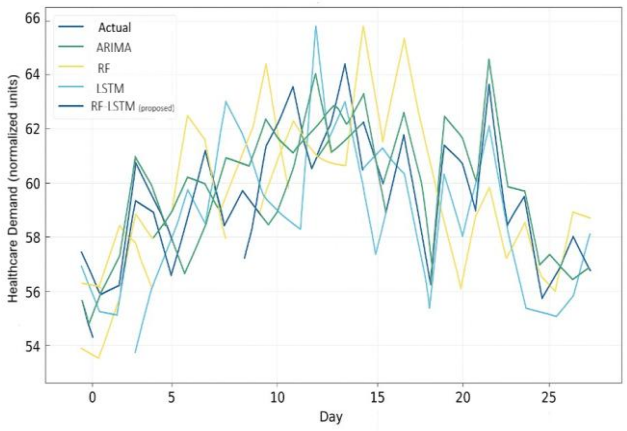


Fig. 3. Model behavior during a simulated peak demand period.

C. Hyperparameter Sensitivity Analysis

1) Effect of RF ensemble size: The impact of the Random Forest ensemble size on the hybrid model performance is shown in (Fig. 4). As the number of trees increases from 100 to 200, a clear decreasing trend in RMSE is observed, indicating improved stability and reduced variance. Beyond 200 trees, only marginal improvements were observed while computational cost increased significantly. Therefore, an ensemble sized 200 trees was selected for the final model configuration.

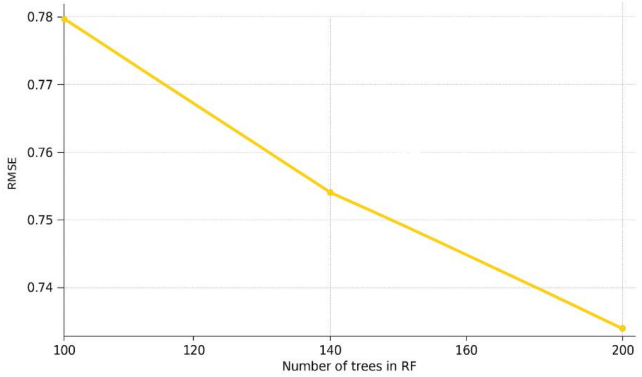


Fig. 4. Effect of RF ensemble size on hybrid RF–LSTM RMSE.

2) Effect of sequence length L on hybrid RF–LSTM MAE performance: To analyze the influence of sequence length on temporal modeling, experiments were conducted using sequence lengths of 7, 10, and 14 days.

As shown in Fig. 5, increasing the sequence length results in a consistent reduction in MAE. Shorter sequences limit the model's ability to capture medium-term dependencies, whereas longer sequences allowing L = 14 significantly enhance temporal learning. A sequence length of 14 days was selected as the optimal input configuration, balancing prediction accuracy and computational efficiency.

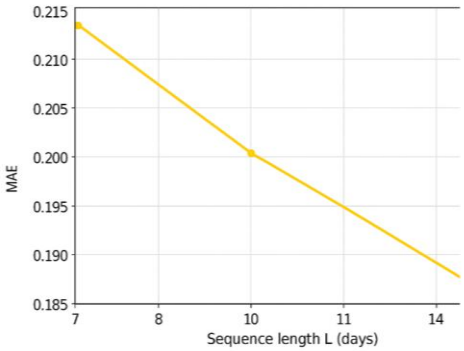


Fig. 5. Effect of sequence length L on hybrid RF–LSTM MAE performance.

D. Error Distribution and Robustness

Analysis of the error distribution and variance revealed that the hybrid approach reduces variability compared to individual models. Residual plots showed narrower confidence intervals, thereby verifying enhanced stability during both outbreak surges and low rates. These results support previous studies on hybrid models, explaining that they are strong enough to manage changes in systems [2,15,20]. The suggested framework demonstrated superior performance relative to both regional and global standards while maintaining clarity and scalability.

V. Discussion

The hybrid RF-LSTM model efficiently integrates two complementary methodologies: ensemble feature extraction and advanced sequence modelling, allowing the system to manage complex, non-linear, and non-stationary healthcare data. From a healthcare perspective, implementing these models into local health visualizations enables the immediate detection of ICU incidents, facilitates flexible resource allocation, and supports strategic planning. This approach supports data-driven governance and long-lasting digital health systems. These findings are also consistent with worldwide trends, where hybrid ensemble and deep learning architectures are improving pandemic preparedness and operational resilience.

The above approaches correspond with the latest international initiatives to utilise AI-based prediction in healthcare systems. The suggested RF-LSTM framework fits with this model because it combines explainable ensemble learning (RF) with temporal adaptability (LSTM). This makes it a good compromise between ease of understanding and predictive accuracy. This combination enables the model to leverage Random Forests' feature-level transparency and LSTMs' sequential learning capabilities, making it especially suitable for healthcare systems characterized by dynamic, diverse data sources.

Fig. 6 demonstrates the variation in MAE over time for ARIMA, RF, LSTM, and RF-LSTM models at different prediction horizons (7, 10, and 14 days). It shows that the prediction errors of all models gradually increase as the prediction horizon lengthens. Nonetheless, the hybrid RF-LSTM consistently maintains the lowest MAE and displays a more natural decline in performance. This indicates that the hybrid model can effectively handle longer prediction periods, providing better reliability and resilience against cumulative errors, thereby enhancing its robustness. The distinct separation between the curves indicates that the hybrid model generalizes more effectively in unstable healthcare scenarios.

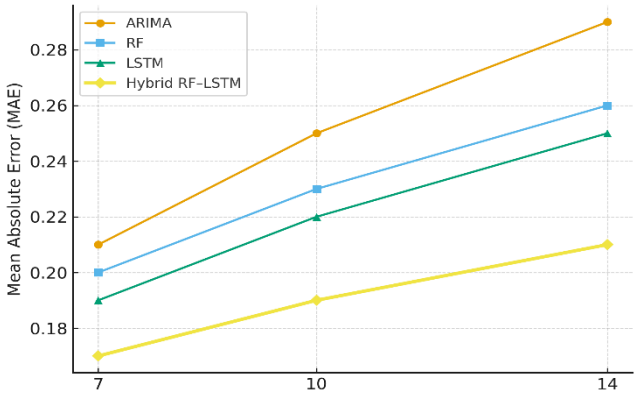


Fig. 6. Temporal variation of MAE across forecasting horizons (7-day, 10-day, and 14-day ahead) for ARIMA, RF, LSTM, and RF-LSTM models, showing the superior stability and accuracy of the hybrid approach.

The RF-LSTM model is more stable and can be applied in a broader range of situations due to its hybrid architecture. Random Forest reduces non-linear variance, and LSTM detects temporal consistency. In combination, they reduce overfitting and adapt to changes in epidemic and operational dynamics. In practical healthcare environments, this improvement can help hospital administrators prepare for surges in ICU demand, use staff effectively, and balance national medical resources during crises.

Overall, the results show that the proposed RF-LSTM model not only enhances predictive accuracy but also helps healthcare operations stay resilient and sustainable. The model demonstrates both technical dependability and practical value for national healthcare forecasting by enhancing data utilization, resource management, and the operation of early warning systems.

A. Limitations and Future Work

Although the suggested model performs well, several limitations require attention. First, it depends on continuous and accurate updates from national health datasets for optimal performance, which may not always be complete or timely. Second, the model's two-stage training process increases computational costs. Third, the RF-LSTM captures complex temporal dynamics; however, its ability to handle larger, more diverse regional datasets remains to be confirmed.

On the other Hand, Future research may target these limitations by exploring an advanced ensemble method that combines attention techniques with Graph Neural Networks (GNNs) to capture correlations across multidimensional healthcare data more effectively. The goal of this approach is to enhance the model's generalizability and interpretability across a broader range of healthcare settings within the Gulf Cooperation Council (GCC) region. Incorporating additional sustainability criteria, both environmental and operational, could also help optimize predictive analytics to better align with Saudi Arabia's Vision 2030 objectives.

VI. Conclusion

This study presented a hybrid Random Forest–Long Short-Term Memory (RF–LSTM) model designed to improve national healthcare demand forecasting in Saudi Arabia through an integrated approach that combines non-linear feature extraction with advanced sequence learning. Motivated by the data-driven transformation goals of Saudi Vision 2030, the proposed model leverages a comprehensive, exclusively Saudi dataset (2020–2024) that includes epidemiological indicators, ICU and bed utilization, vaccination progress, mobility metrics, and policy-response variables. By engineering Random Forest outputs as temporal features and feeding them directly into the LSTM architecture, the framework captures both short-term non-linear interactions and long-term temporal dependencies in a unified predictive pipeline.

The findings demonstrate that the hybrid RF–LSTM model consistently outperforms traditional and single-model baselines—including ARIMA, RF, and LSTM—across multiple forecasting horizons. The model maintains lower error rates and enhanced stability as prediction windows lengthen, highlighting its robustness against cumulative uncertainty and rapidly changing healthcare conditions. From an operational standpoint, the model offers practical value for strategic planning, enabling earlier detection of ICU trends, more flexible allocation of healthcare resources, and improved resilience of national decision-support systems. Its alignment with international AI-healthcare initiatives reinforces its relevance within broader global efforts to strengthen pandemic preparedness and digital-health infrastructure. While the model achieves strong performance, certain limitations remain, including reliance on continuous dataset updates, increased computational requirements due to its two-stage architecture, and the need to validate performance across more diverse regional datasets. Future research should explore integrating attention mechanisms, graph neural networks, and expanded sustainability metrics to enhance generalizability, interpretability, and alignment with Vision 2030 objectives.

Overall, the proposed RF–LSTM framework provides both methodological innovation and operational significance, offering a scalable and data-driven solution for national healthcare forecasting. It represents a meaningful contribution toward building resilient, intelligent, and sustainable healthcare systems in Saudi Arabia and beyond.

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Availability of Data and Materials

The data supporting the findings of this study are openly available in the following repository: Ministry of Health (Saudi Arabia). COVID-19 Open Data Portal [5]: Open Data - Open Data Library (accessed on Jan 2025). the World Health Organization (WHO). COVID-19 Dashboard [21]: Saudi Arabia. (accessed on May 2025).

Ethics Approval

This study did not require ethics approval, as it used only publicly available, anonymized datasets and collected no new data from human subjects.

Conflicts of Interest

The authors declare no conflicts of interest to report regarding the present study.

References

[1] Wu JT, Leung K, Leung GM. Nowcasting and forecasting the potential domestic and international spread of the 2019-nCoV outbreak originating in Wuhan, China: a modelling study. Lancet. 2020;395(10225):689-697

[2] Alshammari, F.; Alanazi, S.; Alotaibi, N.; Zrieq, R.; Alshammari, M. Hybrid Deep Learning for Epidemic Forecasting. IEEE Access 2023, 11, 54121–54135.

[3] Ribeiro MHDM, da Silva RG, Mariani VC, Coelho LDS. Short-term forecasting COVID-19 cumulative confirmed cases: perspectives for Brazil. Chaos Solitons Fractals. 2020; 135:109853.

[4] Almalki, M.J.; Alsubaie, S. COVID-19 Analytics in Saudi Arabia. Sensors 2021, 21, 5158.

[5] Ministry of Health (Saudi Arabia). COVID-19 Open Data Portal. Ministry of Health: Riyadh, Saudi Arabia, 2023. https://data.gov.sa/Data/en/organization/moh

[6] Dawood, S.; Alshammari, A.; Alharbi, A.; et al. Effectiveness of the Tawakkalna Application in Saudi Arabia. Healthcare 2023, 11(5), 765

[7] Chen, R.; Li, S.; Ahmed, M. Decision Support in Healthcare: Advances in AI-Driven Management Systems. Decis. Support Syst. 2021, 147, 113589.

[8] Singh S, Parmar KS, Kumar J, Makkhan SJS. Development of new hybrid model of discrete wavelet decomposition and ARIMA models in application to one month forecast of COVID-19 casualties. Chaos Solitons Fractals. 2020; 135:109866

[9] Moftakhar L, Mozhgan S, Safe MS. Exponentially increasing trend of infected patients with COVID-19 in Iran: comparison of neural network and ARIMA forecasting models. Iran J Public Health. 2020;49(Suppl 1):92.

[10] Kufel T, et al. ARIMA-based forecasting of the dynamics of confirmed COVID-19 cases for selected European countries. Equilibrium. 2020;15(2):181-204.

[11] Roy S, Bhunia GS, Shit PK. Spatial prediction of COVID-19 epidemic using ARIMA techniques in India. Model Earth Syst Environ. 2021; 7:1385-1391.

[12] Wang, P.; Zheng, X.; Li, J. and Zhu, B. Prediction of epidemic trends in covid-19 with logistic model and machine learning technics, Chaos, Solitons & Fractals, vol. 139, p. 110058, 2020.

[13] Ndiaye, B.; Tendeng, L.; and Seck, D. Analysis of the covid-19 pandemic by sir model and machine learning technics for forecasting, arXiv preprint arXiv:2004.01574, 2020.

[14] Borges, D.; Nascimento, M.C. COVID-19 ICU Demand Forecasting: A Two-Stage Prophet–LSTM Approach. Infect. Dis. Model. 2022, 7, 109181.

[15] Punia, S.; Ranjan, P.; Kumar, S.; Choudhary, A. Deep Learning with LSTM and Random Forest Hybrid for Demand Forecasting. Proc. IEEE 2020, 108(12), 2356–2367.

[16] Kaur, M.; Singh, A. Sustainable Healthcare Management through Artificial Intelligence-Driven Forecasting Models. Sustainability 2023, 15, 5892.

[17] Rahman, M.; Lee, J. AI-Powered Predictive Analytics for Sustainable Healthcare Systems: Challenges and Opportunities. J. Clean. Prod. 2024, 438, 140921.

[18] Alabbad, D.A.; Almuhaideb, A.M.; Alsunaidi, S.J.; Alqudaihi, K.S.; Alamoudi, F.A.; Alhobaishi, M.K.; Alaqeel, N.A.; Alshahrani, M.S. Machine Learning Model for Predicting ICU Length of Stay in Saudi Arabia. Inform. Med. Unlocked 2022, 30, 100937.

[19] Cramer, E.Y.; Ray, E.L.; Lopez, V.K.; Bracher, J.; Brennen, A.; Castro Rivadeneira, A.J.; Gerding, A.; Gneiting, T.; House, K.H.; Huang, Y.; Jayawardena, D. Evaluation of Ensemble Probabilistic Forecasts of COVID-19 Mortality. Proc. Natl. Acad. Sci. USA 2022, 119, e2113561119.

[20] Singh, R.; Gupta, A.; Kumar, M. Hybrid Models for Epidemic Trends. Appl. Sci. 2023, 13(2), 812.

[21] World Health Organization (WHO). COVID-19 Dashboard. World Health Organization: Geneva, Switzerland, 2022.

[22] Elmasry, W.; Othman, M.; Kamel, S. Sequence Learning for Temporal Data: Recent Advances and Applications. Pattern Recognit. 2022, 127, 108592.

[23] Hochreiter, S.; Schmidhuber, J. Long Short-Term Memory. Neural Comput. 1997, 9, 1735–1780

[24] Alshammari, B.; Zafar, B. Machine Learning-Based DSS for Healthcare in COVID-19: Case Study of Saudi Arabia. Nanotechnol. Percept. 2024, 20(5), 478–509. Machine Learning-based Decision Support System for Healthcare in the Context of COVID-19: Case Study of Saudi Arabia | Nanotechnology Perceptions

[25] Li, X.; Zhang, Y.; Zhao, J. LSTM-Based COVID-19 Forecasting. PLoS ONE 2024, 19(2), e0283105

Intelligent Platform for Employee Retention Prediction

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***Abstract*—Employee retention is a very important challenge to the organizations since it raises the cost of recruitment, affects domain knowledge retention, and impacts workforce stability. Presented here is a platform-based intelligent employee retention prediction system as a real-time HR decision support tool. As a part of the research, Feedforward Neural Network was initially trained and tested with structured employee data to confirm the relevance of the features and predictive viability, which had recorded an accuracy of 88.7%. This final implementation will integrate an AI-based Chat Widget with a modular pipeline system that will utilize an LLM for performing analytical reasoning on employee attributes and provide human-understandable explanations that will aid the HR decisions. The architecture separates the user interaction layer (Agent) from the prediction and reasoning logic (Pipeline), which makes the system scalable, interpretable, and easily integrable with the workflows of an organization. The proposed platform will show how validated predictive models and LLM-provided reasoning can be integrated in order to provide actionable and explainable employee retention insights.**

***Keywords*—Employee retention; feedforward neural network; Large Language Model; HR analytics; intelligent platform**

I. Introduction

Current organisations have been facing serious employee retention issues due to increase in recruitment costs, onboarding, and the loss of organisational knowledge that comes with employee turnover. High rates of attrition have adverse effects on productivity, team building, and long-term strategic planning. Consequently, more organizations are turning to data-based methods to identify employees who are vulnerable to turnover and develop proactive retention plans.

Deep learning and machine learning methods have gained popularity in predicting employee attrition in recent years. Conventional approaches like decision trees, logistic regression, and ensemble are mainly based on structured historical data and provide little interpretability to HR professionals. Even though neural network-based models enhance predictive accuracy by modeling non-linear relationships among employee attributes, they are typically black boxes and cannot be easily incorporated into real-time HR processes. Also, the majority of available solutions have difficulties integrating unstructured or semi-structured data, including employee feedback or qualitative measures of work attitude.

To overcome these shortcomings, this paper introduces an intelligent, platform-based employee retention prediction system that integrates tested predictive modeling with explainable AI-driven reasoning. In the research stage, a Feedforward Neural Network (FNN) was constructed with structured employee information to confirm the relevance of features and determine predictive ability. The information gained through this model was used in the design of the solution eventually deployed. Predictive intelligence has been integrated into an AI Chat Widget in the operational system, which communicates with a modular GenAI pipeline. A Large Language Model (LLM) serves as an analytical reasoning tool over employee data and is capable of providing human-interpretable explanations to enable HR teams to make informed decisions based on risk factors.

The proposed architecture distinguishes between user interaction (Agent) and prediction and reasoning logic (Pipeline) to provide scalability, modularity, and easy deployment. The system combines predictive modeling with LLM-based explainability to provide an interface between high-accuracy attrition prediction and HR decision support. The design enables organizations to move beyond fixed prediction models to interactive, explainable, and scalable retention analytics platforms.

This paper is organised in the following way. Section II is a literature review on employee attrition prediction and current ML models. Sections III and IV address the research gap and problem formulation. Section V introduces the proposed methodology, which involves the FNN-based validation step and the LLM-based platform architecture. Section VI explains the experimental design and the findings of the predictive model. Section VII explains the implications of the findings and the role of explainability in HR decision-making. Lastly, Section VIII summarizes the paper and provides future research directions.

II. Literature Review

One of the most important workforce analytics is employee turnover prediction because of its financial and operational repercussions on an organization. Different deep learning and machine learning methods have been utilized to perform the analysis of the attrition patterns and come up with prediction methods. This section will examine research literature and will categorize the studies in terms of the methods used.

Pioneering researches used the conventional statistical models like logistic regression (LR) and the ordinary least squares (OLS) regression to forecast turnover. Logistic regression has been extensively used in determining the important attributes of attrition which include salary, job satisfaction, and tenure [15][16][19][20][27][29]. Other studies included regression analysis using employee biodata and

predictive personality which emphasized the significance of predicting job retention [21][34]. In other studies, the survival models and discrete choice analysis were used to distinguish voluntary and involuntary turnover [25]. Its performance in OLS regression coupled with neural networks was established in the analysis of workforce attrition [41]. Logistic regression in HR analytics was also studied, using it on the data of various organizations [30][35].

Decision tree-based models like Gradient Boosting (GB), Random Forest (RF) and XGBoost have gained wide popularity because they provide the capability to model high-order interactions between features [9][17][23][28][32][33]. Ensemble techniques were compared and the findings showed that XGBoost has always been better than other classifiers in turnover prediction [38][43][51]. Other studies suggested combining decision trees with SVM, Naive Bayes, and AdaBoost to enhance their accuracy [7][45][47]. Combination of uplift modeling with retention prediction demonstrated that the other conventional classifiers performed better but uplift modeling offered more precise interventions [55]. Also, other studies were able to combine features selection techniques like Chi-Square and Information Gain to improve the performance of the decision trees [54].

Employee retention prediction has strongly embraced the use of DL techniques, especially the Artificial Neural Networks (ANNs). Research concluded that DL models such as the feedforward neural networks (FNN) and convolutional neural networks (CNN) performed better than traditional machine learning models [8][13][14]. Other studies used a multi-layered deep learning model, which combined demographic factors and measures of employee engagement to enhance the accuracy of predictions [26][31]. Deep autoencoders were used with genetic algorithms (GA) to optimize feature selection in other studies [40]. Solutions based on neural networks, like Brownian Motion Butterfly Optimization have also been suggested to minimize overfitting and better turnover prediction [11][10][53]. Explainable AI methods like SHAP and LIME were also included in the research to understand deep learning models [7].

Certain researches touched upon alternative predictive models, such as uplift model and organizational network model. The uplift modeling that targets employees who are most likely to react to retention-related interventions proved to be more effective in intervention than the traditional classifiers [55]. Besides, Organizational Network Analysis (ONA) was also used to examine the level of employee connectivity within firms and found out that the network structures greatly influence turnover behavior [52].

Some studies combined a number of ML methods to enhance the accuracy of prediction. Employee retention analysis has been suggested to use hybrid models with decision trees and SVM, Naive Bayes, and AdaBoost [7][47]. In other studies, model fusion models have been used, which combines a number of classifiers with the aim of attaining an improved performance in prediction [50]. One research presented a weighted quadratic random forest (WQRF) model, which has improved the classification based on weighted decision trees [50]. Other studies used clustering techniques alongside ANNs and data augmentation, including CTGAN, to enhance the strength of models [42]. Researchers also investigated the stacking, and optimization models to improve the precision of the prediction [48].

Several studies have explored alternative approaches to employee retention prediction. Yanamala (2020) emphasized on the value of big data and machine learning in evaluating the working class [1], while it was Yahia et al. who further went up and introduced a deep data dimension for better predictions [4]. Authors Sexton et al. (2005) and Pérez-Campdesuñer et al. established that neural networks are better than traditional models [5][6]. Rane et al. investigated the applications of AI, machine learning, and deep learning in businesses to retain HRs [18][39]. Shafie et al. were working on ANNs with data augmentation to use in clustering, and El-Rayes et al. (2020) were working on trees to identify useful features to use in turnover analysis [22][24]. Lim et al. proposed a novel approach that uses a deep autoencoder and KNN, to enhance the prediction of the employee turnover [36]. On the same token, Park et al. used advanced ML techniques to predict employee retention by reviewing new trends in the workforce [37][2][39]. Examples of deep learning progress are Al-Darraji et al.'s practice for predicting worker attrition [44] and Cheng's method for HR predictive analytics [49]. In their study, Zhang et al. used machine learning to discover main reasons for attrition [56].

Artificial Neural Networks (ANNs) are recognized by several studies for their strong abilities in predicting if an employee will remain with the company. In Dubey et al.'s (2018) and Al-Darraji et al.'s (2021) studies, it was found that using ANN-based models helped overcome the restrictions of traditional machine learning, since they can show how non-linear relationships shape the patterns of workers [3][44]. Yahia et al. proposed a deep data framework that improves the effectiveness of ANNs in analyzing workforce data [46]. In 2024, Shafie et al. investigated using ANN to cluster data and use data augmentation to boost accuracy [42][12]. Although XGBoost and Random Forest are high in accuracy, ANNs show exceptional performance when trying to model tougher patterns, features, and forms of data. While LSTM only works with sequential information, FNNs are more flexible and scalable, allowing them to handle HR data that can be structured, like employee feedback, or unstructured, like how engaged employees feel. As our dataset doesn't change over time, LSTM models cannot be used. ANNs work better in various industries and are still understandable with explanation techniques such as SHAP and LIME. Given these advantages, our research builds upon ANN-based methodologies to develop a robust, commercially viable employee retention prediction model that enhances HR decision-making.

III. Research Gap

Most of the available methods are focused on increasing accuracy by improving classification based on structured historical data, but they do not put sufficient interest in interpretability and real-time interaction. Because of this, most predictions are often made without enough explanation or actionable context for HR professionals.

Another important factor is that most of the predictive models are developed as stand-alone analytical applications and

are not designed to be integrated into enterprise systems. This limits their operational usage in HR departments because these departments require interactive systems that could respond dynamically to user requests and changing organizational information. There is also a lack of discussion in current literature on how unstructured or semi-structured information, such as qualitative employee feedback or situational indicators of the workplace, is managed.

While these models are capable of producing superior predictive performances, their black-box character implies a challenge for trust and adoption in HR applications. The research gap lies in the development of intelligent platforms which can integrate proven predictive modeling together with explainable and user-friendly AI interfaces to be used for devising retention strategies. This work fills this gap by combining predictive validation with an LLM-powered reasoning layer into a platform-based modular architecture.

IV. Problem Statement

The problem of employee churn is a big hurdle for organizations because the interaction of demographic, professional, and behavioral factors that cause attrition is complex. Though predictive models can be used to estimate turnover risk, in practice, HR teams view them as a challenge to interpreting the predictions and converting them into practical retention measures. This is the point at which the disconnect between prediction and decision-making makes the tools of attrition analysis currently in use less practical.

This needs to be engaging, insightful at a human level, and fit within organisational processes. This proposal is based on the gap that exists between effective attrition prediction and viable HR decision support through integrating predictive intelligence into an AI Chat Widget and a modular pipeline architecture.

V. Methodology

The proposed employee retention prediction system is structured into two stages: predictive model validation methodology coupled with a platform-based deployment that is oriented towards explainable and interactive HR decision support. The general system workflow is represented by the Agent and Pipeline structures depicted in Fig. 1 and Fig. 2 respectively.

A. Understanding and Preprocessing Data

The methodology begins with understanding the nature of data and attributes leading to employee attrition. The dataset contains employee data, which includes demographic data, job-related parameters, and behavioral information. Data is to be pre-processed before feeding into the model in order to ensure the quality and consistency of the data. This involves filling in missing or inconsistent values, encoding categorical variables into numerical forms, and normalizing numerical variables onto a standard scale. These are the preprocessing steps used to guarantee that the data is learning-ready, and feature contributions can therefore be analyzed meaningfully. Because of restrictions of data privacy and confidentiality, a synthetic employee dataset was created in order to try and represent realistic HR attributes and attrition trends while maintaining the statistical properties needed for validating the model.

B. Feedforward Neural Network Predictive Validation

An FNN is designed at the research stage-after preprocessing-to investigate predictive feasibility and authenticate the importance of the selected features. The FNN is selected since it can be used for modeling nonlinear relationships in structured data and it can be utilized for situations with no temporal dependencies. While FNN is the proposed model, additional classical ML models were implemented for comparative evaluation.

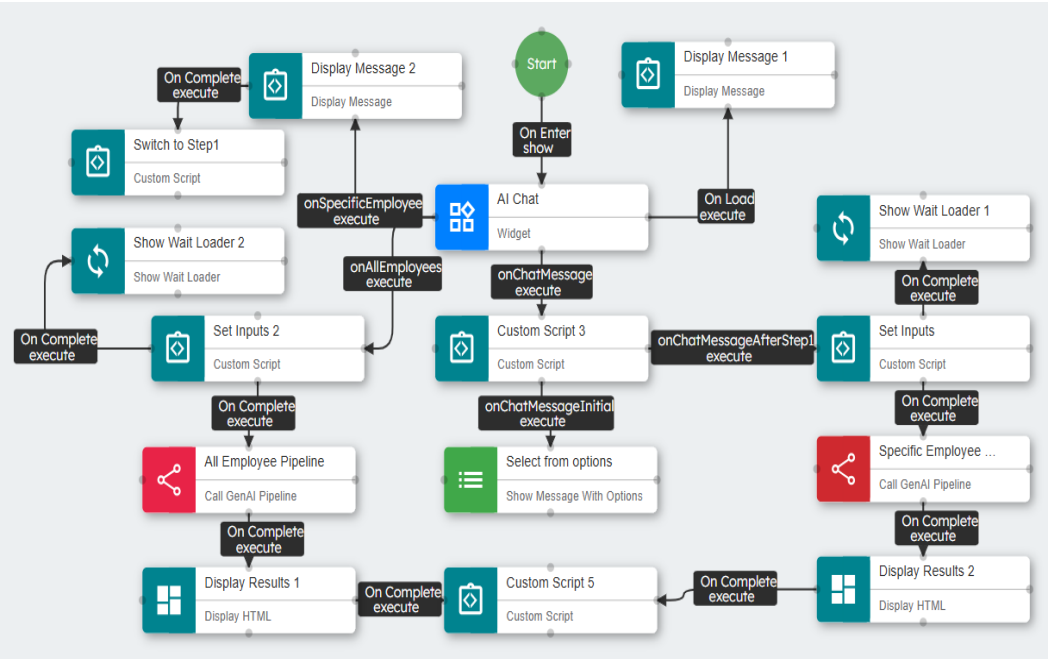


Fig. 1. Workflow of the agent.

The whole network architecture comprises several fully connected layers activated by the Rectified Linear Unit and one output layer activated by the sigmoid function for binary classification. The Adam optimizer trains the model and provides stable convergence with adaptive learning rates. Hyperparameters such as batch size, learning rate, and numbers of neurons were tuned experimentally. The FNN performs with an accuracy of 88.7%, which indicates how well this model achieves the mapping of attrition-related patterns. This model is not deployed as a stand-alone production classifier; nonetheless, it provides a tested predictive basis. The knowledge gained in this step contributes to the design of the system put into practice, especially with respect to the characteristics that substantially support employee retention.

C. Integration-Based Platform Implementation on the LLM.

Once the predictive feasibility has been established with the FNN-based assessment, the system is extended to a platform-based implementation targeted at operational use. This implementation is designed into two main parts, namely the Agent and the Pipeline, as shown in Fig. 1 and Fig. 2.

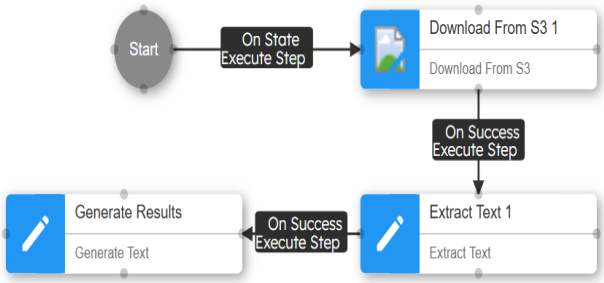


Fig. 2. Workflow of the pipeline.

Accordingly, the Pipeline component is responsible for handling analysis processing and the controlled execution of analytical operations. It reaches out to cloud storage for the employee data uploaded to the system. The pipeline expects structured inputs regarding the approved set of features and invokes a Large Language Model-Gemini 2.0 Flash-through secure API calls. Instead of being a classifier, it conducts analytical reasoning on employee characteristics and issues interpretations regarding attrition risk, accompanied by human-readable explanations. To make the presentation of its results consistent, a fixed structure is applied to the output.

D. AI Chat Widget and User Interaction

This Agent component, illustrated in Fig. 1, is implemented as an AI Chat Widget that represents the main interface of HR professionals. Through this interface, the user can upload employee datasets, select options for analyses, and ask for predictions without directly being involved with models that underlie these operations. In the case that such a request is triggered, the Agent communicates with the Pipeline of Fig. 2, invoking the respective analytical workflow.

The answers that the Pipeline provides are nicely formatted as HTML and then displayed in the Chat Widget. This output will provide insights into the factors of attrition risk, causes, and recommendations to help with HR decision-making. AI Chat Widget reduces the overall complexity of the system and allows a non-technical user to interact with advanced AI capabilities in a straightforward and understandable way. The advanced AI features in an understandable and clear manner.

E. Methodology Summary

In summary, the suggested methodology can be summarized as a two-step procedure: a predictive validation step with the assistance of a Feedforward Neural Network to check the relevance of the features and frame a baseline performance and a deployment-focused architecture, which transfers this intelligence to an LLM-based AI Chat Widget and a system pipeline.

VI. Results

This section contains the quantitative findings obtained during the predictive validation stage and the outputs provided by the implemented AI-based platform.

A. Predictive Model Performance

Table I summarizes the performance of various machine learning models that were used to predict employee attrition. Conventional classifiers like Logistic Regression, Naive Bayes, KNN, Decision Tree, and Random Forest exhibit competitive levels of accuracy on the structured employee data. The Feedforward Neural Network (FNN) proposed in this paper achieves the highest accuracy of 88.7%, which means that it is more accurate in capturing non-linear relationships among employee attributes.

Table I provides results that prove the efficacy of the chosen set of features and the appropriateness of neural network-based models for structured HR data. This assessment is conducted during the research and validation stage to determine predictive feasibility and benchmark model performance. It is not the implemented inference mechanism of the end platform, which focuses on interpretability and decision support.

TABLE I. Comparison of FNN Model with Classical Machine Learning Models

Model	Accuracy (%)
Logistic regression	87.4
Naïve Bayes	85.6
Decision Tree	78.5
KNN	84.3
Random Forest	85.9
Proposed FNN	88.7

B. Platform Outputs and User Interaction

The operational outputs of the deployed system are illustrated in Fig. 3 to Fig. 5. Fig. 3 shows the AI Chat Widget interface through which HR professionals interact with the system. After uploading the employee dataset, users are presented with multiple options, enabling both individual-level and organization-wide retention analysis in an interactive manner.

Fig. 3 presents the output generated for a specific employee analysis. The system provides an assessment of attrition risk along with factors contributing to the identified risk. These

outputs aim to support decision-making by highlighting key attributes influencing the prediction.

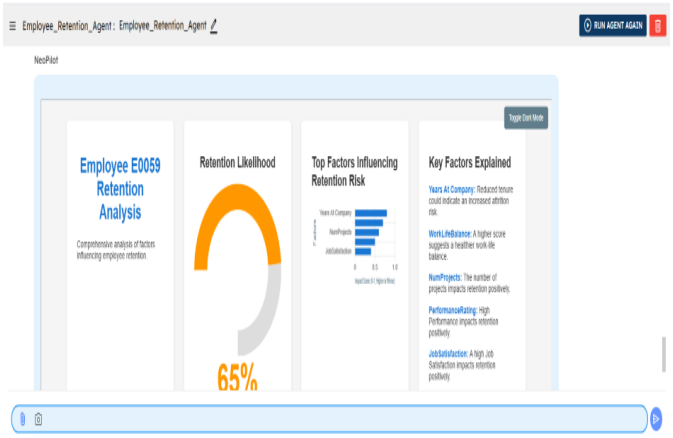


Fig. 3. Output for analysis on a specific employee.

Fig. 4 shows overall analysis of employee retention. This view depicts the risk distribution by departments, major factors causing attrition, and aggregated insights from the organization. Such a result will enable the HR teams to identify retention issues and prioritize intervention strategies at an organizational level.

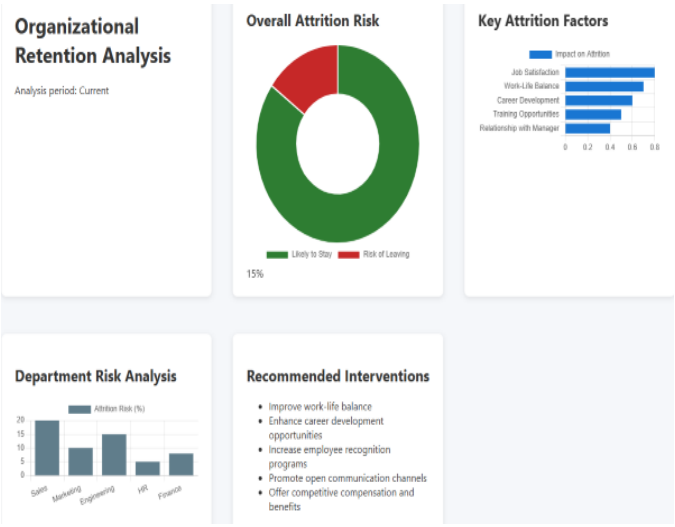


Fig. 4. Overall employee retention analysis.

VII. Discussion

The findings indicate that the neural network-based solutions are more effective than the conventional ML models in predicting employee turnover with using structured HR data. Out of the various models tested, Feedforward Neural Network was the most effective as it gave a firm predictive background and demonstrated the applicability of the features chosen.

Predictive accuracy is, however, not sufficient in practice in HR. Prediction systems of attrition should also be able to facilitate interpretability, trust, and action. Considering this need, the presented system goes beyond prediction to introduce an architecture with proven predictive intelligence into an architecture powered by LLM. The Large Language Model does not substitute the predictive foundation but instead operates as a reasoning and explanation interface which extrapolates predictive signals into interpretation accessible to humans.

The AI Chat Widget and modular GenAI pipeline enables a natural communication process of the HR professionals with the system and abstracts the underlying complexity of the analytical process. The individual and organizational analysis depicted in Fig. 4 and Fig. 5, respectively, indicate the usefulness of this methodology because it involves a combination of risk indicators and explanatory context, which, in turn, champions the proactive retention strategies. The use of the Agent and Pipeline components further increases the scalability of the system and makes easy future system extensions.

The suggested platform does not compare the Large Language Model as an independent predictive classifier. Rather it considers the efficiency of the LLM on the basis of explanation consistency, which is the capacity of the model to offer coherent, human comprehensible explanations to aid HR in decision-making. In this regard, 25 cases of employees were chosen randomly and asked several times. In repeated queries, there was a consistent focus on dominant contributing factors (e.g., job satisfaction, workload, tenure) that the LLM focuses on that are aligned with the FNN output. The plausible explanations that were generated were found to have the right attributes of employees that led to the attrition risk, without bringing on board unfounded or contradictory variables, and therefore, guaranteeing the consistency between the prediction and the rationale.

The LLM-generated explanations are made easy to understand by the HR professionals who do not have a technical background as per the usability considerations. Clarity in the presentation of the risk indicators, contributing factors and the recommendations increases transparency and trust, consequently allowing informed and proactive decisions to be made in regard to retention. These observations affirm the appropriateness of the LLM as an explainability and decision-support subsystem to the proposed system.

VIII. Conclusion

This paper proposes the design of an intelligent employee retention prediction system, based on a platform integrating predictive model validation with explainable AI-driven decision support. The work overcomes one of the major limitations of traditional approaches to predict attrition: the gap existing between high performing predictive models and their practical usability by HR. Testing of the system was conducted using a synthetic employee dataset, generated to simulate realistic HR attributes and attrition patterns for enabling model validation in a way that avoids data privacy and confidentiality concerns.

During the research phase, a Feedforward Neural Network was developed on structured employee data and evaluated to validate feature relevance and predictive feasibility. The accuracy achieved is 88.7%. This outcome established a sound predictive basis for the project and informed the design of the deployed system. In its final form, rather than being a standalone classification, the predictive intelligence has been embedded in an AI Chat Widget and a GenAI pipeline.

The deployed platform applies a Large Language Model to reason analytically and provide human-understandable explanations of its reasoning to support decisions made by HR. By abstracting the analytical complexity and providing interpretable insights through an interactive interface, the system empowers HR professionals to predict attrition risks at both the individual and organizational levels and develop proactive strategies for retention.

Overall, the proposed architecture represents an illustration of how validated predictive modeling and explainable AI can be combined into one scalable, enterprise-ready platform for workforce analytics. Further research would extend the system to include unstructured data sources, such as employee feedback and surveys, and evaluate the platform across a wide range of organizational datasets to further improve generalizability and impact.

REFERENCES

[1] Yanamala, K.K.R., 2020. Predicting employee turnover through machine learning and data analytics. AI, IoT and the Fourth Industrial Revolution Review, 10(2), pp.39-46.

[2] Cheng, Y., 2024. Enhancing Employee Retention Strategies Through Advanced Predictive Analytics. Journal of Recent Trends in Computer Science and Engineering (JRTCSE), 12(1), pp.1-5.

[3] Dubey, A., Maheshwari, I. and Mishra, A., 2018. Predict Employee Retention Using Data Science. Journal of Diversity Management (JDM), 5.

[4] Yahia, N.B., Hlel, J. and Colomo-Palacios, R., 2021. From big data to deep data to support people analytics for employee attrition prediction. Ieee Access, 9, pp.60447-60458.

[5] Sexton, R.S., McMurtrey, S., Michalopoulos, J.O. and Smith, A.M., 2005. Employee turnover: a neural network solution. Computers & Operations Research, 32(10), pp.2635-2651.

[6] Pérez-Campdesuñer, R., De-Miguel-Guzmán, M., Sánchez-Rodríguez, A., García-Vidal, G. and Martínez-Vivar, R., 2018. Exploring neural networks in the analysis of variables that affect the employee turnover in the organization. International Journal of Engineering Business Management, 10, p.1847979018772738.

[7] Ogunbowale, O.A., 2023. Explaining Neural Networks and Random Forest for Employee Retention (Doctoral dissertation, Dublin, National College of Ireland).

[8] Brown, A., Davis, N., Miller, O., Wilson, E., Smith, L. and Lopez, S., Deep Learning Techniques for Enhancing Employee Turnover Prediction Accuracy.

[9] Nandal, M., Grover, V., Sahu, D. and Dogra, M., 2024. Employee Attrition: Analysis of Data Driven Models. EAI Endorsed Transactions on Internet of Things, 10.

[10] [Qadir, M., Noreen, I. and Shah, A.A., 2021. Bi-LSTM deep learning approach for employee churn prediction. Journal of Information Communication Technologies and Robotic Applications, pp.1-10.

[11] [Ganapathisamy, S. and Narayan, V., 2024. A Long Short-Term Memory with Recurrent Neural Network and Brownian Motion Butterfly Optimization for Employee Attrition Prediction. International Journal of Intelligent Engineering & Systems, 17(1).

[12] NAJAFI ZANGANEH, S. and Basirati, M., Enhancing Attrition Prediction: A Method Integrating Independent Components and Long Short-Term Memory (Lstm) Network. Available at SSRN 4789171.

[13] Arqawi, S.M., Rumman, M.A., Zitawi, E.A., Abunasser, B.S. and Abu-Naser, S.S., 2022. Predicting Employee Attrition and Performance Using Deep Learning. Journal of Theoretical and Applied Information Technology, 100(21), pp.6526-6536.

[14] Al-Darraji, S., Honi, D.G., Fallucchi, F., Abdulsada, A.I., Giuliano, R. and Abdulmalik, H.A., 2021. Employee attrition prediction using deep neural networks. Computers, 10(11), p.141.

[15] Ponnuru, S.A., Merugumala, G., Padigala, S., Vanga, R. and Kantapalli, B., 2020. Employee attrition prediction using logistic regression. Int. J. Res. Appl. Sci. Eng. Technol, 8(5), pp.2871-2875.

[16] Setiawan, I.A., Suprihanto, S., Nugraha, A.C. and Hutahaean, J., 2020, April. HR analytics: Employee attrition analysis using logistic regression. In IOP conference series: materials science and engineering (Vol. 830, No. 3, p. 032001). IOP Publishing.

[17] Shankar, R.S., Rajanikanth, J., Sivaramaraju, V.V. and Murthy, K.V.S.S.R., 2018, July. Prediction of employee attrition using datamining. In 2018 ieee international conference on system, computation, automation and networking (icscan) (pp. 1-8). IEEE.

[18] Yang, S. and Islam, M.T., 2020. IBM employee attrition analysis. arXiv preprint arXiv:2012.01286.

[19] Khare, R., Kaloya, D., Choudhary, C.K. and Gupta, G., 2011, January. Employee attrition risk assessment using logistic regression analysis. In Proceedings of the International Conference Advanced Data Analytics Busiess Analytics Intelligence (pp. 1-33).

[20] Nimmagadda, S., Lakshmi, R.J. and Kishan, S.R., 2024. HR Analytics For Predicting Employee Attrition with Logistic Regression. Journal of Informatics Education and Research, 4(2).

[21] Durante, M.K., 2002. A logistic regression analysis of biodata and personality predictors of job retention among detention officers. Arizona State University.

[22] Ghazi, A., Ismail Elsayed, S. and Elsayed Khedr, A., 2021. A proposed model for predicting employee turnover of information technology specialists using data mining techniques. International journal of electrical and computer engineering systems, 12(2), pp.113-121.

[23] Zhang, H., Xu, L., Cheng, X., Chao, K. and Zhao, X., 2018, September. Analysis and prediction of employee turnover characteristics based on machine learning. In 2018 18th International Symposium on Communications and Information Technologies (ISCIT) (pp. 371-376). IEEE.

[24] [24] Quinn, A., Rycraft, J.R. and Schoech, D., 2002. Building a model to predict caseworker and supervisor turnover using a neural network and logistic regression. Journal of Technology in Human Services, 19(4), pp.65-85.

[25] Madariaga, R., Oller, R. and Martori, J.C., 2018. Discrete choice and survival models in employee turnover analysis. Employee Relations, 40(2), pp.381-395.

[26] Poornappriya, T.S. and Gopinath, R., 2021. Employee attrition in human resource using machine learning techniques. Webology, 18(6).

[27] Maharjan, R., 2021. Employee Churn Prediction using Logistic Regression and Support Vector Machine.

[28] [haver, M., Gupta, Y. and Mishra, A.K., 2019, November. Employee turnover prediction system. In 2019 4th International Conference on Information Systems and Computer Networks (ISCON) (pp. 391-394). IEEE.

[29] Ponnuru, S.A., Merugumala, G., Padigala, S., Vanga, R. and Kantapalli, B., 2020. Employee attrition prediction using logistic regression. Int. J. Res. Appl. Sci. Eng. Technol, 8(5), pp.2871-2875.

[30] Nguyen, C., 2020. The impact of training and development, job satisfaction and job performance on young employee retention. Job Satisfaction and Job Performance on Young Employee Retention (May 1, 2020).

[31] Dubey, A., Maheshwari, I. and Mishra, A., 2018. Predict Employee Retention Using Data Science. Journal of Diversity Management (JDM), 5.

[32] Jain, R. and Nayyar, A., 2018, November. Predicting employee attrition using xgboost machine learning approach. In 2018 international conference on system modeling & advancement in research trends (smart) (pp. 113-120). IEEE.

[33] Wild Ali, A.B., 2021. Prediction of employee turn over using random forest classifier with intensive optimized PCA algorithm. Wireless Personal Communications, 119(4), pp.3365-3382.

[34] Jansen, J.A., 2022. Predictors of turnover intent in the executive branch: A multiple logistic regression analysis using federal employee viewpoint survey indices. Hood College.

[35] Karp, A.H., 1998. Using logistic regression to predict customer retention. In Proceedings of the Eleventh Northeast SAS Users Group Conference. http://www. lexjansen. com/nesug/nesug98/solu/p095. pdf (Vol. 15).

[36] Chang, S., Saad, H.S., Aisya, N.Q., Yee, S.P. and Selvam, S., Why do People Stay? A Study on Factors Influencing Employees Retention in the Logistics Industry.

[37] Rane, N.L., Paramesha, M., Choudhary, S.P. and Rane, J., 2024. Artificial intelligence, machine learning, and deep learning for advanced business strategies: a review. Partners Universal International Innovation Journal, 2(3), pp.147-171.

[38] Karimi, M. and Viliyani, K.S., 2024. Employee turnover analysis using machine learning algorithms. arXiv preprint arXiv:2402.03905.

[39] Park, J., Feng, Y. and Jeong, S.P., 2024. Developing an advanced prediction model for new employee turnover intention utilizing machine learning techniques. Scientific Reports, 14(1), p.1221.

[40] Lim, C.S., Malik, E.F., Khaw, K.W., Alnoor, A., Chew, X., Chong, Z.L. and Al Akasheh, M., 2024. Hybrid GA–DeepAutoencoder–KNN Model for Employee Turnover Prediction. Statistics, Optimization & Information Computing, 12(1), pp.75-90.

[41] Marquez, B.Y., Realyvásquez-Vargas, A., Lopez-Esparza, N. and Ramos, C.E., 2024. Application of ordinary least squares regression and neural networks in predicting employee turnover in the industry. Archives of Advanced Engineering Science, 2(1), pp.30-36.

[42] Shafie, M.R., Khosravi, H., Farhadpour, S., Das, S. and Ahmed, I., 2024. A cluster-based human resources analytics for predicting employee turnover using optimized Artificial Neural Networks and data augmentation. Decision Analytics Journal, 11, p.100461.

[43] Yin, Z., Hu, B. and Chen, S., 2024. Predicting employee turnover in the financial company: A comparative study of catboost and xgboost models. Applied and Computational Engineering, 100, pp.86-92.

[44] Gazi, M.S., Nasiruddin, M., Dutta, S., Sikder, R., Huda, C.B. and Islam, M.Z., 2024. Employee Attrition Prediction in the USA: A Machine Learning Approach for HR Analytics and Talent Retention Strategies. Journal of Business and Management Studies, 6(3), pp.47-59.

[45] Zhao, Y., Hryniewicki, M.K., Cheng, F., Fu, B. and Zhu, X., 2019. Employee turnover prediction with machine learning: A reliable approach. In Intelligent Systems and Applications: Proceedings of the 2018 Intelligent Systems Conference (IntelliSys) Volume 2 (pp. 737-758). Springer International Publishing.

[46] Yahia, N.B., Hlel, J. and Colomo-Palacios, R., 2021. From big data to deep data to support people analytics for employee attrition prediction. Ieee Access, 9, pp.60447-60458.

[47] Yiğit, İ.O. and Shourabizadeh, H., 2017, September. An approach for predicting employee churn by using data mining. In 2017 international artificial intelligence and data processing symposium (IDAP) (pp. 1-4). IEEE.

[48] El-Rayes, N., Fang, M., Smith, M. and Taylor, S.M., 2020. Predicting employee attrition using tree-based models. International Journal of Organizational Analysis, 28(6), pp.1273-1291.

[49] Cheng, Y., 2024. Enhancing Employee Retention Strategies Through Advanced Predictive Analytics. Journal of Recent Trends in Computer Science and Engineering (JRTCSE), 12(1), pp.1-5.

[50] Gao, X., Wen, J. and Zhang, C., 2019. An improved random forest algorithm for predicting employee turnover. Mathematical Problems in Engineering, 2019(1), p.4140707.

[51] Ajit, P., 2016. Prediction of employee turnover in organizations using machine learning algorithms. algorithms, 4(5), p.C5.

[52] Younis, S., Ahsan, A. and Chatteur, F.M., 2023. An employee retention model using organizational network analysis for voluntary turnover. Social network analysis and mining, 13(1), p.28.

[53] Mahammad, D.R., Priya, S.L., Thulasimani, T., Mann, S., Mann, S. and Kalra, G., 2025. Analysis and prediction of employee turnover characteristics based on LSTM-RNN-HMM model. In Hybrid and Advanced Technologies (pp. 334-339). CRC Press.

[54] Subhashini, M. and Gopinath, R., 2020. Employee attrition prediction in industry using machine learning techniques. International Journal of Advanced Research in Engineering and Technology, 11(12), pp.3329-3341.

[55] Wijaya, D., DS, J.H., Barus, S., Pasaribu, B., Sirbu, L.I. and Dharma, A., 2021. Uplift modeling VS conventional predictive model: A reliable machine learning model to solve employee turnover. International Journal of Artificial Intelligence Research, 5(1), pp.53-64.

[56] Zhang, H., Xu, L., Cheng, X., Chao, K. and Zhao, X., 2018, September. Analysis and prediction of employee turnover characteristics based on machine learning. In 2018 18th International Symposium on Communications and Information Technologies (ISCIT) (pp. 371-376). IEEE.

Spatial Classification of Fertilizer Requirements Using Fuzzy C-Means on Shallot Agricultural Land

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***Abstract*—Spatial variability in soil fertility constrains productivity in intensive shallot farming, yet fertilizer is frequently applied uniformly across fields. This practice results in nutrient inefficiencies, increased costs, and heightened environmental risks. This study introduces a fertilizer requirement mapping framework utilizing Fuzzy C-Means (FCM) clustering, a machine learning technique for data grouping, applied to in-situ measurements of soil Nitrogen (N), Phosphorus (P), and Potassium (K). The framework was evaluated in a 500 × 500 m shallot field in Srikayangan, Kulon Progo, Indonesia, subdivided into 10 × 10 m management blocks suitable for smallholder operations. Soil NPK levels were measured using IoT sensor nodes and georeferenced with GNSS, while high-resolution RGB imagery from a UAV provided spatial context. Normalized NPK data were clustered with FCM to delineate fertility zones exhibiting nutrient differences. To operationalize clustering results, a nutrient-priority decision logic identified the most limiting nutrient (N, P, or K) for each block. Fertilizer recommendation points were visualized on a UAV-derived orthomosaic map to facilitate interpretation and field application. The results indicate that this approach effectively captures gradual fertility transitions and produces actionable fertilizer zones for site-specific nutrient management (SSNM) in smallholder systems. The study demonstrates the practical integration of fuzzy clustering, IoT-based soil sensing, and UAV mapping to inform precision agriculture decisions.**

Keywords*—Fuzzy C-Means (FCM); soil fertility zoning; NPK (Nitrogen, Phosphorus, Potassium); fertilizer recommendation; precision agriculture; Site-Specific Nutrient Management (SSNM); IoT (Internet of Things); UAV (Unmanned Aerial Vehicle)

I. Introduction

Soil fertility variability represents a significant constraint to productivity and sustainability in intensive vegetable farming. In many fields, soil properties such as nutrient availability, texture, and organic matter content exhibit substantial variation over short distances. Despite this, fertilizer is typically applied uniformly. This disconnect between spatial variability and uniform management leads to inefficient nutrient use, increased costs, and elevated risks of environmental impacts, including nutrient leaching and accumulation [1], [2].

Shallot (Allium cepa var. aggregatum) cultivation, prevalent in Indonesia and Southeast Asia, depends on effective fertilizer management to achieve optimal yield and bulb quality. Grown in narrow beds with intensive inputs, shallots are particularly sensitive to nutrient imbalances. Nitrogen (N), Phosphorus (P), and Potassium (K) are the primary drivers of growth, root development, bulb formation, and stress resistance. The distribution of these nutrients varies according to soil conditions, irrigation practices, and fertilization history, resulting in significant variability even within smallholder plots [1].

Precision agriculture and site-specific nutrient management (SSNM) address this challenge by tailoring fertilizer inputs to spatially variable soil and crop conditions. A central aspect of SSNM involves delineating relatively homogeneous management zones to enable differentiated fertilizer application [1], [3]. Early research employed dense grid-based soil sampling and geostatistical interpolation to generate continuous fertility maps. Although effective, these methods often demand considerable sampling effort and may not readily translate into fertilizer decision rules that are easily adopted by farmers [3].

Clustering-based methods group spatial units—defined areas within a field—into management zones based on similar soil or crop attributes. Fuzzy C-Means (FCM) clustering, a technique that allows data points to partially belong to multiple groups, is widely used in soil fertility assessment, as it captures gradual transitions and inherent uncertainty in soil properties. Unlike hard clustering (which assigns each spatial unit to only one group), FCM gives each spatial unit a degree of membership in multiple clusters, reflecting spatial continuity. Studies have used FCM to delineate management zones based on soil chemical properties (e.g., nutrient levels), electrical conductivity, yield data, and remote sensing (data collected from satellite or aerial images) across cropping systems [3], [8], [9].

Recent research extends FCM zoning by adding multi-nutrient data, principal component analysis, and geospatial techniques. These support variable-rate fertilization and site-specific management. For example, fuzzy clustering has generated nutrient-based zones that capture macro- and micronutrient variability, thereby improving fertilizer targeting [4]-[7]. These studies confirm FCM's suitability for capturing soil heterogeneity and supporting differentiated management. However, most prior work focuses on general fertility zones or composite indices rather than nutrient-specific fertilizer priorities.

At the same time, advances in agricultural sensing technology enable higher-resolution data for precision agriculture [20]. Internet of Things (IoT)-based soil sensors [14] provide near-real-time soil measurements at fine spatial resolution, reducing reliance on labor-intensive laboratory analyses [10], [15], [19]. Unmanned aerial vehicle (UAV) remote sensing also supplies high-resolution information on field structure and crop condition, supporting detailed mapping at the scale of individual beds or plots [11]-[13], [18]. Recent studies highlight the promise of integrating IoT sensing, UAV

imagery, and data analytics into decision-support systems for precision agriculture [17], [18].

Despite these advancements, a gap remains between soil data analysis and the generation of actionable fertilizer recommendations. Few studies have demonstrated direct integration of fuzzy clustering with nutrient-priority logic for N, P, or K at the level of individual spatial units. Additionally, most existing applications operate at coarse spatial scales, which limits their applicability in smallholder vegetable systems where management occurs at the bed scale.

This study addresses these gaps by proposing a spatial classification and decision-support method for mapping fertilizer needs. The method uses Fuzzy C-Means clustering of soil NPK data. It is applied to a 500 × 500 m shallot field in Srikayangan, Kulon Progo, Indonesia. The field is divided into 10 × 10 m blocks for smallholder bed-scale use. Soil N, P, and K were measured with IoT sensors and combined with high-resolution UAV imagery. FCM clustering on normalized NPK data created fertility zones. A nutrient-priority logic then found the most limiting nutrient (N, P, or K) at each block.

This study offers three primary contributions. First, it develops a nutrient-priority logic that translates fuzzy membership degrees into actionable recommendations. Second, it applies FCM clustering at a fine spatial scale consistent with smallholder bed operations. Third, it integrates IoT-based soil sensing and UAV imagery into a straightforward, map-based decision-support output.

This study does not introduce a new clustering algorithm. Rather, it enhances the practicality of FCM-based soil fertility zones by linking fuzzy clustering results with site-specific fertilizer prescriptions. The proposed approach is adaptable to various crops, regions, and sensor configurations where soil nutrient variability necessitates more efficient fertilizer management.

II. Methodology

A. Study Area and Data Acquisition

The study was conducted in an intensively cultivated vegetable field used for seasonal shallot and leafy vegetable production in Desa Srikayangan, Kecamatan Sentolo, Kabupaten Kulon Progo, Yogyakarta, Indonesia. The field in our experiment spans approximately 500 × 500 m and is subdivided into narrow beds and furrows, following local farming practices. The objective of the data acquisition campaign was to capture the spatial variability of soil macronutrients—Nitrogen (N) [16], Phosphorus (P), and Potassium (K), which are essential nutrients plants require in relatively large amounts—and relate it to crop-condition patterns observable from high-resolution UAV (unmanned aerial vehicle) imagery.

A regular sampling grid with a nominal spacing of 10 × 10 m was designed to cover the entire field. Each grid cell (block) was represented by a single sampling point located near the center of the crop bed. At every sampling point, an in-situ NPK soil sensor probe was inserted vertically into the topsoil (0–20 cm) after removing surface residues and ensuring good contact between the probe and the soil [10].

For each point, the probe was held in place until the readings stabilized, and the values of N, P, and K were recorded. To reduce random noise, the insertion and reading process was repeated two or three times within a radius of about 1 m, and the average of these readings was used as the NPK value for the corresponding block. Between sampling points, the probe was cleaned to avoid cross-contamination.

To obtain reference values and assess the consistency of sensor readings, composite soil samples were collected from a subset of grid points. These samples were air-dried and analyzed in the laboratory using standard procedures [4], [5]. The resulting dataset thus consists of triplets, each associated with georeferenced coordinates for a sampling location.

The geographic coordinates of all sampling points were measured using a GNSS receiver mounted on a survey pole, ensuring sub-meter positional accuracy. The in-field NPK sensing and GNSS positioning procedure is illustrated in Fig. 1.



Fig. 1. In-situ soil NPK data acquisition and GNSS-based georeferencing during field sampling.

To obtain a spatially continuous representation of crop condition and field structure, aerial images of the study area were acquired using a fixed-wing unmanned aerial vehicle (UAV) equipped with a nadir-looking RGB camera (Fig. 2). The UAV was programmed to fly an autonomous mission over the 500 × 500 m field along parallel flight lines. The flight altitude was set to approximately 100–120 m above ground level, resulting in a ground sampling distance of a few centimeters per pixel [11],[13].

Forward and side overlaps were configured to at least 70% and 60%, respectively, to ensure reliable image matching. Several ground control points (GCPs) were placed at clearly visible locations within and around the field and surveyed using the same GNSS equipment as the soil sampling points. These GCPs were later used to improve the geometric accuracy of the photogrammetric products.

The raw UAV images were processed using a standard structure-from-motion (SfM) photogrammetry workflow, which includes feature detection and matching, bundle adjustment,

dense point cloud generation, and orthorectification. The resulting orthomosaic was georeferenced in the same projected coordinate system as the GNSS measurements. The georeferenced soil NPK points were then overlaid on the orthomosaic in a geographic information system (GIS), and each 10 × 10 m block was associated with both its NPK values and its corresponding location in the UAV image. This integration enabled subsequent Fuzzy C-Means clustering on the block-level NPK data and the visualization of fertilizer recommendation points directly on the high-resolution UAV map.



Fig. 2. Fixed-wing UAV platform used for high-resolution RGB image acquisition.

B. Data Preprocessing and Block Generation

To support block-level decision making, the study area was discretized into a regular grid of 10 × 10 m cells, hereafter referred to as blocks. Each soil sampling point was assigned to its corresponding block based on spatial location. For blocks with more than one sample, the average values of N, P, and K were computed. Blocks without observations were either excluded from the analysis or filled using simple spatial interpolation (nearest neighbor), depending on their position and the density of surrounding samples.

The raw N, P, and K values may have different units and numerical ranges. To prevent any single nutrient from dominating the clustering process, all variables were normalized prior to analysis. In this study, min–max normalization was used:

$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)}$ Where x_{ij} is the original value of nutrient $j \in \{N, P, K\}$ in block i, and x'_{ij} is the normalized value within the interval $[0,1]$. Each block is then represented as a three-dimensional feature vector.

$$\boldsymbol{x}_i = [N'_i, P'_i, K'_i]$$

Basic quality control was applied to detect and handle outliers (e.g., physically unrealistic values due to sensor error). Outliers were inspected against the laboratory reference data and field notes. If a value was clearly erroneous and could not be confirmed, the corresponding block was removed from further analysis.

C. Fuzzy C-Means Clustering

The core of the proposed approach is the use of the Fuzzy C-Means (FCM) algorithm to partition the blocks into a set of soil fertility clusters based on their normalized N, P, and K values. FCM seeks to minimize the following objective function:

$$J_m = \sum_{i=1}^{n} \sum_{k=1}^{c} u_{ik}^m \parallel \mathbf{x}_i - \mathbf{v}_k \parallel^2$$

where,

- n is the number of blocks,
- c is the number of clusters,
- u_{ik} is the membership degree of block i in cluster k,
- $m > 1$ is the fuzziness exponent (typically $m = 2$),
- $\boldsymbol{v}_k$ is the center of cluster k, and
- $\|\cdot\|$ denotes the Euclidean norm.

In this study, the number of clusters (c) was chosen to represent distinct patterns of nutrient status in the field (e.g., three clusters to capture relatively low, medium, and high fertility combinations or characteristic N–P–K imbalances). The algorithm proceeds iteratively as follows:

- Initialization: Initialize the membership matrix $U[= u_{ik}]$ with random values such that $\sum_{k=1}^{c} u_{ik} = 1$ for all i.
- Cluster center update: Compute cluster centers

$$\mathbf{v}_k = \frac{\sum_{i=1}^{n} u_{ik}^m \mathbf{x}_i}{\sum_{i=1}^{n} u_{ik}^m}$$

for each cluster k.

- Core Membership update: Update membership degrees

$$u_{ik} = \frac{1}{\sum_{j=1}^{c} \left(\frac{\parallel \mathbf{x}_i - \mathbf{v}_k \parallel}{\parallel \mathbf{x}_i - \mathbf{v}_j \parallel} \right)^{\frac{2}{m-1}}}$$

for all blocks i and clusters k.

- Stopping criterion: Repeat steps 2–3 until the change in the membership matrix between two successive iterations falls below a small threshold ε(e.g., 10^{-5}) or a maximum number of iterations is reached.

The implementation was carried out in Python using a custom FCM routine and executed in Google Colab. The output of this step is a set of cluster centers $\{\mathbf{v}_k\}$and a membership matrix that describes the degree to which each block belongs to each cluster.

D. Derivation of Nutrient Priority Classes

To transform the fuzzy clusters into actionable fertilizer recommendations, the nutrient composition of each cluster

center was analyzed. For each cluster k, the relative status of N, P, and K was assessed by comparing the normalized values N'_k, P'_k, and K'_k in v_k to the field-wide distribution or target fertility levels. Clusters in which a particular nutrient exhibits comparatively low values were interpreted as zones where that nutrient is more likely to be limiting.

A simple decision rule was then defined to assign a nutrient priority to each block:

- For each cluster k, determine the "most limiting" nutrient j_k, which is the nutrient with the lowest normalized value in $\mathbf{v}_k$.
- For each block i, compute a nutrient priority score by combining its membership degrees with the cluster-level limiting nutrients. For example, the priority score for nutrient j in block i can be defined as,

$$S_{ij} = \sum_{k:j_k=j} u_{ik}$$

- Assign block i to the nutrient with the highest score $\arg\max_j S_{ij}$, yielding one of three recommendation classes: N-priority, P-priority, or K-priority.

This procedure preserves the fuzzy nature of the underlying clusters while providing a crisp, interpretable label for operational use. Blocks with similar scores for multiple nutrients can be flagged as mixed or flexible zones for further agronomic evaluation if needed.

E. Spatial Mapping and Visualization

The FCM cluster labels (dominant cluster per block) and the nutrient-priority classes were joined back to the 10 × 10 m spatial grid and visualized in a GIS. The fertility clusters were displayed as a zonation map of the shallot field. At the same time, the nutrient-priority classes were represented in a separate map showing whether N, P, or K should be emphasized in each block.

To make the output usable in the field, representative fertilizer recommendation points were selected from within contiguous patches of each nutrient-priority class. In each patch, a few blocks with the highest nutrient-priority scores were chosen as application points. These points were then overlaid on the UAV orthomosaic, allowing farmers and field technicians to locate the recommended areas directly on a detailed image of the shallot beds. The final maps form the basis for suggesting differentiated fertilizer rates (e.g., higher urea doses at N-priority points, higher SP-36 at P-priority points, and higher KCl at K-priority points) instead of a single uniform NPK recommendation for the whole field.

III. Results and Analysis

A. Fuzzy C-Means Zoning of Soil Fertility

The Fuzzy C-Means (FCM) algorithm successfully partitioned the 500 × 500 m field into three main fertility zones based on the N, P, and K measurements at each 10 × 10 m block. Visual inspection of the resulting clusters (Fig. 3) shows that the field is clearly structured into red, green, and blue zones with gradual transitions rather than abrupt boundaries.

Cluster-level analysis indicates that:

- Cluster 1 (Red) corresponds to blocks with high N and relatively low K.
- Cluster 2 (Green) represents blocks with high K but lower N.
- Cluster 3 (Blue) is characterized by relatively high P with more balanced N and K values.

These patterns align with the agronomic interpretation in the field, where some areas receive high N fertilization but remain undersupplied with P and K. In contrast, other areas have accumulated K from previous applications.

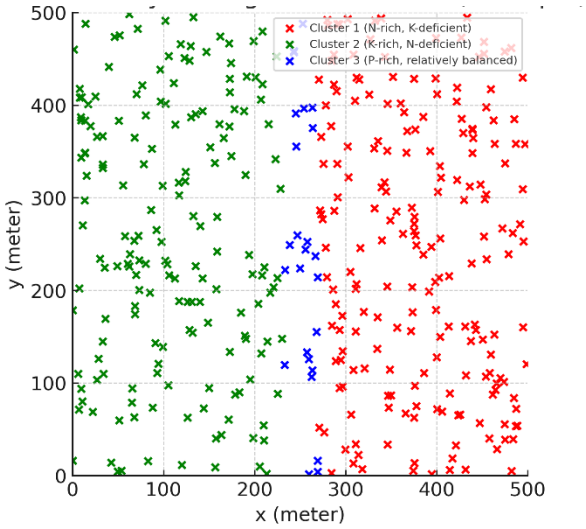


Fig. 3. Soil fertility zoning based on Fuzzy C-Means clustering.

The quality of the clustering was evaluated using two internal indices. The Silhouette Score of 0.61 and Dunn Index of 0.03 suggest that the three clusters are reasonably well separated while still capturing the gradual variability that exists in real soil conditions. These values suggest that FCM offers a reliable representation of the underlying fertility structure and is suitable as a basis for informed spatial decision-making.

B. Spatial Pattern of Nutrient Deficiencies

By comparing the cluster centers with the most fertile reference condition, it is possible to identify which parts of the field are more likely to be deficient in specific nutrients. The cluster map in Fig. 4 shows that:

- The western part of the field is dominated by Cluster 2 (green), indicating high K but relatively low N, and simultaneously showing P deficiency in some blocks.
- The eastern part of the field is dominated by Cluster 1 (red), where N is high but P and K are lower, suggesting a need to supplement P and K rather than N.
- Cluster 3 (blue) appears in intermediate zones with higher P and relatively balanced N and K, acting as a transition between the red and green zones.

This pattern confirms that nutrient limitations are not uniform: the west is mainly limited by P and K, whereas the east

is more constrained by N. Such differences justify the need for site-specific fertilizer management instead of uniform application. Table I summarizes the qualitative interpretation of each cluster based on the N, P, and K status.

TABLE I. INTERPRETATION OF FCM FERTILITY CLUSTERS

Cluster	Dominant color	N status	P status	K status	Interpretation
C1	Red	High	Low–medium	Low	N-rich, K-deficient zone (needs P and K)
C2	Green	Low–medium	Low–medium	High	K-rich, N-deficient zone
C3	Blue	Medium	High	Medium	P-rich, relatively balanced, and stable zone

C. Fertilizer Recommendation Points

To translate the cluster information into operational recommendations, fertilizer application points were determined by selecting blocks with the highest nutrient-priority scores inside each deficiency zone. These points are located near the centers of areas with the strongest shortage, representing locations where additional fertilizer will have the most significant effect while still covering surrounding blocks.

The resulting fertilizer recommendation map is shown in Fig. 4. The background colors represent the FCM clusters as in Fig. 3, while overlaid symbols indicate specific application points for each nutrient:

- Red squares mark N application points, where additional urea is recommended.
- Blue triangles mark P application points, where SP-36 is prioritized.
- Green circles mark K application points, where KCl is prioritized.

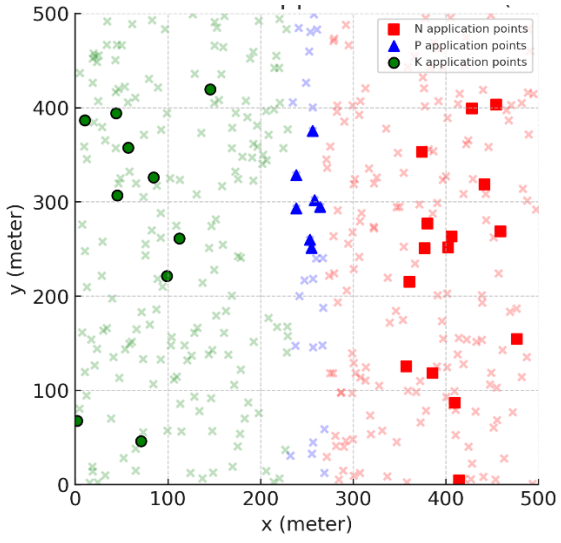


Fig. 4. Fertilizer recommendation points over the FCM zonation map.

Based on the nutrient-priority classification, the corresponding fertilizer types and application rates are summarized in Table II.

TABLE II. FERTILIZER RECOMMENDATION RATES BY NUTRIENT PRIORITY

Nutrient priority	Symbol/color in Fig. 4	Recommended fertilizer and rate (per ha)
N-priority	Red square	Urea 300–350 kg/ha
P-priority	Blue triangle	SP-36 100–120 kg/ha
K-priority	Green circle	KCl 150–200 kg/ha

These recommended doses are intended for the core application points and can be adjusted proportionally for the surrounding blocks, depending on equipment capability and field conditions.

D. Visualization on High-Resolution Spatial Agricultural Map

To make the results directly interpretable by farmers and local extension workers, the nutrient-priority recommendation points were finally overlaid on a high-resolution aerial orthomosaic of the study area (Fig. 5). The orthomosaic was generated from UAV imagery and represents individual crop beds and management units within the 500 × 500 m field.

The coordinates of the 10 × 10 m blocks and the selected fertilizer application points (Section III-C) were transformed into the same spatial reference system as the orthomosaic. Each point was then plotted on top of the image and symbolized according to its recommended nutrient:

- blocks with N-priority were marked as N application points,
- blocks with P-priority were marked as P application points, and
- Blocks with K-priority were marked as K application points.

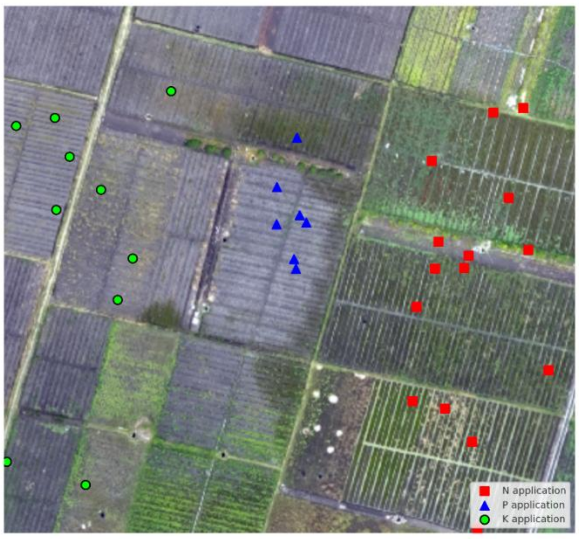


Fig. 5. UAV orthomosaic with FCM-based fertilizer recommendation points.

Fig. 5 shows that many N-priority points coincide with visually lighter or less vigorous plots in the eastern portion of the field. In contrast, P- and K-priority points are concentrated in the western and central plots where crop growth appears uneven or patchy. This spatial correspondence between visual crop condition and the FCM-based nutrient recommendations provides an additional qualitative validation of the proposed method.

By combining the orthomosaic with the fertilizer recommendation points, the resulting map becomes a practical tool for field operations: farmers can visually locate specific beds or parcels that require N, P, or K and adjust their applications accordingly. The map can also be integrated into mobile or web-based interfaces, allowing operators to navigate to the recommended positions using GPS while viewing the underlying UAV image.

E. Discussion

The FCM-based spatial classification clearly revealed that the 500 × 500 m field cannot be treated as a uniform management unit. The three clusters obtained from NPK data describe distinct fertility regimes that are consistent with both the historical fertilization practices and the visual crop patterns observed in the UAV imagery. Cluster 1 (red) represents blocks with relatively high N. However, Cluster 2 (green) corresponds to blocks with high K but lower N, and Cluster 3 (blue) contains blocks with relatively high P and more balanced N and K. These patterns suggest that the field has experienced heterogeneous nutrient accumulation, with specific areas receiving repeated N applications while others have accumulated K or P.

When the cluster information is translated into nutrient-priority classes, a transparent spatial gradient emerges: the western part of the field is dominated by blocks that require additional phosphorus (P) and potassium (K). In contrast, the eastern part shows a concentration of N-priority blocks. The central area is characterized by P-priority points associated with Cluster 3, which has a higher P. However, only moderate N and K. This configuration implies that a uniform NPK recommendation would inevitably over-fertilize some zones (e.g., N in the western plots) and under-fertilize others (e.g., P and K in the west, N in the east). Instead, the proposed method provides differentiated targets: more P and K in the west, more N in the east, and fine-tuned doses in the transition zones.

A key advantage of FCM in this context is its ability to handle gradual transitions and uncertainty. Traditional hard clustering or simple thresholding of nutrient values would force each block into a single, crisp category, creating sharp boundaries between zones that may not exist in reality. In contrast, FCM assigns membership degrees to multiple clusters for each block. The nutrient-priority scores derived from these memberships enable the method to highlight "core" deficiency zones, where a single nutrient is clearly limiting, while also acknowledging mixed or ambiguous areas. This is reflected in the placement of fertilizer recommendation points, which tend to appear in the centers of homogeneous patches, rather than directly on the boundaries between different fertility regimes. This is agronomically reasonable because edge blocks can often be managed with intermediate or blended doses.

The overlay of fertilizer recommendation points on the UAV orthomosaic further strengthens the interpretation. In the eastern plots where N-priority points cluster, the imagery shows lighter coloration and less vigorous canopy growth, typical of N deficiency. Conversely, several P- and K-priority points are located in western or central plots, where the vegetation pattern is patchy or where crop rows appear uneven. The spatial agreement between model-derived recommendations and visual symptoms from high-resolution imagery serves as an independent, qualitative validation of the approach. It also demonstrates how proximal sensing (soil sampling and FCM analysis) and remote sensing (UAV imagery) can be combined into a single, intuitive decision-support product for farmers.

From a management perspective, the generated maps enable site-specific fertilization at a resolution that is compatible with the scale of individual beds or farmer-owned subplots. By applying urea only around the N-priority points in the east (300–350 kg/ha), and focusing SP-36 and KCl around P- and K-priority points in the west and center, the farmer can reallocate a fixed fertilizer budget more efficiently rather than increasing total input. This has two important implications: 1) potential economic benefits, through savings in fertilizer where it is not needed and yield gains where deficiencies are corrected; and 2) environmental benefits, by reducing the risk of nitrate leaching and K or P accumulation in already fertile zones. Although yield measurements are not yet included in this study, the spatial pattern of recommendations is consistent with these expected outcomes.

At the same time, several limitations should be acknowledged. First, the analysis is based on a single sampling campaign, which captures spatial but not temporal variability; nutrient dynamics across seasons or cropping cycles are not yet modeled. Second, the block size of 10 × 10 m represents a compromise between spatial detail and sampling feasibility. Smaller blocks could reveal finer heterogeneity but would require more intensive sampling, while larger blocks might mask important within-block variability. Third, the fertilizer doses used in the recommendation map are derived from general agronomic guidelines; they would ideally be adjusted using response curves or economic optimization to quantify the benefits of site-specific management fully. Finally, the clustering quality, although supported by the Silhouette Score (0.61) and Dunn Index (0.03), could be further evaluated by comparing alternative clustering methods (e.g., k-means, Gaussian mixture models) and by validating the zones against actual yield data.

Despite these limitations, the study demonstrates that integrating FCM clustering with nutrient-priority analysis and UAV imagery can produce operationally meaningful fertilizer recommendation maps. The methodology is generic and can be extended to other fields, additional nutrients, or different sensor sources, and can be embedded into an IoT-based platform, such as Agri Watch Net, to support near-real-time decision-making. Future work will focus on multi-seasonal data, yield-based validation, and coupling the nutrient-priority maps with variable-rate application technologies to quantify the economic and environmental benefits of adopting this approach.

Although this study is demonstrated using a shallot field in Srikayangan, Indonesia, the contribution of this work is not limited to a specific crop or geographic context. The proposed framework is methodologically generic and can be applied to any agricultural system where 1) soil macronutrients can be measured at spatial sampling points (via sensors or laboratory analysis), 2) a management grid can be defined according to operational field units, and 3) spatial transitions in soil fertility are expected. The use of Fuzzy C-Means clustering combined with nutrient-priority decision logic is independent of crop type and location, and therefore transferable to other horticultural crops, cereal systems, and smallholder or commercial farming contexts. In this sense, the Srikayangan field serves as a representative testbed to demonstrate the operational feasibility of translating fuzzy soil fertility classification into actionable fertilizer recommendations, rather than as a location-specific solution.

IV. Conclusion

This study presented a spatial classification and decision-support framework for fertilizer requirement mapping based on Fuzzy C-Means clustering of soil NPK data integrated with IoT-based sensing and UAV imagery. By applying the proposed approach at a fine spatial resolution compatible with smallholder bed-scale management, the results demonstrate that soil fertility within a single field can exhibit substantial spatial differentiation, making uniform fertilizer application inefficient and potentially wasteful.

The use of fuzzy clustering enables the representation of gradual transitions in soil nutrient availability, while the introduced nutrient-priority decision logic bridges the gap between fuzzy classification outputs and actionable fertilizer recommendations. Rather than producing only generalized fertility zones, the proposed framework identifies which macronutrient—Nitrogen, Phosphorus, or Potassium—should be prioritized at each management block, thereby enhancing the operational relevance of site-specific nutrient management.

Although the framework was demonstrated using a shallot field in Srikayangan, Indonesia, its contribution lies in the methodological integration and decision-support logic rather than the specific field context. The approach is generic and transferable to other crops, regions, and agricultural systems where spatial variability in soil nutrients necessitates more targeted fertilizer management. By combining fuzzy clustering with high-resolution sensing and intuitive spatial visualization, this work provides a practical pathway for translating soil data into actionable management decisions.

Overall, the proposed framework advances the practical usability of FCM-based soil fertility zonation for precision agriculture by linking data-driven spatial analysis with fertilizer decision-making, thereby supporting more efficient, economical, and sustainable nutrient management practices.

V. Future Work

Future research will focus on extending the proposed framework in several directions. First, multi-season soil and crop data will be incorporated to capture temporal nutrient dynamics and improve the robustness of fertilizer recommendations. Second, the derived nutrient-priority zones will be validated against measured yield and economic return data to quantify agronomic and financial benefits. Third, comparative experiments with alternative clustering and interpolation methods, such as k-means and geostatistical kriging, will be conducted to evaluate methodological trade-offs. Finally, the integration of the proposed approach with variable-rate fertilizer application technologies and mobile decision-support interfaces will be explored to facilitate real-time, data-driven nutrient management at scale.

Acknowledgment

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References

[1] J. A. Thomasson, R. Sui, M. S. Cox, and K. A. Al-Rajehy, "Soil variability and site-specific nutrient management," Precision Agriculture, vol. 2, no. 1, pp. 43–57, 2001, doi: 10.1023/A:1013314910435.

[2] A. Dobermann and T. Fairhurst, "Rice: Nutrient Disorders & Nutrient Management," Potash & Phosphate Institute, Singapore, 2000.

[3] Y. Li, Z. Shi, C. Wu, H. Li, and F. Li, "Determination of potential management zones from soil electrical conductivity, yield and crop data using fuzzy c-means clustering," J. Zhejiang Univ. Sci. B, vol. 9, no. 1, pp. 68–76, 2008, doi: 10.1631/jzus.B071067.

[4] A. Venugopal, P. S. Raju, R. G. Durgaprasad, and M. Venkateswarlu, "Nutrient variability mapping and demarcating management zones using fuzzy cluster analysis for variable-rate fertilization," Sustainability, vol. 16, no. 5, art. no. 2095, 2024, doi: 10.3390/su16052095.

[5] M. Venkateswarlu, S. Rallapalli, A. Singh, and S. Raju, "Macro- and micronutrient-based soil fertility zonation using fuzzy logic and geospatial techniques," Scientific Reports, vol. 15, art. no. 26772, 2025, doi: 10.1038/s41598-025-26772-x.

[6] P. V. Bhagwan, R. K. Naik, and M. L. Narayana, "Delineation and evaluation of management zones for site-specific nutrient management using PCA and fuzzy c-means clustering," Scientific Reports, vol. 15, art. no. 18431, 2025, doi: 10.1038/s41598-025-18431-y.

[7] P. V. Bhagwan, R. K. Naik, and M. L. Narayana, "Delineating soil fertility management zones using geostatistics and fuzzy clustering techniques," Environmental Monitoring and Assessment, vol. 197, no. 2, art. no. 92, 2025, doi: 10.1007/s10661-025-09234-6.

[8] W. Zhao, X. Zhang, H. Li, and Y. Wang, "Comparison of SOFM, fuzzy c-means, and k-means clustering algorithms for soil environment regionalization," Environmental Research, vol. 225, art. no. 115564, 2023, doi: 10.1016/j.envres.2023.115564.

[9] P. Servadio, S. Bergonzoli, and F. Marinari, "Delineation of management zones based on soil compaction using fuzzy clustering," Spanish Journal of Agricultural Research, vol. 16, no. 3, art. no. e0207, 2018, doi: 10.5424/sjar/2018163-12847.

[10] R. M. Hujja, I. Ernanto, M. Auzan, and R. Sumiharto, "Independent soil node sensor prototype as part of a smart farming system," International Journal of Scientific & Technology Research, vol. 9, no. 8, pp. 200–204, 2020.

[11] A. Harjoko, R. M. Hujja, and L. Awaludin, "Aerial agricultural monitoring using image processing: A comparative study," International Journal of Advanced Research in Science, Engineering and Technology, vol. 5, no. 6, pp. 6232–6237, 2018.

[12] M. G. R. Satriorini, R. Sumiharto, and R. M. Hujja, "Digital image-based orchid growth monitoring system," International Journal of Electrical and Information Systems, vol. 6, no. 2, pp. 85–94, 2023.

[13] A. Saputra, N. R. Masithoh, R. Sumiharto, and R. M. Hujja, "Plant growth monitoring using image analysis for agricultural applications," in Proc. Int. Conf. Agricultural and Food Sciences, 2022, pp. 55–60.

[14] A. Ashari, R. M. Hujja, and L. Kurniasih, Internet of Things dan Aplikasinya: Menghubungkan Dunia Fisik dan Digital untuk Kehidupan yang Lebih Cerdas. Yogyakarta, Indonesia: Deepublish, 2025.

[15] D. Pascoal, R. Costa, and J. Santos, "IoT sensors for precision agriculture: Architectures, challenges, and applications," Scientific Reports, vol. 14, art. no. 11245, 2024, doi: 10.1038/s41598-024-11245-3.

[16] A. M. Ali, H. M. Salem, and B. Singh, "Site-specific nitrogen fertilizer management using canopy reflectance sensors, chlorophyll meters, and leaf color charts: A review," Nitrogen, vol. 5, no. 4, pp. 828–856, 2024, doi: 10.3390/nitrogen5040054.

[17] A. B. Rashid, M. Al Mamun, and S. Rahman, "Integration of AI, IoT, and UAVs for precision agriculture: A review and framework," Results in Engineering, vol. 19, art. no. 100812, 2025, doi: 10.1016/j.rineng.2025.100812.

[18] X. Chen, Y. Liu, and H. Zhang, "Dynamic monitoring and precision fertilization decision system integrating UAV remote sensing and GIS," Agriculture, vol. 15, no. 2, art. no. 214, 2025, doi: 10.3390/agriculture15020214.

[19] K. Gunasekaran, R. Aravind, and P. Kumar, "Real-time soil fertility analysis using IoT and fuzzy clustering techniques," Frontiers in Soil Science, vol. 5, art. no. 1298456, 2025, doi: 10.3389/fsoil.2025.1298456.

[20] Y. Li, H. Wu, and Z. Shi, "Delineation of site-specific management zones using fuzzy clustering in precision agriculture," Computers and Electronics in Agriculture, vol. 65, no. 2, pp. 154–166, 2007, doi: 10.1016/j.compag.2008.07.005.

CleanCity IoT: A Vehicle-Mounted Platform for Real-Time Urban Air-Quality Monitoring and Forecasting in Resource-Constrained African Cities

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***Abstract*—Urban air pollution is a growing public-health challenge in African cities, yet traditional monitoring stations are sparse and expensive. The paper presents CleanCity IoT, a deployed, low-cost, vehicle-mounted air-quality platform that combines IoT sensors, GSM connectivity, cloud aggregation, and machine learning to produce near-real-time exposure maps and 2-hour forecasts for multiple pollutants. Each device integrates low-cost sensors for PM2.5, PM10, NO_2, O_3, SO_2, and CO_2, alongside temperature and humidity. Measurements are geotagged and transmitted over mobile networks form vehicles to a cloud backend, where data are validated, stored, and visualized through a user-friendly dashboard that also issues automated alerts and periodic reports. Using a dataset collected in Kigali and secondary cities via routine vehicular routes, the paper introduces the training of a multivariate time-series model to forecast short-horizon pollutant levels, supporting proactive health guidance and regulatory action. The system reports a performance in terms of latency, uptime, coverage, and data quality, and evaluate forecast accuracy using MAE/RMSE/MAPE and event-oriented metrics for spike prediction. Results indicate that CleanCity IoT provides reliable, scalable, and cost-effective urban air-quality intelligence, closing key gaps in spatiotemporal coverage while enabling citizen access, policy support, and social impact. The platform demonstrates a practical blueprint for African cities to operationalize air-quality intelligence using existing mobile infrastructure and locally developed technology.**

Keywords*—CleanCity IoT; air quality; mobile sensing; multivariate forecasting; spike detection

I. Introduction

Urban air pollution has emerged as one of the fastest-growing environmental and public-health threats in African cities such as Kigali, Rwanda, driven by rapid urbanization, motorization, and industrial expansion [1][2]. The World Health Organization (WHO) reports that air pollution causes over seven million premature deaths annually, while nearly 90% of the global population is exposed to pollutant concentrations exceeding recommended limits. In many low- and middle-income countries, fine particulate matter ($PM_{2.5}$ and PM_{10}) and gaseous pollutants such as nitrogen dioxide (NO_2), sulfur dioxide (SO_2), ozone (O_3), and carbon dioxide (CO_2) remain poorly monitored, limiting the capacity for evidence-based policymaking and citizen awareness [3]. Recent environmental assessments in Kigali have revealed that $PM_{2.5}$ concentrations during peak hours often surpass 50 µg/m³, nearly double the WHO 24-hour guideline, highlighting an urgent need for high-resolution, real-time monitoring systems [4].

Conventional air-quality monitoring infrastructures, which depend on fixed high-precision stations, provide accurate but spatially limited data. Their high installation and maintenance costs prevent widespread deployment across large or topographically diverse urban areas. Consequently, most African cities rely on sparse or intermittent measurements that fail to capture micro-scale variations and short-term pollution spikes. In response, researchers have turned to low-cost Internet of Things (IoT)–based sensing networks that offer dense, distributed data acquisition at a fraction of the traditional cost [4], [5]. Among the most effective configurations are vehicle-mounted sensor systems, which leverage the mobility of public-service vehicles, taxis, and buses to achieve city-wide spatial coverage without constructing new fixed stations [5] [6] [7].

Earlier studies such as [8] on affordable vehicle-mounted monitoring, [9] on IoT devices for municipal vehicles, and [6] on bus-based monitoring platforms have demonstrated the technical feasibility of mobile air-quality mapping and visualization. These systems collect particulate and gaseous pollutants while traversing city corridors, producing near-real-time datasets for spatial pattern analysis. However, most prior implementations primarily focused on measurement and visualization, offering limited integration of predictive analytics, alert systems, and policy-support mechanisms—features crucial for proactive environmental management, especially in data-scarce regions.

Building upon these efforts, this study introduces CleanCity IoT, a low-cost, scalable, and mobile air-quality monitoring and forecasting platform developed at the University of Rwanda in collaboration with national and regional partners. Each CleanCity IoT unit integrates low-cost sensors for $PM_{2.5}$, PM_{10}, NO_2, SO_2, O_3, and CO_2, along with temperature and humidity modules, controlled by an ESP32 microcontroller equipped with

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GSM connectivity. The devices are mounted on moving vehicles, enabling spatially continuous air-quality sampling across Kigali and secondary cities. Data are transmitted via mobile networks to a cloud server (ThingSpeak), where they are cleaned, stored, and visualized through a real-time web dashboard featuring pollution heat maps, alert notifications, and automated reporting tools. Fig. 1 illustrates the overall CleanCity IoT ecosystem, including its sensing, communication, and analytics layers.

A distinctive feature of CleanCity IoT is the inclusion of a machine-learning forecasting module that predicts pollutant levels up to two hours ahead based on multivariate time-series data. This capability enables early warnings and supports informed interventions by environmental authorities, health agencies, and city planners. Furthermore, by making air-quality information publicly accessible through a user-friendly dashboard, the system strengthens community engagement and promotes citizen science, aligning with Rwanda's Smart-City and environmental-sustainability initiatives.

The proposed study builds upon the foundational work by [10], [11], who developed an IoT-edge-based prototype for detecting transportation-related pollution spikes in Kigali. Their system demonstrated the feasibility of using low-cost IoT networks for real-time air-quality monitoring in urban transport corridors. However, while the earlier prototype focused primarily on localized pollution detection and data transmission through edge networks, the present research extends this framework into a fully integrated CleanCity IoT system that includes mobile GSM-based data collection, cloud dashboard visualization, and machine-learning-driven forecasting. Thus, this study represents both continuation and enhancement of the ACEIoT initiative's earlier work, translating edge-level monitoring into a scalable, citizen-centered solution for smart urban management.

A. Contributions

The key contributions of this work are as follows:

- Design and deployment of a vehicle-mounted IoT device integrating multi-pollutant gas and particulate sensors with GSM-based real-time communication.
- Implementation of a cloud-hosted dashboard providing visualization, alerting, and reporting functionalities for stakeholders.
- Development of a multivariate machine-learning model for two-hour-ahead pollutant prediction, supporting proactive urban-health responses.
- Field validation of the system in Kigali and secondary cities, demonstrating low-cost scalability, data reliability, and practical usability.
- Promotion of local innovation and social impact, reinforcing Rwanda's vision for smart and sustainable urban management.

Through these contributions, CleanCity IoT establishes a practical, home-grown framework for real-time, predictive, and socially inclusive air-quality intelligence applicable to cities across Africa.

B. Paper Organization

The remainder of this paper is structured as follows: Section II reviews related work on mobile air-quality sensing and forecasting techniques. Section III describes the system design, algorithm construction and hardware implementation. Section IV presents data-processing and machine-learning methodologies. Section V discusses experimental results and performance evaluation, and Section VI concludes with key findings and future research directions.

II. Related Work

A. Conventional and Fixed-Station Monitoring

Traditional air-quality surveillance depends on reference-grade analyzers that provide highly accurate but spatially limited data. These stations, typically operated by environmental agencies, can cost more than USD 50,000 per unit, with significant yearly maintenance expenses [8]. Such systems monitor only a few fixed locations, resulting in low spatial coverage that fails to capture localized variations in pollutants caused by traffic density, topography, or industrial activities. While essential for calibration and regulatory baselines, fixed networks are financially unsustainable for widespread deployment in developing countries.

B. Emergence of Low-Cost IoT Sensor Networks

Advances in sensor miniaturization, embedded microcontrollers, and cloud connectivity have led to low-cost IoT-based monitoring systems [12], [13]. These frameworks employ microcontrollers such as Arduino or ESP32 and communication technologies including Wi-Fi, GSM, or LoRa to transmit environmental data in real time. Gubbi *et al.* (2013) outlined a scalable IoT architecture for smart environments that has since inspired numerous urban-sensing deployments. Although low-cost sensors are less accurate than reference analyzers, they enable dense spatial coverage, data fusion, and temporal tracking when coupled with calibration algorithms or machine learning [5], [14].

C. Mobile and Vehicle-Mounted Sensing Approaches

To improve spatial resolution, several researchers have adopted mobile sensing using vehicles as carriers. The paper [12] designed an affordable vehicle-mounted system for dynamic air-quality mapping. In the papers [6] implemented a bus-based monitoring platform integrated with cloud dashboards for real-time visualization. The paper [9] deployed IoT modules on municipally governed vehicles to track NO_2 and particulate matter across city zones. The paper in [7] proposed a vehicular sensor network architecture for real-time pollution analysis, while the paper [15] validated low-cost mobile sensors for hyperlocal monitoring in London. These projects proved the feasibility of vehicular IoT systems, but most emphasized data collection and visualization, with limited inclusion of predictive analytics, alerts, or decision-support tools.

A recent Rwandan contribution in the paper [10] introduced an IoT-edge-based system for detecting transportation pollution spikes using embedded edge computing. Their implementation at the Africa Centre of Excellence in Internet of Things (ACEIoT) validated the use of localized edge devices for

vehicular pollution tracking. Building on this foundation, the current CleanCity IoT framework enhances mobility, scalability, and predictive intelligence through GSM-based data transmission and cloud-integrated analytics.

D. Cloud-Based Data Aggregation and Visualization

Cloud computing has become central to IoT ecosystems for environmental data management. Platforms such as ThingSpeak, AWS IoT Core, and Azure IoT Hub support data ingestion, storage, and visualization in real time [1], [6], [13], [14], [16], [17]. The papers [2], [18] [6] demonstrated city-wide dashboards for pollutant tracking, and [7] discussed open-source architectures for mobile-data integration with geographic information systems. Nevertheless, most cloud-based implementations stop at visualization, lacking automated alerting, policy analytics, and citizen-accessible interfaces key enablers for social impact.

E. Machine-Learning Forecasting for Air Quality

Accurate short-term forecasting of air pollutants enables preventive interventions. Statistical models such as ARIMA and VAR have been widely used for one-step-ahead predictions, but deep-learning approaches now dominate multivariate time-series forecasting [19]. LSTM and GRU networks, as explored in paper [20] outperform linear models in capturing nonlinear temporal dependencies of $PM_{2.5}$ and NO_2 concentrations. Despite these advances, few studies integrate such predictive analytics directly into mobile, low-cost IoT frameworks, particularly within African contexts where both connectivity and calibration data are limited.

Quantitatively, low-cost sensor units in these studies ranged from USD 150–300 per node, achieved spatial resolutions up to 100m, and showed mean deviations of ±10-20% compared with reference instruments [6], [7], [12]. Such performance is adequate for mapping and trend detection but insufficient for health-critical forecasting without data calibration and model correction.

F. Research Gap and Motivation

Despite the progress summarized above, major limitations persist:

- Lack of integrated forecasting and alerting modules within mobile IoT systems.
- Absence of region-specific deployments in sub-Saharan Africa using GSM infrastructure for scalable connectivity.
- Minimal incorporation of citizen-accessible dashboards and community engagement mechanisms.

The CleanCity IoT platform directly addresses these challenges by combining multi-pollutant IoT sensing, GSM data transmission, cloud-based visualization, and machine-learning-driven forecasting. The project exemplifies a locally developed, cost-effective solution advancing both environmental intelligence and social awareness.

The reviewed literature highlights a steady evolution from fixed-station monitoring toward IoT-enabled, mobile, and data-driven frameworks as shown in Table I. However, none fully integrate predictive analytics, social accessibility, and regional scalability within a single platform. Section III therefore presents the system design and implementation of the proposed CleanCity IoT solution, detailing its hardware architecture, communication model, and cloud-analytics workflow.

TABLE I. COMPARATIVE SUMMARY OF RELATED IOT AND MOBILE AIR-QUALITY MONITORING SYSTEMS

Author & Year	Platform System	Methodology Features	Key Contribution	Identified Limitation
Santana et al. (2021)	Vehicle-mounted AQ mapping	ESP32 + GSM; $PM_{2.5}$ / NO_2 sensing	Affordable mobile monitoring	No predictive analytics
Ivanova et al. (2020)	IoT on municipal vehicles	Wi-Fi IoT nodes; CO PM sensors	Dynamic city-wide mapping	Limited citizen interface
Correia et al. (2023)	Bus-based AQ system	Cloud dashboard visualization	Real-time city dashboards	No forecasting capability
Zherka & Tafa (2023)	Vehicular sensor network	On-board sensors + data fusion	Real-time analysis	Lacks scalability
Zboralski & Kunz (2024)	Mobile GIS framework	Cloud integration	Open-source architecture	No alert or policy module
CleanCity IoT (this work)	Vehicle IoT + GSM + ML	ESP32 + GSM + ThingSpeak + LSTM	Real-time forecasting + dashboard + alerts	-------

III. METHODOLOGY

A. Overview of the Proposed Framework

The CleanCity IoT framework is designed as an end-to-end intelligent air-quality monitoring and forecasting system that leverages Internet of Things (IoT), cloud computing, and machine learning (ML) technologies to provide real-time insights into urban pollution dynamics. The framework aims to transform conventional monitoring often limited to fixed stations into a mobile, scalable, and predictive sensing ecosystem suited for low-resource contexts such as Rwandan cities.

In Fig. 1, the system operates through four tightly integrated layers: 1) sensing and acquisition, 2) communication and transmission, 3) cloud storage and analytics, and 4) visualization and forecasting. Each layer contributes specific functionalities, forming a pipeline that converts raw sensor readings into actionable intelligence for environmental management and policy decision-making.

In the sensing and acquisition layer, a suite of low-cost environmental sensors continuously measures air pollutants including particulate matter ($PM_{2.5}$, PM_{10}), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), ozone (O_3), and carbon dioxide (CO_2), alongside ambient parameters such as temperature and humidity. These sensors are interfaced with an ESP32 microcontroller integrated with a SIM800L GSM module, enabling both data collection and mobile transmission from vehicle-mounted units.

The communication and transmission layer employs GSM/GPRS connectivity for real-time data delivery to cloud infrastructure. This design choice compared to Wi-Fi or LoRa is motivated by the wide availability of mobile networks across Rwandan cities and highways, ensuring scalability and mobility without dependency on fixed infrastructure.

The cloud layer utilizes the ThingSpeak IoT platform, which serves as both a data repository and preliminary analytics engine. Each sensing node transmits periodic measurements (every 30 seconds to 1 minute) to predefined ThingSpeak channels through HTTP POST requests. The platform aggregates, timestamps, and visualizes incoming data streams, while also allowing external APIs for integration with advanced analytical tools such as MATLAB, Python, or Node-RED for extended processing and forecasting.

The visualization and forecasting layer bridge the system's technical outputs with end-user interaction. A custom Air Quality Dashboard accessible via web or mobile interface—displays real-time pollutant levels, temporal trends, and geospatial mapping of emission zones. Historical datasets retrieved from ThingSpeak are used to train a Long Short-Term Memory (LSTM)-based predictive model, which forecasts pollutant concentrations two hours ahead. This predictive feature enhances early-warning capabilities and supports data-driven policy interventions by environmental authorities.

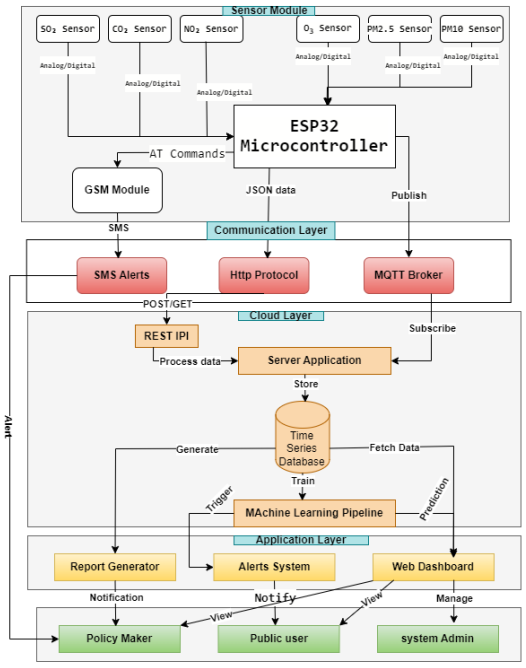


Fig. 1. Proposed framework.

B. Hardware Design and Components

The CleanCity IoT hardware architecture was designed to achieve low-cost, high-mobility, and energy-efficient air-quality monitoring while maintaining compatibility with existing mobile communication networks. The system integrates multiple sensors, a microcontroller unit, and a GSM communication interface, all mounted within a compact enclosure suitable for vehicular deployment.

1) Main controller: ESP32 (LilyGO T-Call SIM800L): At the core of the system lies the LilyGO T-Call ESP32 board on Fig. 2, which combines a dual-core 32-bit Xtensa processor with an embedded SIM800L GSM/GPRS module. The ESP32 manages sensor data acquisition, preprocessing, and transmission, while the GSM modem handles real-time communication with the cloud platform. The built-in UART, ADC, and GPIO interfaces facilitate multi-sensor connectivity, and the board supports 3.3 V logic with a stable 5 V input via USB or Li-ion battery.

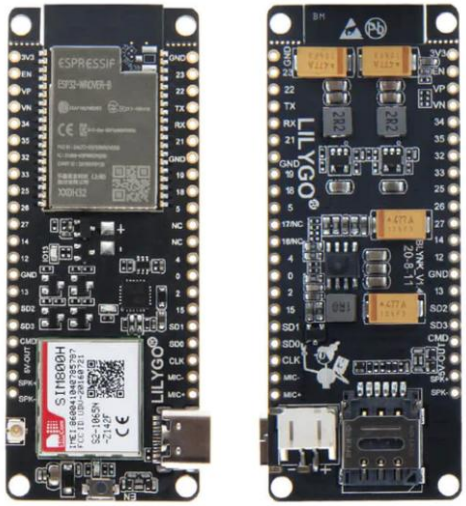


Fig. 2. LilyGO T-Call SIM800L.

The SIM800L module provides reliable 2G cellular connectivity, using HTTP POST requests to upload sensor readings to ThingSpeak channels. The use of GSM ensures that each node remains fully mobile and independent of Wi-Fi coverage, a critical feature for vehicle-mounted monitoring units in Rwandan cities and peri-urban areas.

2) Sensor suite: The CleanCity IoT system employs a diverse set of environmental sensors to capture the most relevant atmospheric parameters affecting air quality. Each sensor was selected for its low cost, stability, and proven performance in mobile IoT applications.

3) PMS5003 – particulate matter ($PM_{2.5}$ and PM_{10}): The Plantower PMS5003 in Fig. 3 is a laser-scattering particulate matter sensor capable of measuring fine and coarse particles ($PM_{2.5}$ and PM_{10}) in real time. It uses a light-scattering principle combined with a digital signal processor to calculate mass concentration in micrograms per cubic meter (µg/m³). The sensor communicates via UART and offers high sensitivity and accuracy suitable for vehicular environments, making it ideal for continuous mobile air-quality monitoring.

4) MQ-131 – Ozone (O_3) sensor: The MQ-131 sensor in Fig. 4 detects ozone concentrations using a tin dioxide (SnO_2)-based semiconductor layer. When O_3 gas contacts the sensitive surface, it alters the material's conductivity proportionally to the gas concentration. The analog output from the sensor is fed to the ESP32's ADC pin, which converts it into a corresponding O_3 level in parts per million (ppm). This sensor was chosen for

its low cost and reasonable response time, essential for detecting short-term pollution spikes.



Fig. 3. Plantower PMS5003.



Fig. 4. MQ-131 sensor.

5) MICS-6814 – Nitrogen Dioxide (NO_2) Sensor: The MICS-6814 in Fig. 5 is a compact three-channel semiconductor gas sensor that simultaneously measures NO_2, CO, and NH_3 gases. It is particularly suitable for mobile IoT applications due to its low power consumption and small form factor. For this project, the NO_2 channel was primarily used, with calibration coefficients adjusted based on the manufacturer's characterization curve. Its analog signal provides ppm-level readings processed by the ESP32's 12-bit ADC.



Fig. 5. Nitrogen Dioxide (NO_2) sensor.

6) AGSM-SO_2-5 Sulfur Dioxide (SO_2) sensor: The AGSM-SO_2-5 in Fig. 6 is an electrochemical-type sensor used to detect sulfur dioxide concentrations in ambient air. The sensor produces a small current proportional to the SO_2 gas concentration, which is converted to voltage using an external resistor circuit and read through an ADC input. This sensor type offers high selectivity and low detection limits, enabling reliable SO_2 measurement even in mixed-gas environments. Its readings are periodically calibrated against baseline voltages under clean-air conditions.



Fig. 6. Sulfur Dioxide (SO_2) sensor.

7) MG-811 Carbon Dioxide (CO_2) sensor: The MG-811 sensor in Fig. 7 measures carbon dioxide (CO_2) concentration using a solid electrolyte cell. The sensor outputs an analog voltage that decreases as CO_2 concentration increases. It operates between 0–10,000 ppm and provides stable performance for mobile applications when coupled with proper temperature compensation. The MG-811 data complements the other gas readings by offering insights into combustion-related emissions.



Fig. 7. Carbon Dioxide (CO_2) sensor.

8) DHT11 temperature and humidity sensor: The DHT11 digital sensor in Fig. 8 monitors ambient temperature and relative humidity, parameters that directly influence gas sensor accuracy and pollutant dispersion. Its single-wire digital output simplifies integration with the ESP32 microcontroller. The temperature and humidity data collected are used to normalize and interpret gas readings, reducing variability due to environmental factors.



Fig. 8. DHT11 temperature and humidity sensor.

C. Custom PCB Design and Circuit Integration

To ensure a compact, reliable, and vibration-resistant mobile sensing unit, the system incorporates a custom-designed PCB, created using EasyEDA and manufactured as a single-layer board. The PCB consolidates all key components including the LilyGO T-Call ESP32, PMS5003 particulate matter sensor, MQ131 ozone module, CJMCU-6814 multi-gas sensor (NO_2 +

SO_2), and analog SO_2 sensor interface into a unified hardware platform optimized for vehicular deployment.

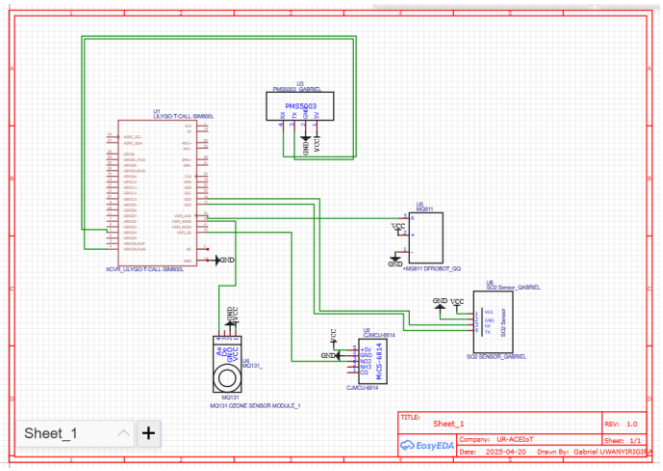


Fig. 9. Schematic diagram of clean city IoT system.

The PCB layout in Fig. 9 follows a structured placement strategy, with the PMS5003 connector positioned on the upper-left side to minimize trace length for the UART interface, while the MQ131 and CJMCU-6814 modules are placed on the right to avoid electromagnetic interference from the GSM modem. Dedicated headers provide labeled terminals for VCC, GND, RX, and TX, ensuring clear wiring during assembly and simplifying sensor maintenance or replacement. The bottom section houses the footprint for the LilyGO T-Call board, providing direct access to GSM, UART, and ADC lines without intermediate wiring.

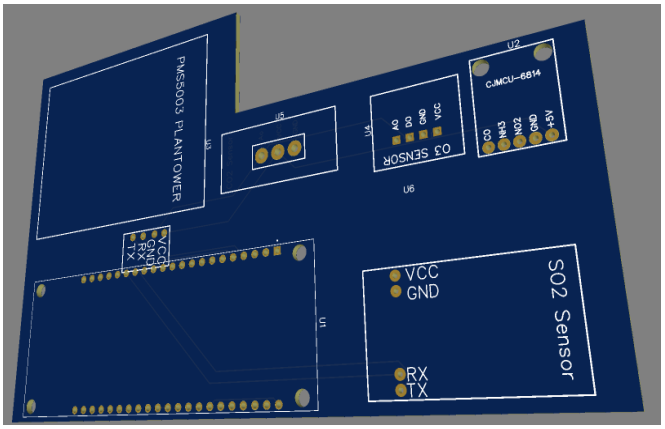


Fig. 10. 3D view of the custom PCB design for the CleanCity IoT device.

The corresponding circuit schematic (Fig. 10) illustrates the electrical interconnections between all sensing modules and the ESP32 controller. UART pins are assigned to the PMS5003 (U3) and SO_2 sensor interface, while the MQ131 analog output is routed to an ADC input. The CJMCU-6814 module is powered by a stable 5V rail, and its NO_2/SO_2 analog channels are fed into separate ADC lines for accurate digital conversion. Ground planes and decoupling capacitors are incorporated to enhance signal stability and reduce noise, which is critical for gas sensor accuracy. The PCB also accommodates optional onboard filtering capacitors for the analog channels, further increasing measurement reliability.

This custom PCB significantly enhances the robustness of the CleanCity IoT device compared to breadboard-based prototypes. By minimizing loose wiring, standardizing sensor interfaces, and optimizing component placement, the board improves electrical reliability, reduces interference from the GSM module, and ensures consistent sensor readings during mobile operation. It also enables rapid replication of the device for larger-scale deployments in Kigali or other Rwandan cities.

D. Data Acquisition and Transmission

The CleanCity IoT system collects, processes, and transmits multi-sensor environmental data in real time through a unified acquisition pipeline. The design ensures synchronized sampling across all sensing modules, reliable communication via GSM, and consistent data formatting for cloud integration.

E. Sensor Data Acquisition Cycle

Each monitoring node performs periodic measurements of particulate matter, gaseous pollutants, and ambient conditions.

- Particulate Matter ($PM_{2.5}$ and PM_{10}): The PMS5003 sensor provides continuous data through a UART interface, reporting particle concentrations in µg/m³.
- Gaseous Pollutants: O_3, NO_2, SO_2, and CO_2 levels are sensed using analog sensors (MQ-131, MICS-6814, AGSM-SO_2-5, and MG-811). Their analog voltages are sampled by the ESP32's 12-bit ADC and converted to concentration values (ppm) using calibration curves derived from reference data.
- Ambient Conditions: The DHT11 sensor provides temperature and relative-humidity readings, which are used for contextual adjustment of gas-sensor responses.

To reduce random noise and ensure stability, multiple readings are averaged within each cycle before transmission. The resulting dataset per interval includes parameters as shown in Table II.

TABLE II. PARAMETERS ACQUIRED DURING EACH SAMPLING CYCLE

Parameter	Symbol	Unit
$PM_{2.5}$ concentration	PM2.5	µg/m³
PM_{10} concentration	PM10	µg/m³
Ozone	O_3	ppm
Nitrogen Dioxide	NO_2	ppm
Sulfur Dioxide	SO_2	ppm
Carbon Dioxide	CO_2	ppm
Temperature	T	°C
Humidity	H	%

F. Data Pre-Processing and Packet Formation

Before transmission, each sensor reading undergoes a lightweight pre-processing pipeline to improve data reliability and ensure consistency across the full dataset. First, a noise-filtering procedure is applied to remove spurious or invalid sensor values. Given a raw reading x_i for pollutant j, the system checks whether it falls within the predefined operational range $[L_j, U_j]$. This filtering step is mathematically expressed as:

$$x_i' = \begin{cases} x_i & \text{ιφ } L_j \le x_i \le U_j \\ \text{NαN} & \text{οτηερωισε} \end{cases} \quad (1)$$

Ensuring that negative values, extreme spikes, and sensor glitches do not propagate into the cloud dataset.

Following outlier removal, each pollutant value is normalized into standard physical units (µg/m³ or ppm) using a linear scaling transformation. This normalization converts raw sensor outputs into a consistent range defined by calibration limits, allowing accurate comparison across sensors. The conversion is achieved using Eq. (2).

$$x_{norm} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \times (S_{max} - S_{min}) + S_{min} \quad (2)$$

where x_{max} and x_{min} are the sensor's calibrated electrical bounds and S_{max} , S_{min} correspond to the standardized environmental scale. This operation ensures homogeneous units throughout the dataset, which is essential for downstream analytics.

Each sanitized and normalized reading is then assigned a timestamp to preserve temporal integrity. The timestamp t_k originates either from the GSM network clock or the ESP32's internal real-time counter. The final structured data packet transmitted at time k is represented as,

$$D_k = \{DeviceID, PM_{2.5}, PM_{10}, O_3, NO_2, SO_2, CO_2, T, H, t_k\} \quad (3)$$

capturing all pollutants, environmental conditions, and metadata in a single, machine-readable structure compatible with ThingSpeak's REST API.

G. GSM-Based Data Transmission

The LilyGO T-Call ESP32 integrates a SIM800L GSM/GPRS modem, allowing each mobile sensing unit to transmit air-quality data directly to the cloud without requiring Wi-Fi or external gateways. Once a complete measurement vector

$$z_t = [PM_{2.5}, PM_{10}, O_3, NO_2, SO_2, CO_2, T, H] \quad (4)$$

is pre-processed, the system encapsulates the data into a structured transmission packet. The full packet sent at time t is expressed as:

$$P_t = \{DeviceID, z_t, t\} \quad (5)$$

Every transmission cycle follows a periodic schedule, where the upload interval is defined as

$$\Delta t = t_k - t_{k-1} \quad (6)$$

and during the experimental deployment, $\Delta t \approx 30$ s, providing a balance between data granularity and power efficiency for vehicular operation. The SIM800L modem performs an HTTP POST request over GPRS, where the payload corresponds to the encoded packet Pt. The uplink transmission can be represented as

$$\mathcal{T}(P_t) \rightarrow \text{ThingSpeak Channel} \quad (7)$$

where $\mathcal{T}(\mathrm{P_t})$ denotes the GSM-based upload operation. Once the server acknowledges receipt, ThingSpeak updates the real-time charts for all monitored pollutants. To ensure time-series completeness, the system incorporates a local retransmission buffer. If a temporary network outage occurs, packets are stored in a local queue

$$Q = \{P_{t_1}, P_{t_2}, \ldots, P_{t_m}\} \quad (8)$$

and are automatically resent once connectivity is restored. Successful transmission empties the queue according to

$$Q \leftarrow Q \setminus P_{t_i} \quad (9)$$

This queue-based recovery mechanism guarantees robustness in urban mobility conditions, where cellular coverage may momentarily fluctuate. As a result, the system achieves reliable, timestamped uploads essential for downstream analytics, ML model training, and spatiotemporal pollution mapping.

H. Cloud Integration and Dashboard Development

The CleanCity IoT system relies on ThingSpeak Cloud as the central platform for ingesting, storing, and visualizing sensor data in real time. Each monitoring node continuously uploads the structured packet Pt to a dedicated ThingSpeak channel, where the information is automatically timestamped and organized across eight data fields. The cloud interface provides dashboards, charts, and API endpoints that support both manual inspection and automated analytical tasks such as forecasting and multi-pollutant correlation studies.

To quantify the data-handling performance of the cloud layer, the expected number of uploaded records over an observation period T is expressed as,

$$N_T = \frac{T}{\Delta t} \quad (10)$$

where, Δt represents the transmission interval (approximately 30 seconds in this deployment). This relation determines the temporal granularity and the total volume of data streamed into the cloud. The corresponding data throughput, crucial for evaluating network and storage efficiency, is computed using

$$R_{up} = \frac{N_T \times P_k}{T} \quad (11)$$

where, P_k denotes the average packet size in bytes. These metrics confirm that the system maintains consistent upload behavior, even under mobile conditions. In ThingSpeak, pollutant concentrations are further processed to compute an Air Quality Index (AQI). For each pollutant iii, the platform evaluates a sub-index using

$$I_i = \frac{I_{high} - I_{low}}{C_{high} - C_{low}} (C_i - C_{low}) + I_{low} \quad (12)$$

where the constants correspond to standard AQI breakpoints.

The overall AQI at time t is determined by,

$$AQI = \max(I_i) \quad (13)$$

allowing the system to categorize air quality levels and support early-warning notifications when thresholds are exceeded.

The cloud platform also enables multi-variable diagnostic analysis, particularly through pollutant correlation. The linear

relationship between any two-pollutant series x_i and x_j is computed using the Pearson coefficient,

$$r_{ij} = \frac{\sum_{k=1}^{n}(x_{i,k}-\overline{x_i})(x_{j,k}-\overline{x_j})}{\sqrt{\sum_{k=1}^{n}(x_{i,k}-\overline{x_i})^2}\sqrt{\sum_{k=1}^{n}(x_{j,k}-\overline{x_j})^2}} \quad (14)$$

This allows identification of pollutant sources with similar temporal behaviors, such as $PM_{2.5}$ and NO_2 often linked to traffic emissions. To ensure reliability, ThingSpeak computes a data completeness index over any period T as,

$$C_T = \frac{N_s}{N_t} \times 100\ \% \quad (15)$$

where Ns and Nt are the numbers of successfully uploaded and total expected packets, respectively. This metric is essential for confirming the robustness of GSM-based data acquisition, especially in mobile environments where connectivity might fluctuate. Through this cloud architecture, CleanCity IoT achieves real-time visualization, long-term storage, and automated analytic capability, making it suitable for continuous urban air-quality monitoring and predictive modeling.

I. Machine Learning Model Development

The dataset collected from the ThingSpeak cloud was used to train a Long Short-Term Memory (LSTM) neural network for short-term air-quality forecasting. The choice of LSTM was motivated by its ability to capture nonlinear temporal dependencies in multivariate time-series data, making it suitable for predicting pollutant levels under changing meteorological and traffic conditions. To prepare the data, each environmental variable was standardized to ensure consistent scaling across all pollutants. This normalization follows the transformation.

$$\hat{z}_t^{(i)} = \frac{z_t^{(i)}-\mu_i}{\sigma_i} \quad (16)$$

where, $\hat{z}_t^{(i)}$ denotes the original reading of feature i at time t, and $\mu_i$and σ_i represent the corresponding mean and standard deviation. A sliding window of length L was then used to construct input sequences for the model. Each multivariate input window is defined as,

$$X_t = [\tilde{z}_{t-L+1}, \tilde{z}_{t-L+2}, \ldots, \tilde{z}_t] \in R^{L\times 8} \quad (17)$$

while the prediction target for horizon H is given by,

$$y_t = z_{t+H} \quad (18)$$

The LSTM learns a nonlinear mapping

$$\hat{y}_t = f_\theta(X_t) \quad (18)$$

where, f_θ denotes the trained neural-network function parameterized by θ. The training objective is to minimize the Mean Squared Error (MSE):

$$\mathcal{L}\mathrm{MSE}(\theta) = \frac{1}{N}\sum_{t=1}^{N}|y_t - \hat{y}_t||_2^2 \quad (19)$$

Model performance was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination R^2, expressed respectively as

$$MAE_j = \frac{1}{N}\sum_{t=1}^{N}\left|y_t^{(j)} - \widehat{y_t^{(j)}}\right| \quad (20)$$

$$RMSE_j = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(y_t^{(j)} - \widehat{y_t^{(j)}}\right)^2} \quad (21)$$

$$MAPE_j = \frac{100}{N}\sum_{t=1}^{N}\left|\frac{y_t^{(j)}-\widehat{y_t^{(j)}}}{y_t^{(j)}}\right| \quad (22)$$

$$R_j^2 = 1 - \frac{\sum_{t=1}^{N}\left(y_t^{(j)}-\widehat{y_t^{(j)}}\right)^2}{\sum_{t=1}^{N}\left(y_t^{(j)}-\overline{y^{(j)}}\right)^2} \quad (23)$$

These performance indicators assess the reliability of the LSTM model in forecasting pollutant levels such as $PM_{2.5}$, PM_{10}, NO_2, SO_2, O_3, CO_2, temperature, and humidity. By using standardized inputs and multivariate temporal windows, the model is able to produce stable forecasts up to two hours ahead, enabling early-warning capabilities and supporting real-time decision-making for environmental monitoring.

IV. Results and Discussion

A. Dataset Characteristics

The CleanCity IoT mobile sensing unit collected a total of 6,484 multivariate records during vehicular movement across urban road segments in Kigali. Each record contains synchronized measurements of particulate pollution ($PM_{2.5}$, PM_{10}), gaseous pollutants (NO_2, SO_2, O_3, CO_2), and meteorological variables (temperature and relative humidity). Data were transmitted at an average 30-second sampling interval, resulting in a dense and continuous time-series suitable for both statistical analysis and machine learning–based forecasting.

The temporal behavior of the dataset is illustrated in Fig. 11, which shows the evolution of $PM_{2.5}$, PM_{10}, NO_2, and temperature over several days. The plots reveal clear short-term fluctuations driven by traffic movement, road dust resuspension, and localized emission hotspots commonly encountered during mobile sensing. The temperature curve exhibits a pronounced diurnal cycle, confirming environmental consistency and stable sensor response.

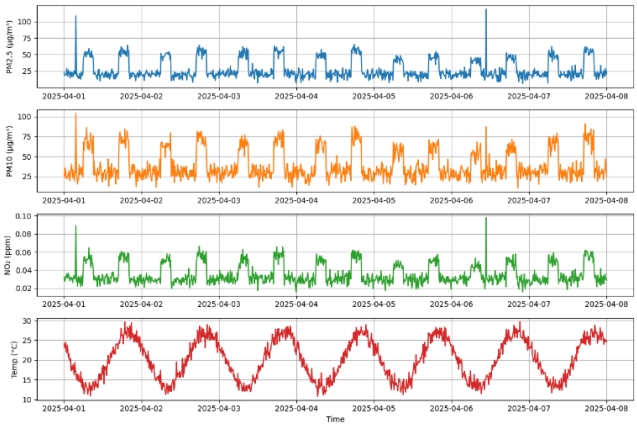


Fig. 11. Time-series variation of key air-quality parameters ($PM_{2.5}$, PM_{10}, NO_2) and meteorological variables collected from the CleanCity IoT mobile sensing system.

To further assess data richness and distributional characteristics, histogram plots for all pollutants and environmental variables are shown in Fig. 12. These distributions demonstrate substantial variability across measured concentrations, with PM_{10} and $PM_{2.5}$ showing multimodal behavior associated with alternating high-traffic and low-traffic conditions. Gaseous pollutants (NO_2, SO_2, O_3) present narrower distributions, typical of background urban air composition, while CO_2 ranges reflect both ambient outdoor levels and intermittent vehicle exhaust influence.

The completeness of the dataset was evaluated using the metric.

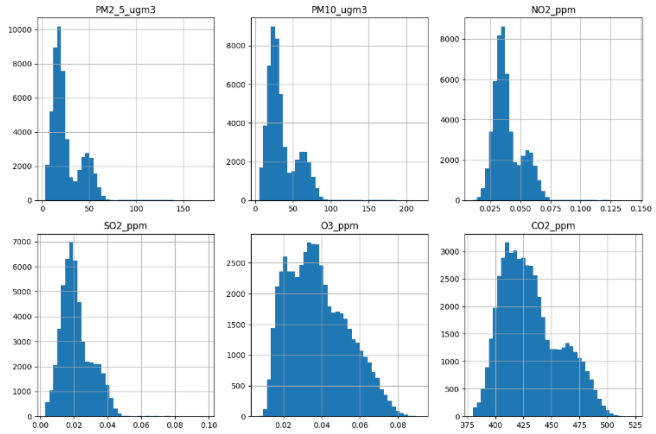


Fig. 12. Distribution of pollutant and environmental variables, illustrating concentration variability and underlying statistical patterns within the dataset.

where, N_S is the number of successfully uploaded samples and N_t is the expected number of samples based on the configured transmission interval. The system maintained high data availability across the monitoring period, confirming robust GSM connectivity and effective packet buffering in the LilyGO T-Call ESP32 board. Collectively, the time-series behavior, variable distributions, and high completeness rate validate the dataset as a reliable basis for subsequent LSTM-based forecasting and statistical analysis of urban air-quality dynamics.

B. System Performance Evaluation

The CleanCity IoT mobile sensing platform was deployed on a vehicle and evaluated under real urban operating conditions to assess communication stability, data reliability, environmental robustness, and cloud-integration performance. The LilyGO T-Call ESP32 board, equipped with the SIM800L GSM/GPRS module, demonstrated stable mobile connectivity throughout the monitoring period. The system achieved a high upload success rate, with most packets reaching the cloud on the first transmission attempt. Occasional GSM signal drops were mitigated by the built-in buffering mechanism, allowing queued packets to be retransmitted automatically once connectivity resumed.

The sensor suite also exhibited consistent and predictable behavior, as demonstrated by the correlation structure among the measured variables in Fig. 13. Strong positive correlations between $PM_{2.5}$ and PM_{10} confirm expected particulate co-variability in traffic-related environments, while moderate relationships between gaseous pollutants reflect common emission sources along the vehicle routes. The negative correlation between temperature and humidity follows typical micro-meteorological conditions in Kigali's urban climate, further validating sensor stability.

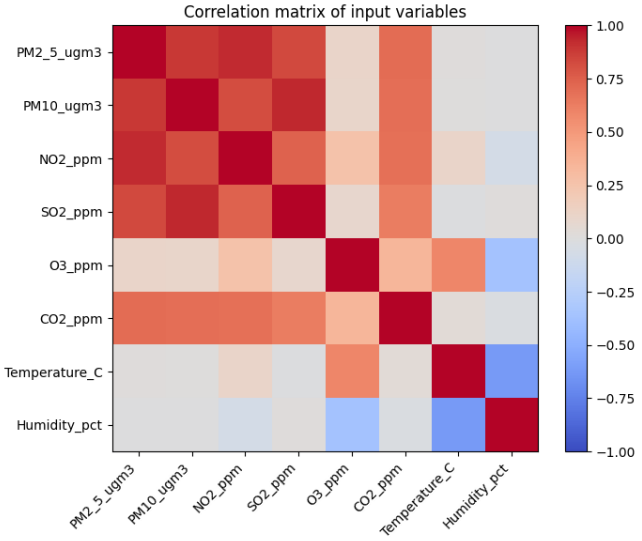


Fig. 13. Correlation matrix illustrating interdependencies between pollutant concentrations and meteorological variables

The data transmission latency averaged 2-4 seconds per packet during motion, consistent with typical GSM-based IoT deployments. The cloud dashboard updated in near real time, enabling effective monitoring of pollutant trends and environmental changes as the vehicle traversed different locations. Additionally, the hardware system demonstrated resilience to vibration, temperature changes, and power fluctuations during mobile operation. Overall, the system performance confirms that the CleanCity IoT platform is reliable for continuous mobile sensing in urban environments, maintaining stable communication, accurate sensing behavior, and real-time cloud integration suitable for further analytics and forecasting applications.

C. Machine Learning Model Performance

The cleaned and preprocessed multivariate dataset was used to train an LSTM-based forecasting model designed to predict short-term pollutant concentrations in real time. Input sequences were constructed using sliding windows of length L, where each window (Eq 16) represents the normalized and filtered sensor readings across all eight variables. The model produces a prediction (Eq 18) where f_θ denotes the LSTM, network parameterized by θ.

Model training converged smoothly, with the mean squared error (MSE) for both training and validation sets decreasing consistently, as shown in Fig. 14. The validation curve remained stable without divergence, indicating good generalization and absence of overfitting.

1) Prediction accuracy on key pollutants: The prediction performance for $PM_{2.5}$ and PM_{10} is shown in Fig. 15, where the predicted values closely follow the temporal structure of the true sensor measurements. The model successfully captures

peaks, transitions, and low-concentration periods, demonstrating strong short-term forecasting capability.

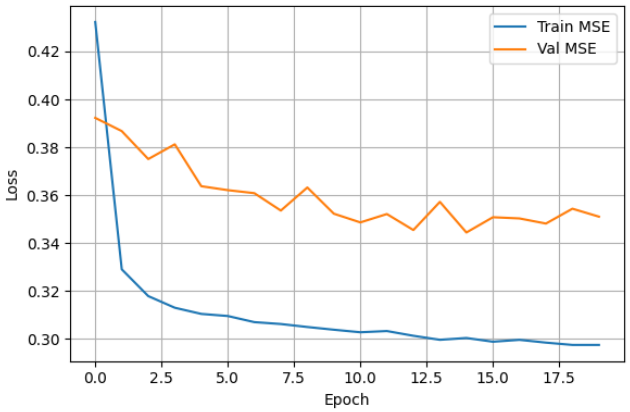


Fig. 14. Training and validation loss curves of the LSTM model, demonstrating convergence behavior and generalization performance.

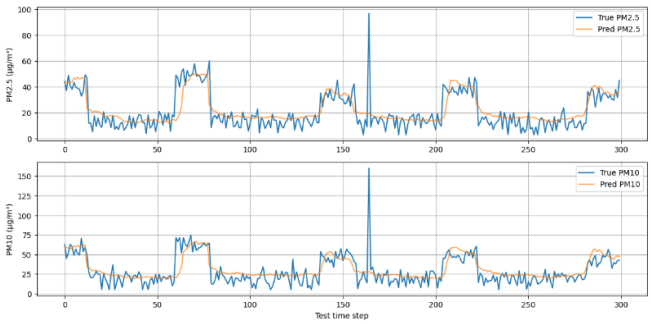


Fig. 15. Comparison between ground-truth and LSTM-predicted concentrations for $PM_{2.5}$ and PM_{10} over selected test windows.

2) Model fit across all variables: Scatter plots comparing predicted versus true values for all pollutants and environmental variables are shown in Fig. 16. The clustering of points around the 1:1 line demonstrates strong model agreement, especially for CO_2, temperature, O_3, and NO_2. Variability in $PM_{2.5}$ and SO_2 predictions reflects the intrinsic noisiness of mobile-sensing particulate measurements.

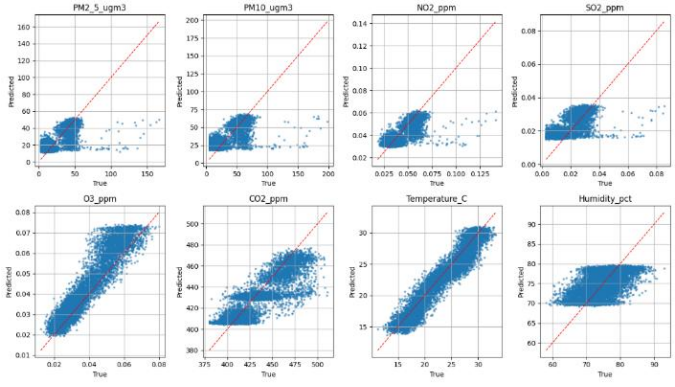


Fig. 16. Scatter plots comparing true and predicted values for all variables, with the 1:1 reference line indicating model accuracy.

3) Error distribution: To further examine predictive behavior, Fig. 17 presents the error distribution for $PM_{2.5}$. The histogram shows a narrow, approximately Gaussian distribution centered close to zero, indicating low systematic bias and moderate variance in short-term particulate predictions.

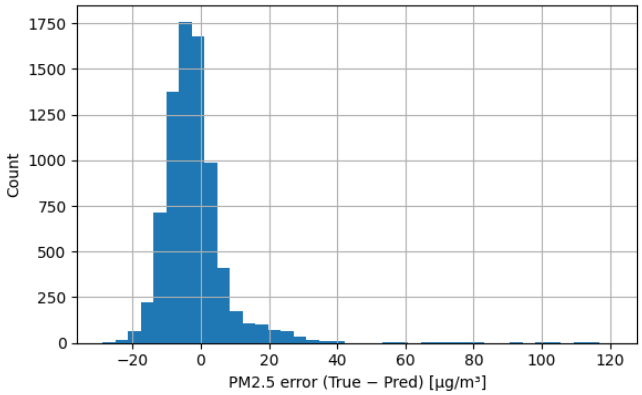


Fig. 17. Error distribution of $PM_{2.5}$ predictions, highlighting bias and variance characteristics of the LSTM model.

4) Quantitative metrics: Summarizes the evaluation metrics for each variable, including MAE, RMSE, and MAPE. The LSTM model achieved strong predictive performance for temperature, CO_2, O_3, and NO_2, while $PM_{2.5}$ and PM_{10} exhibited higher relative errors due to their higher temporal variability and sensitivity to rapid environmental changes (Table III) during vehicle motion.

TABLE III. PERFORMANCE METRICS (MAE, RMSE, MAPE) OF THE LSTM MODEL ACROSS ALL POLLUTANTS AND ENVIRONMENTAL VARIABLES

Variable	MAE	RMSE	MAPE_percent
PM2_5_ugm3	6.83	10.45	61.41
PM10_ugm3	9.26	13.72	56.24
NO2_ppm	0.005	0.007	12.993
SO2_ppm	0.006	0.007	68.230
O3_ppm	0.005	0.006	14.537
CO2_ppm	10.64	14.39	2.42
Temperature_C	1.19	1.49	5.40
Humidity_pct	3.25	4.06	4.40

Overall, the LSTM model demonstrates strong capability in short-term pollutant forecasting across multiple variables. Stability in the loss curve, tight clustering in scatter plots, realistic error distributions, and favorable MAE/RMSE/MAPE scores confirm that the forecasting framework is effective for real-time deployment in mobile urban air-quality monitoring systems.

D. Assembled Edge Device with Deployed Model

The complete air-quality monitoring unit was integrated into a compact, weather-resistant enclosure and mounted on the front of a motorcycle to enable continuous mobile sensing across urban routes. As shown in Fig. 18, the device securely attaches to the motorcycle's suspension frame, ensuring minimal vibration interference while maintaining unobstructed airflow to

the sensing chamber. The embedded ESP32–SIM800L controller executes the trained machine-learning model directly on the edge, enabling on-device preprocessing, anomaly filtering, and real-time prediction without reliance on cloud-based computation.



Fig. 18. Clean city IoT device mounted on motorcycle.

The internal hardware layout, presented in Fig. 19, illustrates the modular arrangement of components including the PM and gas sensors, power system, GSM communication module, and microcontroller. The wiring architecture was optimized to reduce electromagnetic interference and to maintain sensor accuracy during mobile operation. This assembly design ensures robustness under typical road conditions while maintaining low power consumption, making it suitable for long-term vehicular deployments.



Fig. 19. Internal hardware layout of clean city IoT device.

E. Dashboard for Remote Monitoring

A web-based dashboard was developed to provide real-time visualization and remote access to sensor measurements, model inferences, and device status. The interface, shown in Fig. 20, displays pollutant concentrations (PM2.5, PM10, SO_2, NO_2, O_3, CO_2) alongside temperature and humidity, each represented with intuitive color codes and threshold indicators. This enables rapid interpretation of air-quality conditions by operators and supports downstream analytics such as hotspot identification and route-based pollution profiling.

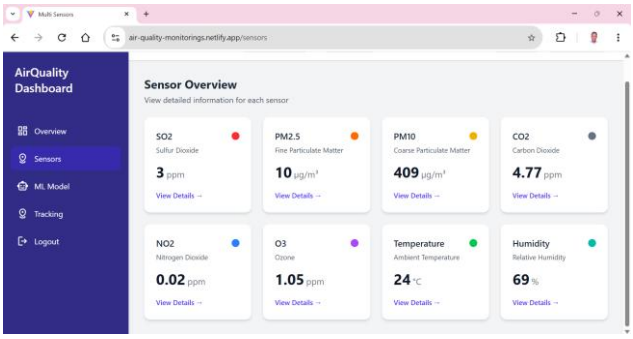


Fig. 20. Web-based remote monitoring dashboard of clean city IoT device.

The dashboard integrates seamlessly with the GSM-enabled edge devices via the cloud backend, allowing continuous updates at fixed intervals. Users may access detailed historical charts, inspect sensor-level readings, or monitor multiple devices simultaneously. This platform improves situational awareness and supports data-driven decision-making for urban air-quality management.

V. Discussion

The results obtained from the mobile air-quality monitoring platform highlight the strong potential of integrating low-cost sensing, edge intelligence, and mobile data acquisition to provide high-resolution pollution insights in dynamic urban environments. The temporal plots and distribution analyses demonstrate that the system successfully captured realistic pollutant patterns, including recurring diurnal behaviors, peak concentrations along traffic corridors, and rapid fluctuations associated with vehicle-dense areas. These trends align with previously reported characteristics of mobile sensing platforms, reinforcing the reliability of the collected dataset.

The performance of the LSTM model reflects both the strengths and inherent challenges of forecasting air-quality parameters in mobile conditions. Temperature, humidity, CO_2, and O_3 predictions achieved low MAE and RMSE values, indicating that their temporal structures exhibit smoother and more predictable patterns that are well-suited to sequence-learning models. Conversely, higher error values observed for PM2.5 and PM10 are consistent with the behavior of particulate pollutants, which often vary sharply due to localized dust sources, abrupt vehicle acceleration, wind disturbances, or sudden micro-spikes near emission points. These high-frequency fluctuations pose a challenge for recurrent models, which assume gradual temporal transitions. Despite this, the predicted sequences still closely follow the underlying pollutant trends, suggesting that the LSTM architecture provides valuable short-term predictive capability.

The correlation matrix further reinforces the internal consistency of the dataset by revealing strong associations between combustion-related pollutants (PM2.5, PM10, NO_2, SO_2). These relationships are well documented in air-quality literature and confirm that the system effectively captured realistic vehicular emission profiles. The inclusion of

meteorological parameters in the model input contributed to performance stability by providing contextual information on atmospheric dispersion, temperature-dependent sensor responses, and humidity-driven particle behavior.

Operationally, the motorcycle-mounted sensing device (Fig. 18, Fig 20) validated the practicality of a low-power, mobile, GSM-enabled platform for real-time air-quality assessment. The device maintained stable measurements during movement and reliably transmitted data to the cloud dashboard. The remote monitoring interface (Fig. 20) enabled seamless visualization of pollutant levels, supporting quick interpretation and forming a foundation for future large-scale deployments. This capability is particularly valuable in resource-constrained environments where installing dense networks of fixed monitoring stations is not feasible.

Nonetheless, several limitations were observed. The elevated prediction errors for particulate matter indicate the need for more advanced filtering or hybrid modeling techniques such as Kalman filters, temporal attention mechanisms, or transformer-based architectures better suited for abrupt pollutant variability. Occasional GSM transmission delays highlight a trade-off between mobile connectivity and data continuity, suggesting that buffering strategies or 4G/LTE-based modules may be advantageous in future iterations. Sensor drift and long-term degradation pose additional challenges, underscoring the importance of periodic recalibration, redundancy, or sensor fusion approaches to maintain long-term reliability.

The findings demonstrate that mobile IoT sensing combined with edge-deployed machine-learning models provide a powerful and scalable approach to capturing granular air-quality information. It offers a practical pathway toward city-wide mobile pollution mapping, intelligent fleet monitoring, and data-driven environmental planning, especially in developing urban regions where cost-effective solutions are essential.

VI. Conclusion, Recommendations, and Future Work

This study presented a mobile air-quality monitoring platform that integrates low-cost sensors, an ESP32–SIM800L edge device, GSM-based communication, and an LSTM prediction model to enable high-resolution pollution monitoring in dynamic urban environments. The mobile system successfully captured realistic temporal patterns of key pollutants including PM2.5, PM10, SO_2, NO_2, and O_3 while simultaneously collecting meteorological variables relevant to dispersion and atmospheric behavior. The experimental results demonstrated that the model accurately predicted smoother variables such as temperature, humidity, CO_2, and O_3, while exhibiting higher, yet consistent, errors for particulate matter due to its inherently abrupt and highly localized fluctuations. Overall, the system validated the feasibility of using a low-cost, edge-intelligent, mobile sensing approach to complement existing fixed monitoring infrastructures particularly in regions where traditional stations are sparse or economically prohibitive. The combination of real-time edge inference and cloud-based visualization provides a scalable foundation for city-wide monitoring, rapid hotspot identification, and informed environmental planning.

Model prediction errors for PM2.5 and PM10 highlight the need for more advanced temporal modeling techniques capable of handling sudden spikes and high-frequency variability. Network latency introduced by GSM connectivity suggests exploring more robust communication protocols and buffering strategies for uninterrupted data flow. Additionally, long-term reliability will require periodic sensor calibration, redundancy mechanisms, and drift-compensation strategies to maintain accuracy during extended deployments.

Based on these findings, the following recommendations are proposed:

- Adopt advanced hybrid modeling techniques**:** such as temporal attention mechanisms, transformer-based architectures, or Kalman-filter-enhanced LSTM to improve particulate matter forecasting.
- Upgrade communication infrastructure to LTE/4G or MQTT-based lightweight protocols to minimize transmission delays and enhance scalability.
- Implement periodic calibration schedules and sensor redundancy to mitigate drift, aging, and environmental contamination.
- Integrate geospatial and meteorological data sources (GIS layers, wind maps, road classifications) for more context-aware predictions and hotspot analysis.

Future work will focus on addressing these challenges by extending the system to support multi-node collaborative sensing, employing federated learning for distributed model updates, and exploring adaptive edge inference that dynamically adjusts sampling rates depending on environmental conditions. Additional work will investigate long-term deployment performance, data fusion with satellite products, and integration with policy tools for real-time air-quality alerts.

In conclusion, this research provides a practical, scalable, and cost-effective framework for mobile air-quality monitoring in rapidly urbanizing regions. By combining IoT sensing, edge computing, and machine learning, the system offers a promising direction for enhancing environmental intelligence and supporting evidence-based public health interventions.

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References

[1] S. A. Siddiqui, N. Fatima, and A. Ahmad, “Smart Air Pollution Monitoring System with Smog Prediction Model using Machine Learning,” Int. J. Adv. Comput. Sci. Appl., vol. 12, no. 8, pp. 401–409, 2021, doi: 10.14569/IJACSA.2021.0120846.

[2] E. R. I. Mogo, A. Lerno, C. Abdeta, and O. Olufemi, “Mounting an effective socio-ecological response to non-communicable diseases in Africa’s cities,” Cities Heal., vol. 6, no. 1, pp. 51–56, 2022, doi: 10.1080/23748834.2019.1688911.

[3] G. Rincon, G. Morantes, A. Garcia-Angulo, S. Mota, M. del P. Cornejo-Rodriguez, and B. Jones, “Understanding particulate matter emissions from cooking meals, health impacts and policy path in Ecuador,” Sci.

Total Environ., vol. 982, p. 179628, Jun. 2025, doi: 10.1016/J.SCITOTENV.2025.179628.

[4] R. Subramanian et al., "Research article Air pollution in Kigali, Rwanda: spatial and temporal variability, source contributions, and the impact of car-free Sundays," Clean Air J., vol. 30, no. 2, pp. 1–15, 2020, doi: 10.17159/CAJ/2020/30/2.8023.

[5] D. Zboralski and M. Kunz, "Mobile systems for assessing air quality: available solutions and application examples," Bull. Geogr. Phys. Geogr. Ser., vol. 27, no. 27, pp. 5–26, 2024, doi: 10.12775/bgeo-2024-0007.

[6] C. Correia et al., "A Low-Cost Sensor System Installed in Buses to Monitor Air Quality in Cities," Int. J. Environ. Res. Public Health, vol. 20, no. 5, 2023, doi: 10.3390/ijerph20054073.

[7] B. Zherka and Z. Tafa, "A Vehicle Sensor Network for Real-Time Air Pollution Analysis," J. Adv. Inf. Technol., vol. 14, no. 1, pp. 39–45, 2023, doi: 10.12720/jait.14.1.39-45.

[8] P. Santana, A. Almeida, P. Mariano, C. Correia, V. Martins, and S. M. Almeida, "Air quality mapping and visualisation: An affordable solution based on a vehicle-mounted sensor network," J. Clean. Prod., vol. 315, p. 128194, Sep. 2021, doi: 10.1016/J.JCLEPRO.2021.128194.

[9] K. Ivanova, T. Branzov, and N. Ivanova, "IoT on the roofs of municipally governed vehicles for air pollution tracking," CEUR Workshop Proc., vol. 2803, pp. 172–177, 2020.

[10] Nizeyimana, Eric, Hwang, Junseok, Zirikana, Jules, Karikumutima, Bonaventure, Mihigo, Irene Niyonambaza, Nizeyimana, Pacifique, Hanyurwimfura, Damien, Nsenga, " Revolutionizing Air Pollution Spikes Analysis With a Blockchain - Driven Machine Learning Framework," Trans. Emerg. Telecommun. Technol., vol. 36, no. 5, 2025, doi: 10.1002/ett.70143.

[11] E. Nizeyimana, J. Nsenga, R. Shibasaki, D. Hanyurwimfura, and J. Hwang, "Design of Smart IoT Device for Monitoring Short-term Exposure to Air Pollution Peaks," Int. J. Adv. Comput. Sci. Appl., vol. 13, no. 1, 2022, doi: 10.14569/IJACSA.2022.0130103.

[12] P. Santana, A. Almeida, P. Mariano, C. Correia, V. Martins, and S. M. Almeida, "Air quality mapping and visualisation: An affordable solution based on a vehicle-mounted sensor network," J. Clean. Prod., vol. 315, no. July, 2021, doi: 10.1016/j.jclepro.2021.128194.

[13] P. Bansal, "Charging of electric vehicles: Technology and policy implications," J. Sci. Policy Gov., vol. 6, no. 1, pp. 1–20, 2015.

[14] V. Devasekhar and P. Natarajan, "Prediction of Air Quality and Pollution using Statistical Methods and Machine Learning Techniques," Int. J. Adv. Comput. Sci. Appl., vol. 14, no. 4, pp. 927–937, 2023, doi: 10.14569/IJACSA.2023.01404103.

[15] H. S. Russell, L. B. Frederickson, M. O. B. Sørensen, J. A. Schmidt, O. Hertel, and M. S. Johnson, "Hyperlocal Air Pollution in London: Validating Low-Cost Sensors for Mobile Measurements from Vehicles," ACS ES&T Air, vol. 1, no. 6, pp. 438–450, 2024, doi: 10.1021/acsestair.3c00043.

[16] S. Saleh, A. S. Abohamama, and A. S. Tolba, "Intelligent Real-Time Air Quality Index Classification for Smart Home Digital Twins," Int. J. Adv. Comput. Sci. Appl., vol. 16, no. 3, pp. 309–323, 2025, doi: 10.14569/IJACSA.2025.0160331.

[17] A. H. M. Shaberi, S. Dzulkifly, W. S. Li, and Y. F. A. Gaus, "Machine Learning Approaches for Predicting Occupancy Patterns and its Influence on Indoor Air Quality in Office Environments," Int. J. Adv. Comput. Sci. Appl., vol. 15, no. 9, pp. 853–860, 2024, doi: 10.14569/IJACSA.2024.0150987.

[18] A. A. Aserkar, S. R. Godla, Y. A. Baker El-Ebiary, Krishnamoorthy, and J. V. N. Ramesh, "Real-time Air Quality Monitoring in Smart Cities using IoT-enabled Advanced Optical Sensors," Int. J. Adv. Comput. Sci. Appl., vol. 15, no. 4, pp. 840–848, 2024, doi: 10.14569/IJACSA.2024.0150487.

[19] Y. Wang, R. Sun, Q. Cheng, and W. Y. Ochieng, "Measurement Quality Control Aided Multisensor System for Improved Vehicle Navigation in Urban Areas," IEEE Trans. Ind. Electron., vol. 71, no. 6, pp. 6407–6417, 2024, doi: 10.1109/TIE.2023.3288188.

[20] Q. Zhang, Y. Han, V. O. K. Li, and J. C. K. Lam, "Deep-AIR: A Hybrid CNN-LSTM Framework for Fine-Grained Air Pollution Estimation and Forecast in Metropolitan Cities," IEEE Access, vol. 10, pp. 55818–55841, 2022, doi: 10.1109/ACCESS.2022.3174853.

From Consensus to Chaos: A Vulnerability Assessment of the RAFT Algorithm

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***Abstract*—In recent decades, the RAFT distributed consensus algorithm has become a main pillar of the distributed systems ecosystem, ensuring data consistency and fault tolerance across multiple nodes. Although the fact that RAFT is well known for its simplicity, reliability, and efficiency, its security properties are not fully recognized, leaving implementations vulnerable to different kinds of attacks and threats, which can transform the RAFT harmony of consensus into a chaos of data inconsistency. This paper presents a systematic security analysis of the RAFT protocol, with a specific focus on its susceptibility to security threats such as message replay attacks and message forgery attacks. Examined how a malicious actor can exploit the protocol's message-passing mechanism to reintroduce old messages, disrupting the consensus process and leading to data inconsistency. The practical feasibility of these attacks is examined through simulated scenarios, and the key weaknesses in RAFT's design that enable them are identified. To address these vulnerabilities, a novel approach based on cryptography, authenticated message verification, and freshness check is proposed. This proposed solution provides a framework for enhancing the security of the RAFT implementations and guiding the development of more resilient distributed systems.**

***Keywords*—RAFT; consensus protocol; security; distributed systems; message forgery; replay attacks; cryptography**

I. Introduction

The world today is surrounded by distributed systems everywhere, which operate behind the scenes, seamlessly coordinating tasks across multiple computer-based systems, often geographically scattered [2]. From global communication networks to critical financial transactions, these systems rely on fundamental principles of distributed systems to ensure reliability and data consistency [1]. A core component of this reliability is the distributed consensus algorithm, which enables autonomous nodes to agree on a single value, even in the presence of network failures or node crashes [9]. In recent decades, the RAFT distributed consensus algorithm has become a main pillar of the distributed systems ecosystem.

The RAFT algorithm is a foundational element for ensuring data integrity in distributed consensus. Designed for understandability and implementation ease [3], it has not only simplified the process of building resilient distributed applications but has also become a standard of comparison for new consensus research. RAFT achieves its primary goal of fault tolerance by replicating state across nodes, making it resilient against system failures and crashes.

However, while RAFT is well-known for its fault tolerance and simplicity, the consensus mechanism itself typically operates under a "fail-stop" model (node crashes or network partitions), assuming non-malicious failures [10]. Consequently, the security concerns regarding its design, particularly its mitigation against active, malicious attacks, are often not fully integrated or covered in standard implementations [4, 5]. This gap leaves implementations vulnerable to threats and attacks that can compromise the RAFT state machine and data integrity established by the protocol, potentially leading to data corruption and service disruption in critical applications [8].

This gap in the existing RAFT implementation poses a significant risk of vulnerability; a secure consensus algorithm is more than just ensuring agreement; it's about safeguarding the entire ecosystem of distributed systems, protecting data, preventing disruptions, and ultimately, mitigating failures and data corruption. In particular, the fact that the protocol does not have its own end-to-end security mechanisms makes it vulnerable to potential threats, including replay attacks and message forgery attacks, which target the RAFT's message passing mechanism and disrupt the consensus process. Therefore, this paper, in the coming sections, analyzes and evaluates the RAFT algorithm's security properties, demonstrating its design weaknesses with a focus on its susceptibility to message replay attacks and forgery attacks. The primary objective of this research is to propose and validate a novel, modular, and lightweight security enhancement that is based on encryption and authenticated message verification to mitigate these vulnerabilities and enhance the RAFT security implementations.

To achieve this objective, the subsequent sections of this paper first build the necessary foundational Distributed Systems and Consensus Background in Section II. Then Section III dives deeper into the details of the RAFT Distributed Consensus Protocol. Section IV provides a thorough Security Analysis of the RAFT vulnerabilities, focusing on message integrity. Section V presents the Related Work concerning secure RAFT implementations and countermeasures, justifying the research gap. Section VI introduces the Proposed Solution for mitigating the identified security concerns. Section VII details the Methodology used for testing and validation, followed by Section VIII, which presents the Results of the simulated attacks and the performance evaluation. Section IX provides a dedicated Discussion of the findings, their implications, and researchers point of view. Section X offers the Conclusion of this research outcome. Finally, Section XI outlines directions for future study.

II. Background

A. Distributed Systems

Distributed systems are the core basis of today's technology ecosystem, from powering global communication networks to orchestrating critical financial transactions, distributed systems can be defined as a collection of autonomous computing elements (nodes) that appears to users as a single coherent system [1], within this single system the collection of nodes regardless of their number, locations, or components, operate as a unified whole, no matter where, when, and how interaction between a user and the system takes place.

The distributed system provides the means for components of a single distributed application to communicate with each other. At the same time, it hides the differences in hardware and operating systems from each application; this can be orchestrated using a middleware.

In a sense, middleware to a distributed system is the same as an operating system to a computer: a manager of resources offering its applications to efficiently share and deploy those resources across a network [2].

The basic distributed systems architecture and the relationship between its main components: hardware, applications, the operating system, and the middleware layer, which acts as a very essential role in coordinating communication and abstracting hardware differences across the network, is illustrated in Fig. 1.

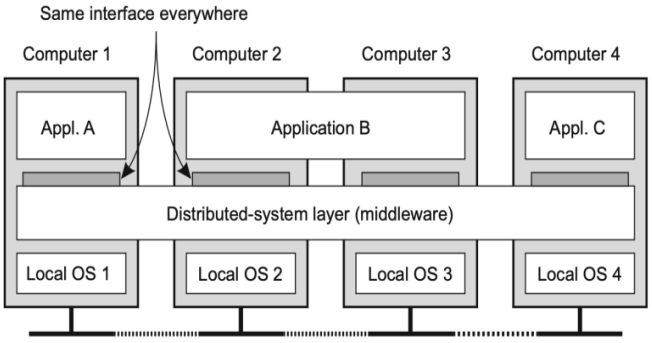


Fig. 1. The middleware layer extends over multiple machines and offers each application the same interface.

The middleware, nodes, applications, and this ever-expanding realm of distributed systems need to assure stability and consistency of communication and exchanged messages, and keep all parties informed of all correct and recent updates on the system, here the important role of the consensus algorithm, which addresses these needs, is thus witnessed.

B. Distributed Consensus

Consensus in general means agreement made by multiple parties; for example, if a group of friends decides to have lunch, which restaurant to order from is an agreement. Basically, consensus has the same meaning in computer science, especially in distributed systems, as it can be defined as a process where multiple nodes of a distributed system agree on values of messages, transactions, or objects. It is a basic challenge in distributed systems. However, once the nodes agree on a value, that agreement should be final.

Some of the earliest implementations of consensus algorithms relied on voting-based mechanisms, which provide reasonable fault tolerance and have strong mathematical proofs to ensure integrity and stability. Some of the popular voting-based algorithms include Paxos and Raft. Paxos was originally first proposed by Leslie Lamport in 1989, however it was published by the end of 2001 due to many factors, including, of course, its well-known high level of complexity, which hindered its widespread adoption. In response to this, the Raft algorithm was introduced in 2014 by Diego Ongaro as a simpler alternative to Paxos. Raft's design emphasizes simplicity and manageability while maintaining the same level of fault tolerance and consistency as its predecessors.

III. Raft Distributed Consensus Protocol

This section provides a brief overview of the Raft distributed consensus algorithm. For a more detailed description, please refer to the original paper “In search of an understandable consensus algorithm” [3].

A. The Raft

Raft is a highly common and reliable distributed consensus algorithm designed as a more understandable and easily implementable alternative to its complex predecessor, the Paxos algorithm. Raft is a fault-tolerant protocol that depends on a single elected leader, log replication, and a probability approach.

To understand how Raft works, let's imagine a server cluster of three nodes or replicas, each hosts a state machine, log, and raft protocol, as long as they all begin with the same state and perform the same operations in the same order then they should all end up with the same state, anytime a replica receives a command such as setting a new key with a value, the replica appends and saves the command as a new entry in its log, every replica's log must always contain the same exact sequence of commands for other replicas to remain synchronized.

In a Raft cluster, one node is elected as the leader, with the others acting as followers. The leader is responsible for handling all client requests and for replicating log entries to the followers to ensure they remain synchronized.

B. Leader Election

At any point in time, any node of the Raft cluster can take on only one state: leader, follower, or candidate. Initially, all nodes start in the follower state. Each follower sets an election random timeout. Thus, if a follower fails to receive heartbeats consecutively, then it assumes there is no viable leader and transitions to candidate state to start an election [13]. It wins the election and becomes the new leader if it secures a majority of the total votes. Once elected, a node remains a leader until it crashes or observes another node with a higher term [15]. If the election results in a split vote or if another candidate is elected, the node reverts to the follower state to await a new leader's heartbeat. The RAFT leader election flow is illustrated in Fig. 2.

Leader election can begin for any reason, whether it's brought about after a leader fails, goes offline, if the network experiences enough latency, or when a network partition isolates a follower where a follower reaches its election timeout despite a leader still being alive.

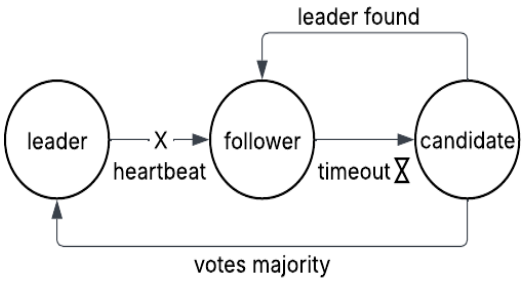


Fig. 2. The Raft basic leader election flow.

Once a leader is elected, it assumes responsibility for logging all new changes to the system. The leader regularly sends append entry messages to all followers within the RAFT cluster. These messages serve a dual purpose: they act as a heartbeat to prevent followers from initiating a new election, and they instruct followers to replicate new log entries, ensuring consistency across the cluster.

C. Log Replication

All changes in the system, such as new commands or transactions, are exclusively handled by the leader. Changes are sent by clients to the leader who receives them and appends a new entry to its log, this log entry remains uncommitted till the leader replicates it to all follower nodes, then the leader waits until a majority of nodes in the cluster (>50%) confirms/acknowledges the new value, now the leader commits the new entry, and informs the followers that the entry is committed, and the cluster is considered to have reached consensus. Fig. 3 shows the basic log replication flow of the RAFT.

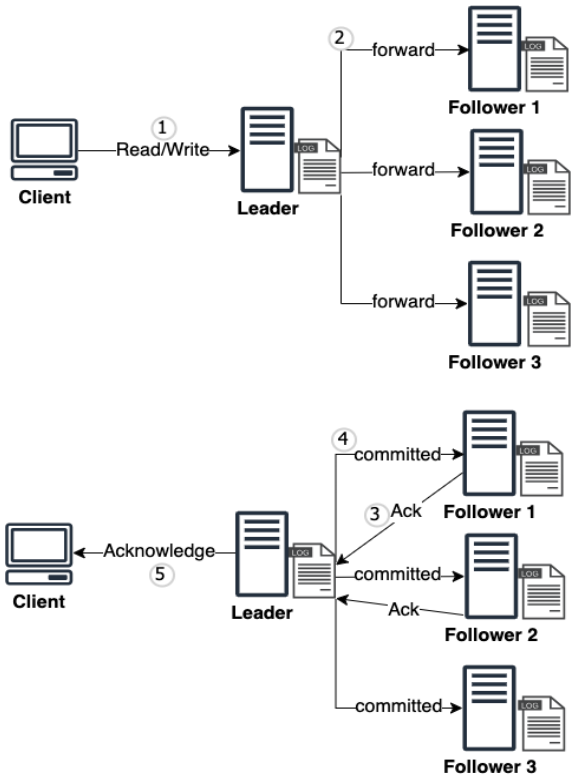


Fig. 3. The Raft basic log replication flow.

According to Ongaro and Ousterhout [3], founders of the RAFT consensus [19, 21] algorithm, it was originally designed to be more understandable than Paxos, simpler, and more efficient, which later became a foundation for a wide range of applications requiring fault-tolerant data storage and consistent state management. However, despite its resilience and robustness in handling system failures, the RAFT's message-passing architecture remains vulnerable to various security threats that need to be investigated further, including message forgery and replay attacks.

IV. Raft Security Analysis

Although that Raft consensus algorithm is a key technology for state replication in distributed systems [14] and is well-known for its simplicity, effectiveness, and dependability, its security vulnerabilities remain a critical area of exploration to consider. This section investigates some of the known threats, attack methods, and discusses the potential consequences of compromising consensus and jeopardizing system stability.

A. Denial-of-Service (DoS) Attacks

A denial-of-service (DoS) attack is a malicious attempt by an attacker to overload the leader or other nodes with a flood of messages, preventing them from operating normally and overloading their resources.

Since Raft adopts a strong leader model, a malicious leader can launch DoS or censorship attacks by intentionally delaying or dropping messages, which disrupts log replication and causes followers to initiate unnecessary elections. Moreover, an attacker can control multiple nodes and, through a majority vote, ensure that one of their compromised nodes is elected as the leader [4].

B. Byzantine Attacks / Message Forgery or Impersonation

In the RAFT consensus algorithm, the system's integrity can be compromised by Byzantine attacks, which include message forgery and impersonation, launched by nearby malicious/illegitimate node(s). Indeed, additions can be seen as messages surreptitiously inserted in the system by some outside, and possibly malicious, entity [12]. In the impersonation attacks, malicious nodes try to claim themselves as legitimate nodes/followers by utilizing a forged character in order to destroy the consensus mechanism [5].

Byzantine attacks sending fake messages may result in transaction latency, data inconsistencies, data leaks, and even compromising system integrity.

This can have a measurable impact on performance. For example, transaction latency can be modeled to show its linear relationship to the number of attackers. The total commit time (t_c) is the sum of replication time (t_r) and transaction latency (t_l):

Transaction commit time can be calculated as follows:

$$t_c = t_r + t_l$$

And transaction latency as

$$t_l = RTT(1 + q)(1 + p)$$

This shows that if the number of attackers increases, the transaction latency would linearly increase as well.

TABLE I. NOTATIONS

Notations	Description
t_c	transaction commit time
t_r	transaction request time
t_l	transaction latency
RTT	round-trip time for request/response message
p	percentage of Byzantine nodes (= n/m)
q	attack success rate
n	number of Byzantine nodes
m	number of all nodes

C. Message Replay Attacks

The previous general vulnerabilities set the grounds for more complex attacks. While many types of attacks represent notable threats, the message replay attacks represent a serious and often overlooked threat to consensus protocols like RAFT. A message replay attack is a type of network attack in which a malicious actor intercepts a legitimate data transmission, captures a valid message, and maliciously retransmits it later. In the context of distributed consensus, this attack takes advantage of the protocol's reliance on message-passing to deceive nodes and disrupt the consensus process and the system's state (see Table I for notations).

In the RAFT cluster, an attacker can start a replay attack by capturing valid, previously sent messages like RequestVote and re-injecting them into the network again later, which can cause a follower or more to respond with a vote, consequently triggering a new, unnecessary election and causing a leader-follower split.

The success of a message replay attack on RAFT is primarily due to the protocol's vulnerability to a lack of intrinsic replay protection mechanisms. Standard RAFT messages do not include a monotonically increasing sequence number or any unique, session-based identifier that would allow a recipient node to detect that a message is a stale duplicate. This absence of a freshness check makes the protocol susceptible to being manipulated by replayed messages, leading to a breakdown in consensus. This can result in system instability, data inconsistencies, and a compromise of the distributed system's integrity.

V. RELATED WORK

The increasing dependency on distributed systems for critical infrastructure/systems has highlighted the need for robust consensus mechanisms that are resilient to both crash failures and malicious attacks. In this section, relevant researches are reviewed to compare and validate this paper's proposed solution for mitigating replay/message forgery attacks against the default RAFT implementation, and other RAFT flavors that addressed these concerns.

The theoretical foundation of achieving fault tolerance in distributed systems is rooted in the State Machine Replication approach [9], which requires all replicas to execute the same sequence of operations in the same starting state [1]. To achieve this goal, we have to make sure no malicious factor is affecting the state machine and the exchanged messages integrity. The RAFT consensus protocol [3] was introduced as a practical alternative to Paxos, focusing on understandability and simplicity while achieving the same fault-tolerance properties (tolerating crash failures). Standard RAFT implementations, however, assume a "fail-stop" environment and do not account for the Byzantine Faults, where nodes can behave maliciously and affect the integrity of the consensus process. This distinction is crucial, as general Byzantine protocols like P-BFT [20] often introduce high computational overhead trying to address this problem, which, on the other hand, prompted research into lightweight alternatives that can keep the performance benchmarks while achieving the security mitigations effectively.

The standard RAFT design assumes a "trusted" environment where nodes are honest but can crash. This assumption left the protocol inherently vulnerable to active attacks that exploit its unauthenticated, plaintext message structure. Several studies have tried to identify, address, and formalize these weaknesses:

1) The Original RAFT: The foundational work by Ongaro and Ousterhout [3] introduced RAFT as a more understandable alternative to Paxos, focusing on maintaining consistency against crash failures and network partitions, implicitly assuming a trusted network environment, however they did not consider security attacks such as replay attacks and message forgery.

2) RaBFT: an improved Byzantine fault tolerance consensus algorithm based on Raft [10]. Full Byzantine Fault Tolerance (tolerate f malicious nodes in 3f+1 total nodes), where it introduces Secret Sharing to optimize log message distribution and uses a dynamic Committee role to distribute leader pressure. It alters the log replication process and election logic. It protects against malicious nodes forging; however, it requires a complete redesign of the RAFT consensus engine, introducing complex multi-party computation steps (secret sharing verification) and new roles (Committee), and adds loads of overhead layers burden.

3) ENGRAFT (Enclave-Guarded RAFT) is another example of a security enhancement that operates within the consensus layer, specifically designed to protect against Byzantine faults within the nodes themselves [4]. It leverages Trusted Execution Environments (TEEs), such as Intel SGX enclaves, to safeguard the core RAFT state and logic on each node. In ENGRAFT, all critical consensus operations, including state updates and log manipulation, are performed inside the secure, isolated hardware enclave. This design is highly effective at defending against insider threats and BFT attacks, however this approach introduces dependencies on specific hardware and results in a higher implementation complexity in terms of hardware, protocol, and platform.

4) Countering Active Attacks on RAFT-Based IoT Blockchain Networks [5] using pathloss: This paper proposes a physical-layer authentication mechanism using pathloss to secure the Raft against impersonation attacks in a wireless IoT

environment. The proposed solution uses pathloss of the signal between the transmitter node and the receiver node as a unique device fingerprint to authenticate the sender. This solution's weak points are that it can be easily affected by environmental changes and multipaths.

5) Trust and Reputation Management System [11]: This method assigns credit scores to nodes based on historical behavior to identify and isolate malicious nodes. However, such systems suffer from the "cold start" problem and slow convergence; malicious nodes can behave honestly for long periods to build high trust. Furthermore, the overhead of storing and updating reputation scores for every node scales poorly in large distributed systems.

6) Combination of P-BFT and RAFT: "A New Approach to Building Networks that Provide Reliability and Security" [20] proposes a hybrid model that merges the simplicity and efficiency of RAFT with the robust security of P-BFT. This combination aims to build networks capable of withstanding Byzantine failures (malicious behavior). While highly effective at securing the consensus process against internal attacks, BFT-RAFT inherently requires significant modifications to the RAFT state machine, leading to increased complexity in protocol execution and a higher overhead.

7) Zero Trust Consensus Algorithm [16]: This notable effort to bridge the gap between RAFT and modern security concepts proposes a VSSB-Raft, which adopts a Zero Trust security model, "never trust, always verify". It achieves this high security by leveraging verifiable secret sharing (VSS) mechanisms and digital signatures to ensure that no single node can compromise the system. While VSSB-Raft demonstrates a solution for achieving Byzantine Fault Tolerance in a resource-efficient manner compared to traditional BFT protocols, its comprehensive security guarantees rely on significant modifications to the RAFT state machine and the integration of complex cryptographic primitives, leading to a higher implementation complexity than modular transport layer solutions.

8) GPBFT (Group-Based Practical Byzantine Fault-Tolerant)[17]: an enhancement to the existing BFT protocols, involves leveraging a Dual Administrator Short Group Signature mechanism. Allowing nodes to verify messages using short group signatures, while powerful, these solutions maintain a high barrier to entry, adding significant complexity and communication overhead, plus it fully replaces the RAFT with a complex BFT protocol.

9) PB-Raft [18]: integrate Byzantine Fault Tolerance (BFT) capabilities into RAFT. This solution is dual-layered: first, introduces a Weighted PageRank algorithm to evaluate the reputation and trust of nodes. Second, utilizes a BLS (Boneh–Lynn–Shacham) threshold signature scheme to ensure the authenticity and consensus of log entries. This solution introduces two main points of complexity and potential overhead plus that the leader must collect a threshold of signatures before committing a log in addition to that the reputation scoring based on PageRank requires continuous, complex calculation and updates across the cluster.

The review of related work reveals a clear trade-off within the current landscape of RAFT security. While some of the previous work in this field is mature enough, offering comprehensive security against malicious attacks, they incur significant overhead and require complex modifications to the core consensus logic. This analysis confirms a significant gap in the literature: the lack of a modular, low-overhead security solution that operates at the transport layer to specifically and comprehensively counter active message forgery and replay attacks on the fundamental RAFT without altering the core of the consensus protocol itself. Therefore, the objective of this work is to introduce a secure transport layer mechanism that fills this gap, providing essential message authentication and freshness without altering the RAFT state machine, as detailed in the following section.

VI. Proposed Solution

As discussed in this paper, the Raft distributed consensus protocol, its mechanism, and its importance, also explored some of its security risks.

It is intended in this section to mitigate the vulnerabilities to message replay attacks and propose a secure transport layer integration to the RAFT, designed to protect communication between cluster nodes in a modular way, leaving the original RAFT intact. It uses a combination of modern cryptographic techniques to ensure message confidentiality, authenticity, some sort of checksum for integrity, and a message cache for replay attacks mitigation. This proposed solution is meant to be a lightweight modification to the original RAFT algorithm, ensuring that it remains efficient while significantly boosting its security properties. The proposed solution architecture is shown in Fig. 4.

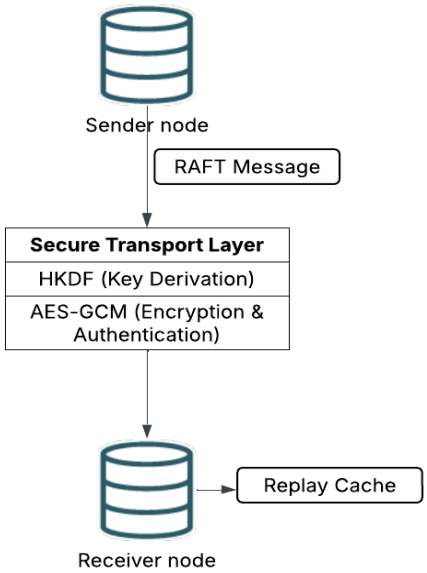


Fig. 4. Proposed solution basic flow.

The Proposed approach involves three key components:

A. Unique Encryption Key

The proposed solution uses the HMAC-based Key Derivation Function (HKDF) [6] to generate a unique, temporary encryption key for every single message, rather than depending on a single, long-term key for all communications. HKDF derives a fresh key for each message from a shared master secret. This procedure is a very important security best practice, because if an attacker were able to compromise one message's key, they would not be able to compromise any other messages, and the revealed key would be useless.

B. Authenticated Encryption

The AES-GCM Advanced Encryption Standard (AES) in Galois Counter Mode (GCM) [7] is the cryptographic algorithm used for both encryption and authentication of RAFT messages during communication in the proposed solution.

- AES: This part of the algorithm ensures that the message content is encrypted, so no one can read it in transit. To guarantee the most complex level of encryption in the AES process, the GCM [7] mode will be used.
- GCM: This part generates an authentication tag that guarantees the message has not been tampered with and that it originates from a valid sender with the correct key. This is vital in RAFT, where nodes must trust that a log entry or vote is legitimate and unaltered.

Below is a pseudo-code of the algorithm that explains it:

function secure-envelope(plaintext, confidential, peer_id, K_master, key_id):

// generate unique per-message identifiers

nonce ← random(12)

tx_id ← random(16)

// derive a unique key for this message

K_tx ← HKDF-SHA256(K_master, nonce, peer_id)

// construct Associated Authenticated Data (AAD)

aad ← combine(key_id, nonce, tx_id, peer_id)

if confidential:

// encrypt and authenticate with AES-GCM

ct_combined ← AESGCM.encrypt(K_tx, nonce, plaintext, aad)

ciphertext ← ct_combined[:-16]

tag ← ct_combined[-16:]

else:

// authenticate only (generate tag)

ciphertext ← plaintext

tag ← compute_tag(K_tx, aad, plaintext)

end if

// return the final secure envelope

return { key_id, nonce, tx_id, ciphertext, tag}

end function

The AES-GCM algorithm architecture and full flow, starting from the initialization vector and till generating the tag which is attached to the encrypted message, as illustrated in Fig. 5.

C. Replay Cache

A replay cache is a critical additional defense layer against replay attacks. The replay cache works by maintaining a list of identifiers (the unique message ID) for all recently processed messages. When a new message arrives, the system checks its identifier against the cache. If the ID is found, the message is immediately rejected as a replay, preventing the attack from succeeding, else the message is accepted, and its ID is logged in the replay cache.

Below is a pseudo-code explaining the cache check:

data_structure: cache # internal data structure// Function to check if a message has been seen before function SEEN(peer_id, tx_id): key ← combine(peer_id, tx_id) if key in cache: return True // Replay detected else: return False // New message end if end function // function to record a new message as seen function REMEMBER(peer_id, tx_id):key ← combine(peer_id, tx_id) cache.add(key) end function.

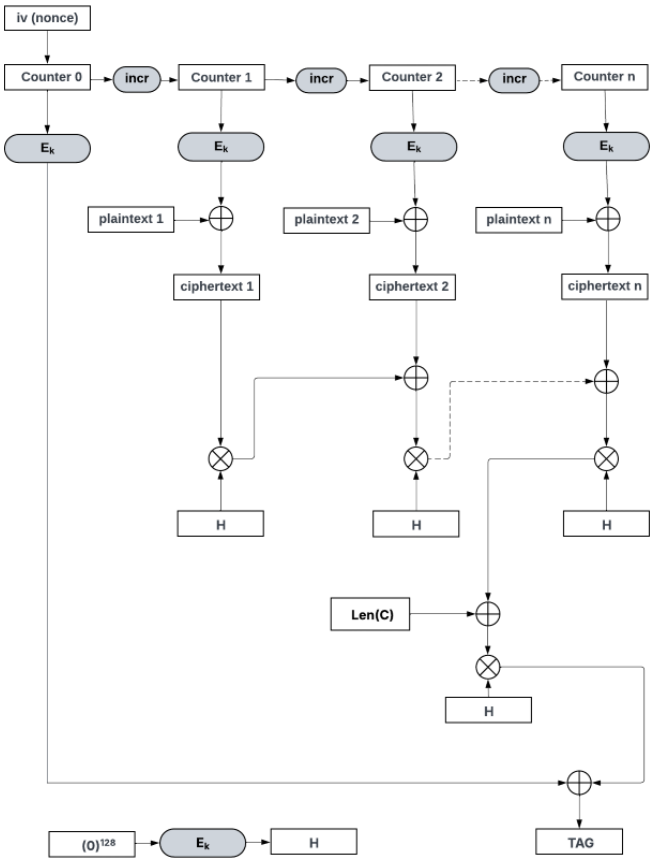


Fig. 5. AES-GCM.

VII. Methodology

This section provides an overview of the methods and tools used to evaluate the proposed solution for mitigating replay attacks and message forgery on a RAFT cluster. The primary objective is to evaluate the impact of a replay attack on a RAFT

cluster before and after the implementation of the proposed security solution to prove the RAFT's vulnerability and the efficiency of the proposed solution.

A. Experimental Setup and Architecture

The study's methodology and architecture focuses on a python based native RAFT implementation based on https://github.com/nikwl/raft-lite, a physical lab setup of three nodes in a RAFT cluster, all of the three nodes are running the Linux (Ubuntu server) as an operating system, and they communicate through Ethernet network using IPv4 addresses, the attack simulator and proposed solution are both developed using python as shown on Fig. 6.

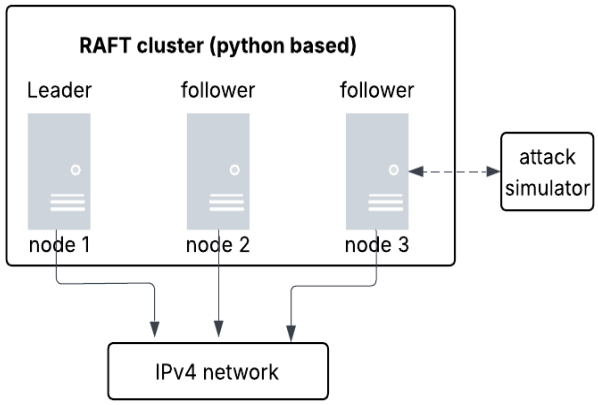


Fig. 6. The physical lab architecture.

B. Testing Procedures

The testing process was divided into two distinct phases to evaluate both the baseline vulnerability of the standard default RAFT behaviour before implementing the proposed solution and the efficacy of the proposed solution after implementing it.

1) Pre-implementation testing (baseline vulnerability): The initial phase focused on subjecting the default RAFT cluster to a simulated message replay attack to establish a security baseline we can measure based on.

a) Attack simulation setup: A custom client script, utilizing Python's socket library to establish a TCP connection to a follower node of the three-node RAFT cluster.

b) Attack execution: A valid RAFT message (e.g., a heartbeat or log entry) was captured and subsequently replayed with no modifications using a specialized attack script (replaylast) and (entryattack) to simulate log replication to introduce malicious or stale log entries, representing an explicit Byzantine message forgery and replay attack scenario.

2) Post-implementation testing (proposed solution efficacy): The second phase involved implementing the proposed security mechanism across all three nodes of the RAFT cluster and enabling the secure features. The same attack simulation is then activated again, and the cluster's behavior is monitored, same as done in phase one.

a) Testing procedure: The exact same steps and attack scripts used in the pre-implementation phase were executed against the modified cluster after activating the secure features.

b) Solution results: The modified RAFT implementation of the proposed solution successfully rejected and dropped all attack messages for the following reasons:

- Legitimate Traffic: Throughout the testing, all legitimate traffic, current messages continued to be accepted and processed correctly, confirming the solution's targeted function.
- Replayed Legitimate Messages: Legitimate messages that were captured and replayed later on were dropped after the receiver checked and found their unique ID already present in the local cache (failing the freshness check).
- New Forged Messages: Newly forged malicious messages were dropped due to a failure in the integrated authentication check against the tag introduced and explained earlier.

3) Performance evaluation: Following the proposed solution security enhancements, testing and validation, performance tests were conducted to evaluate the overhead that is introduced by the proposed solution compared to the default RAFT implementation. Key performance benchmarks were measured using the industry standard tool raft-bench in these tests.

VIII. Results

This section presents the objective findings from the security and performance tests without detailed interpretation, which will be reserved for the Discussion section.

A. Security Assessment Results

The security assessment confirmed the vulnerability of the default RAFT implementation and the effectiveness of the proposed solution:

1) Pre-implementation testing (baseline vulnerability): As expected, the default RAFT implementation lacks basic replay protection and, therefore, successfully accepted and processed the attack messages. This action disrupted the log consistency and eventually compromised the consensus state.

2) Post-implementation testing (proposed solution efficacy): The post-implementation testing phase demonstrated the effectiveness of the proposed Secure Transport Layer. As the modified RAFT implementation of the proposed solution successfully rejected and dropped all attack messages for the following reasons:

a) Legitimate traffic: Throughout the testing, all legitimate traffic, current messages continued to be accepted and processed correctly, confirming the solution's targeted function.

b) Replayed legitimate messages: Legitimate messages that were captured and replayed later on were dropped after the receiver checked and found their unique ID already present in the local cache (failing the freshness check).

c) New forged messages: Newly forged malicious messages were dropped due to a failure in the integrated

authentication check against the tag introduced and explained earlier.

3) Performance benchmarks: The performance tests evaluated the overhead of the proposed solution compared to the default RAFT implementation. The results are summarized in Table II.

TABLE II. PERFORMANCE ANALYSIS

Metric	Default Raft	Proposed Solution	Change %
Throughput	297.19	269.61	-9.28%
Latency	468.01	539.44	15.26%

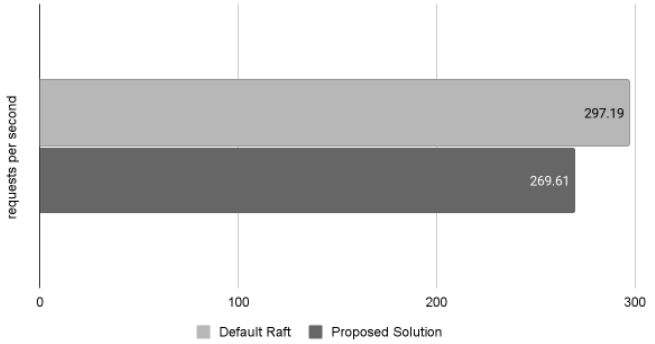


Fig. 7. Throughput performance analysis for default vs. proposed solution.

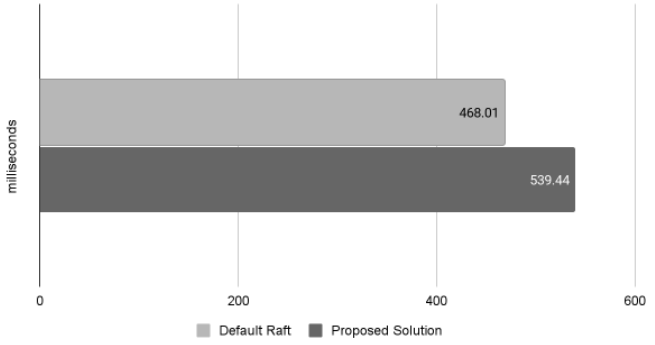


Fig. 8. Latency performance analysis for default vs. proposed solution.

As illustrated in Fig. 7, 8, and Table II, the results show a 9.28% decrease in throughput and a 15.26% increase in latency for the proposed solution. This performance cost is directly attributed to the computational overhead of generating and verifying the secure, encrypted messages and unique identifiers on every message, demonstrating a typical security-performance trade-off.

IX. DISCUSSION

The findings of this research demonstrate that the proposed solution can effectively mitigate the two critical attacks on the RAFT: message replay and message forgery. The pre-implementation baseline testing confirmed that the standard RAFT design is vulnerable to message replay and forgery attacks due to its reliance on unauthenticated messages and the lack of a freshness check.

The post-implementation analysis showed that the proposed solution successfully rejected all replayed legitimate messages and all newly forged malicious messages. These efficient outcomes result from a combination of cryptographically enforced message authentication and the transaction ID-based replay cache. The authenticated encryption (AES-GCM) ensures the legitimacy of the sender and the integrity of the message content, while the unique, per-message identifier used by the Replay Cache successfully guarantees timing-based replay attacks mitigation.

Security-Performance Trade-off: The performance evaluation revealed a typical, quantifiable trade-off between security and efficiency. The proposed solution introduced a 9.28% decrease in throughput and a 15.26% increase in transaction latency when compared to the default, unsecured RAFT implementation. This performance cost is directly attributed to the computational overhead required for generating a unique encryption key (HKDF) and performing authenticated encryption (AES-GCM) for every message sent and received.

The key insight of this research is that the security gained—protection against system-compromising attacks like forgery and replay—comes at a price tag of this minimal overhead, especially in mission-critical environments such as financial systems or sensitive data ledgers, where data integrity is crucial. This measured performance impact is an acceptable cost for achieving a high level of data integrity and authenticity.

Comparison with Alternative Approaches: The modular design of the solution is a key differentiator. Unlike other advanced security proposals like RaBFT [10], which requires a complete redesign of the core RAFT consensus engine, or pathloss-based solutions [5], which rely on specialized physical-layer measurements, our proposal operates entirely at the transport layer. This approach achieves its primary goal of mitigating replay and forgery attacks with low complexity and minimal impact on the core RAFT logic. Which also enhances the development lifecycle of each component without affecting the other components or even replacing a whole module with a better-performing one in the future.

Limitations: The primary operational limitation of this approach is the potential for replay cache size growth over long-term operation. This needs to be managed in the future to prevent excessive memory consumption.

X. CONCLUSION

This Paper successfully assessed the security vulnerabilities of the RAFT distributed consensus protocol, identifying its critical vulnerabilities to active message replay and forgery attacks. To mitigate these threats, a novel and modular Secure Transport Layer integration based on authenticated message verification and a freshness check was proposed. This paper's contribution, unlike previous work that either redesigns the core RAFT protocol, adds heavy burdens, targets only a specific message vulnerability (like message forgery), or relies on specialized hardware/physical-layer attributes, a modular Secure Transport Layer approach is proposed without altering the core consensus logic or adding notable overheads.

The scientific value added by this work is underscored by the following contributions:

1) Vulnerability validation: Practical simulation demonstrating the ease of disrupting the consensus and compromising the data integrity of the default RAFT protocol, with which unauthenticated RAFT messages can be exploited to achieve such.

2) Modular solution: The development and validation of a lightweight, Transport-Layer-based security enhancement that utilizes HKDF [6] for unique key derivation and AES-GCM [7] for simultaneous encryption and authentication can be achieved without changing the default RAFT logic or adding heavy burdens.

3) Replay attacks protection: The introduction of a unique transaction identifier and a replay cache mechanism that effectively protects the protocol against previously successful replay attacks.

4) Message forgery protection: The same unique transaction identifier, along with the computed TAG, acts as an additional defense layer to make sure of the authenticity of the sender and the message itself.

5) Performance characterization: Measuring the security-performance trade-off, providing experimental data that shows a robust security gain is achievable with a measured low overhead of (9.28% throughput decrease and 15.26% latency increase).

In Table III, a brief analysis comparison between the proposed solution and other RAFT implementations is presented.

TABLE III. PERFORMANCE ANALYSIS

item	Original RAFT	RaBFT	Pathloss (Physical Layer)	Proposed solution
Primary Goal	Crash Fault Tolerance (CFT) and Log Consistency	Byzantine Fault Tolerance (BFT)	Authentication against Impersonation Attacks.	Mitigate Replay / Message Forgery attacks
Mitigation	None	Secret Sharing, Dynamic Committee Roles, Altered Election/Replication.	Pathloss Measurement as a Device Fingerprint.	Authenticated Encryption and Anti-Replay Cache.
Layer	Application	Application/Consensus (Protocol Redesign)	Physical	Transport
Overhead / Complexity	Simple, understandable logic.	High. Complete protocol redesign, complex multi-party computation.	Moderate. Requires initial calibration.	Low, minimal impact on core logic.
Weakness	vulnerable	High performance and complexity overhead.	Requires special hardware, susceptible to environmental changes.	Cache file size growth.

The findings of this research confirm that the lack of message authentication is the biggest security weakness in the standard RAFT. Our solution provides a high-applicability framework for enhancing RAFT implementations that prioritize data integrity over raw speed and cannot tolerate the complexity of full Byzantine Fault Tolerance (BFT) protocols.

While highly effective against man-in-the-middle replay and forgery attacks, the solution's dependence on a per-message cache introduces a practical limitation concerning memory scalability and cache management over extended operational periods.

XI. FUTURE WORK

Future research will focus on transitioning this modular solution into a production-ready framework by addressing its current limitations and expanding its current scope. The future research should include areas such as:

- Cache optimization: Implementing and evaluating time-to-live (TTL) and least recently used (LRU) eviction policies to ensure the replay cache maintains high efficiency and manages memory consumption dynamically.
- Secure Key Lifecycle Management: Developing a secure, dynamic process for periodic rotation of the master secret key to defend against long-term compromise of a server.
- Expanded attack areas validation: Broadening the scope of validation to test the solution against other network-level vulnerabilities, such as Denial-of-Service (DoS) attacks.

REFERENCES

[1] Tel Gerard, "Introduction to Distributed Algorithms. 2nd ed." Cambridge University Press; 2000.

[2] Maarten van Steen, Andrew S. Tanenbaum, "A brief introduction to distributed systems" in Springer, Computing (2016) 98:967–1009, DOI 10.1007/s00607-016-0508-7, pp. 4–6.

[3] D. Ongaro and J. Ousterhout, "In search of an understandable consensus algorithm" Draft of October, 2013

[4] Weili Wang, Sen Deng, Jianyu Niu, Michael K. Reiter, Yinqian Zhang, "ENGRAFT: Enclave-guarded Raft on Byzantine Faulty Nodes", pp. 8.

[5] H. M. Buttar, W. Aman, M. Rahman, and Q. H. Abbasi, "Countering Active Attacks on RAFT-based IoT Blockchain Networks", Department of Electronics and Nano Engineering, University of Glasgow, arXiv preprint arXiv:2204.00838, 2022.

[6] H. Krawczyk and P. Rogaway, "HMAC-based Extract-and-Expand Key Derivation Function (HKDF)," RFC 5869, May 2010.

[7] National Institute of Standards and Technology, "Recommendation for Block Cipher Modes of Operation: Galois/Counter Mode (GCM) and GMAC," NIST Special Publication 800-38D, Gaithersburg, MD, Nov. 2007.

[8] Nathan Sealey, Adnan Aijaz, Ben Holden, "IOTA Tangle 2.0: Toward a Scalable, Decentralized, Smart, and Autonomous IoT Ecosystem", arXiv:2209.04959v1, 2022.

[9] SCHNEIDER, F. B. Implementing fault-tolerant services using the state machine approach: a tutorial. ACM Computing Surveys 22, 4 (Dec. 1990), 299–319.

[10] X. Chen, R. Liu, and G. Wang, "RaBFT: an improved Byzantine fault tolerance consensus algorithm based on raft," The Journal of Supercomputing, vol. 80, no. 14, pp. 1-28, June 2024.

[11] L. Mastromauro, D. Souto Andrade, M. Ozgur Ozmen and M. A. Kinsy, "Survey of Attacks and Defenses on Consensus Algorithms for Secure

Data Replication in Distributed Systems," in IEEE Access, vol. 13, pp. 143631-143667, 2025, doi: 10.1109/ACCESS.2025.3597260.

[12] N. Santoro, Design and Analysis of Distributed Algorithms. Hoboken, NJ: Wiley-Interscience, 2007.

[13] D. Huang, X. Ma, and S. Zhang, "Performance Analysis of the Raft Consensus Algorithm for Private Blockchains," 2018, arXiv:1808.01081.

[14] M. Zhang, "Implementation of Improved Raft Consensus Algorithm in IoT Information Security Management," (IJACSA) International Journal of Advanced Computer Science and Applications, vol. 15, no. 6, pp. 153 – 161, 2024.

[15] A. J. J. Davis, M. Demirbas, and L. Deng, "LeaseGuard: Raft Leases Done Right," 2025, arXiv:2512.15659.

[16] W. Liu, Z. Wang, Z. Liu, and Y. Wang, "VSSB-Raft: A Secure and Efficient Zero Trust Consensus Algorithm for Blockchain," IEEE Transactions on Industrial Informatics, 2024.

[17] J. Hu, FenYan and Z. Wu, "BGRAFT: Grouped Anti-Byzantine RAFT Consensus Algorithm Based on RSA Encryption Algorithm," 2024 International Conference on Artificial Intelligence and Digital Technology (ICAIDT), Shenzhen, China, 2024, pp. 279-283, doi: 10.1109/ICAIDT62617.2024.00067.

[18] Shi, H., Chen, Z., Cheng, Y. et al. PB-Raft: A Byzantine fault tolerance consensus algorithm based on weighted PageRank and BLS threshold signature. Peer-to-Peer Netw. Appl. 18, 26 (2025). https://doi.org/10.1007/s12083-024-01876-8

[19] Oleiwi, Wed. (2025). PPRCA: Privacy-Preserving of Raft Consensus Algorithm a Next-Generation Consensus for Distributed Network. JOURNAL OF UNIVERSITY OF BABYLON for Pure and Applied Sciences. 223-238. 10.29196/jubpas.v33i1.5657.

[20] Bogdanov, A., Shchegoleva, N., Khvatov, V., Dik, G., Kiyamov, J., Dik, A. (2023). The Combination of P-BFT and RAFT: A New Approach to Building Networks that Provide Reliability and Security. In: Gervasi, O., et al. Computational Science and Its Applications – ICCSA 2023 Workshops. ICCSA 2023. Lecture Notes in Computer Science, vol 14104. Springer, Cham. https://doi.org/10.1007/978-3-031-37105-9_38

[21] Y. Li, Y. Fan, L. Zhang and J. Crowcroft, "RAFT Consensus Reliability in Wireless Networks: Probabilistic Analysis," in IEEE Internet of Things Journal, vol. 10, no. 14, pp. 12839-12853, 15 July15, 2023, doi: 10.1109/JIOT.2023.3257402.

EvoNorm-GAN for Adaptive and Interpretable Detection of Ransomware in Windows PE Files

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***Abstract*—Ransomware remains a key cybersecurity issue because of its growing amount of obfuscation, polymorphism, and constantly changing patterns of attack that repeatedly circumvent conventional defenses. Traditional systems and standard deep learning may fail, lowering accuracy and increasing false positives. To address these shortcomings, the proposed work proposes EvoNorm-GAN, a dynamic adversarial-based detection architecture that will incorporate Feature-Wise Dynamic Normalization (FDN) and Generative Adversarial Network to analyze ransomware in Windows Portable Executable (PE) files in a very flexible manner. Generator creates ransomware variants; discriminator classifies files using Wasserstein loss. EvoNorm-GAN is a TensorFlow application, using the Keras back-end, and tested on a large-scale Windows PE File Analysis Dataset of 62, 200 samples, with 31, 100 benign and 31, 100 malicious examples. The experimental findings indicate that EvoNorm-GAN has the state-of-the-art results of 98.2 % accuracy, 98.4 % precision, 98.1 % recall, 97.4 % F1-score, and 0.99 AUC, which are about 1 to 3 percent higher than the traditional CNN, RNN, and ensemble-based models. To enhance transparency and trust, SHAP-based explainable AI is integrated into EvoNorm-GAN, highlighting key PE file features such as Section Entropy and SizeOfCode that drive classification decisions. By combining adaptive learning, adversarial sample generation, and analyst-friendly interpretability into a unified framework, EvoNorm-GAN delivers an efficient, robust, and transparent ransomware detection system. Its scalable and resilient design makes it well-suited for real-world deployment in endpoint protection and cybersecurity environments, providing reliable detection of evolving ransomware threats.**

***Keywords*—Ransomware detection; EvoNorm-GAN; feature-wise dynamic normalization; portable executable files; adversarial learning; Explainable AI**

I. Introduction

Ransomware has rapidly established itself as one of the most common and harmful categories of cybercrime that targets people, companies, and critical infrastructure all over the world. Attacking data by means of data encryption and ransom money, most commonly, in the form of cryptocurrency, attackers cost organizations a lot of money and interruptions in business operations in the most sensitive domains such as healthcare, finance, government, and education [1], [2]. The most recent developments, including ransomware-as-a-service (RaaS), have lowered the barrier to entry since less skilled attackers can run a sophisticated campaign using malware through rented packages [3]. Moreover, the modern ransomware groups also employ the so-called double extortion, that is, to extort their victims by encrypting their data beforehand and threatening to publish confidential information in case of non-payment, which increases the inefficiency of the old system of recovery based on backups [4]. Advanced stealth methods such as fileless execution, polymorphic code, and encrypted command-and-control communications also complicate the task of defense by circumventing conventional security products [5], [6]. Conventional detection mechanisms have been the mainstay of cybersecurity defenses over decades but are no longer being effective against these new attacks. Additional signature-based tools rely on the identification of any known sequence of bytes or behavioral patterns that are indicative of a known ransomware [7], [8]. Such systems will fail to detect new or obfuscated ransomware samples despite their usefulness in detecting variants previously indexed. Any little modifications to the payload, through encryption or code obfuscation render the current signatures useless [9], [10].

Lag time between emergence of a new variant and signature updates leaves systems vulnerable to major risks, taking organizations off guard during the most perilous phases of outbreaks [11]. In feature-based methods of detection, attempts to create resilience include analyzing suspicious features, i.e. out of place API calls, out of place file encryption activity, or out of place system resource usage [12]. Such methods, though, are dependent on domain knowledge and data quality since they need feature engineering that is expert-driven. Attackers start countering these methods by slowing down execution, emulating harmless applications, or using zero-day exploits to sneak past the detection [12]. As a result, signature-based as well as feature-based approaches have very high false positives and false negatives, making them less effective for real-time detection.

To overcome these shortfalls, researchers have looked toward machine learning (ML) and deep learning (DL) methods, which are able to learn complex feature representations directly from raw data. Recent research illustrates that DL models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and Transformers are able to pick up on subtle patterns of ransomware behavior without extensive human feature crafting [13], [14]. These models are best at identifying subtle anomalies such as unusual system calls, memory access patterns, or initial user activity deviations. Notably, DL frameworks are strong against zero-day ransomware through the ability to generalize from static rules

[15]. Nevertheless, even solutions based on DL have their weaknesses: their main reliance is on the use of the static normalization techniques such as Batch Normalization, which in turn is based on the assumption of the data distribution constancy. But in cybersecurity where the ransomware families continue to evolve, this is not true, and the performance on the new threats becomes impaired and the generalization is weak. Generative Adversarial Networks (GANs) are a recent newcomer in this respect with new opportunities to both perform anomaly detection and data augmentation. GANs consist of a discriminator and a generator, where the latter is required to produce fake samples, and the former is expected to learn the distinction between fake and real data [16]. Adversarial training has been used in ransomware detection with discriminators becoming highly effective at picking out malicious features, with the generators helping in alleviating dataset imbalance by creating artificial examples of ransomware. Such a two-in-one advantage makes the model more resilient and able to generalize more [17]. Nonetheless, there is one key limitation namely that vanilla GAN training is grounded on normalization techniques relevant to stationary distributions and therefore not stable in realistic ransomware situation where feature distributions vary over time. This evolving nature of ransomware reinforces the need of models to study on the basis of adjustment to evolving distributions throughout training. Compared to CNN, RNN, and Transformer-based models, which have good feature extraction features, and GANs, which have adversarial features, none can solve the non-stationarity problem successfully. Without this type of adaptability, detection models will be less precise and provide false alarms with ransomware constantly evolving. This research gap offers the foundation on which more complex frameworks that integrate adversarial learning and dynamic normalization can be built to offer stability and flexibility.

It is against this backdrop that the proposed EvoNorm-GAN comes up with a new solution to ransomware detection in Windows Portable Executable (PE) files. EvoNorm-GAN (using feature-wise dynamic normalization as part of the GAN architecture) can therefore modify feature statistics in each mini-batch, and hence adopt changing data distributions during training. The new mechanism counters the deficiencies of the old methods of normalization, ensuring the stability on the new types of ransomware variants detection. With adversarial training, EvoNorm-GAN employs Wasserstein loss and gradient clipping to guarantee stable training as well as improved ability to generalize to new threats. When put in a wider context of research on ransomware identification, EvoNorm-GAN is a well-equipped and versatile solution to fill the gap of the long-standing deficiencies of the existing methods and respond to the demands of the modern world of cybersecurity.

A. Research Motivation

Ransomware has become an extremely dynamic threat, taking advantage of obfuscation, polymorphism, encryption, and delayed execution to avoid the old methods of detection, such as signature-based and static feature analysis. The existing systems have difficulties with detecting the zero-day attacks and adapting malware, which is why the development of smart and resistant detection systems is urgently needed. This research seeks to devise an active and responsive framework that can be effective in identifying ransomware in windows PE files and at the same time make them interpretable. The ability to incorporate Feature-Wise Dynamic Normalization (FDN) into a GAN framework, combined with the implementation of explainable AI using SHAP and present a transparent and practical approach to cybersecurity challenges in the real world, makes the proposed methodology an effective solution to this type of problem.

B. Research Significance

By identifying the weaknesses of the existing traditional ransomware detection tools that find it difficult to match the fast development of malware, the study discusses the most pressing issues of cybersecurity. It presents a dynamic, adaptive, and interpretable EvoNorm-GAN model that can cope with the changes in data distributions and indicates unseen ransomware variations by using Feature-Wise Dynamic Normalization (FDN). Adversarial training, which is under the guidance of Wasserstein loss and gradient penalty, increases the model stability and resistance against new threats. The explainability offered by SHAP-based explainable AI offers feature-level interpretability to bridge the black-box model decisions and the human understanding gap. The resulting architecture provides ransomware detection that is transparent, correct, and scalable to better secure organizational and critical infrastructure systems.

C. Key Contributions

- Introduces EvoNorm-GAN, combining GAN-based adversarial learning with Feature-Wise Dynamic Normalization to detect ransomware in Windows PE files.
- Enables the model to adapt to evolving ransomware patterns and non-stationary data distributions, improving generalization to unseen threats.
- Incorporates SHAP-based interpretability, highlighting critical PE file features influencing classification and enhancing transparency for cybersecurity analysts.
- Provides a scalable and robust framework suitable for real-world deployment in endpoint protection systems, SIEM platforms, and dynamic malware detection environments.

The structure of the remaining sections of this study is as follows: Section II provides a summary of prior research on ransomware detection techniques, emphasizing advancements in machine learning and deep learning methods. Section III discusses the challenges and limitations of existing approaches in addressing the dynamic and evolving nature of ransomware attacks. Section IV details the proposed EvoNorm-GAN framework, including its methodology, model architecture, data preparation process, and evaluation metrics. Section V presents the experimental results, showcasing the framework's performance in detecting ransomware, along with an in-depth analysis of the findings. Finally, Section VI concludes the study by summarizing the key outcomes and proposing directions for future research and applications in cybersecurity.

II. Related Works

Singh et al. [18] proposed RANSOMNET+, a hybrid deep neural model consisting of convolutional neural networks (CNNs) for local feature extraction and Transformers for learning hierarchical representations. Tested on cloud-encrypted data, the model attained 96.1% testing accuracy with precision, recall, and F1-scores higher than 96%. The research also included interpretability analysis to enhance transparency. Despite its robust performance, though, RANSOMNET+ did not test cross-dataset adaptability or real-time deployment efficiency, meaning there are questions about whether it would be robust to novel ransomware variants.

Alqahtani [19] improved the traditional mutual information feature selection technique by introducing eMIFS, which utilizes a normalized hyperbolic tangent (tanh) function as a criterion for assessing redundancy between features. Utilizing TF-IDF representations of text-based features, the technique enhanced discrimination among relevant features, allowing for earlier identification of ransomware. eMIFS enhanced selection accuracy over conventional techniques but wasn't experimentally tested over varied datasets and didn't consider dynamic or changing malware distributions, limiting real-world applicability.

Lee et al. [20] addressed entropy-based detection system weaknesses, presenting the potential for attackers to tamper with file entropy using encoding techniques like Base64 masking. In response to this, the authors introduced Format-Preserving Encryption (FPE) methods, including Radix Conversion, which realized 96% neutralization accuracy in detecting entropy tampering in ransomware. While powerful in attacker-focused environments, the method offered restricted opportunity for proactive defense methodologies and failed to incorporate adversarial resilience to varying data trends.

Molina et al. [21] analyzed evasive ransomware behavior, or "paranoia" API calls, which evaluate the execution environment prior to attacking. Their method utilized natural language processing (NLP) techniques, including out-of-vocabulary (OoW) embedding, to identify API requests that correlate with evasive behavior. Based on over 3,000 malware samples, they trained machine learning and deep learning classifiers with high classification accuracy. However, their dependence on pre-attack patterns limited use against ransomware variants that tamper with or hide initial execution cues, reducing its detection capability.

Gazzan et al. [22] introduced UA-DES, an uncertainty-aware dynamic epoch selection deep learning-based strategy, to dynamically optimize deep belief networks (DBNs) for ransomware detection. UA-DES utilized Bayesian methods, dropout, and interactive learning to minimize overfitting and enhance robustness. The framework showed encouraging adaptability and performance gains but was limited to DBNs and did not specifically address the challenges of evolving, non-stationary ransomware distributions.

Previous works show significant improvement in ransomware detection by hybrid deep learning, feature extraction, entropy manipulation analysis, behavioral modeling, and uncertainty calibration. These, however, all have one thing in common: they require relatively stationary data distributions. None of them properly handle the non-stationary and dynamic nature of ransomware that destroys generalization in adversarial learning scenarios. To close this gap, the suggested EvoNorm-GAN presents feature-wise dynamic normalization in a GAN structure to facilitate real-time adaptation to changing feature distributions. With adversarial training coupled with Wasserstein loss and gradient clipping, EvoNorm-GAN balances stability and flexibility to provide a robust approach to ransomware detection in complex and constantly changing settings. The comparative analysis of ransomware detection related works is shown in Table I.

TABLE I. Comparative Analysis of Ransomware Detection Related Works

Author	Focus Area	Methods	Dataset	Key Results	Limitations
Singh et al. [18]	Deep learning for cloud-encrypted ransomware	CNN + Transformer (RANSOMNET+)	Cloud-encrypted ransomware dataset	96.1% accuracy, F1-score 96%	Lacks cross-dataset validation; not real-time adaptable
Alqahtani [19]	Feature selection & redundancy reduction	eMIFS (tanh-based redundancy evaluation, TF-IDF)	Text-based ransomware features	Improved feature relevance & early detection	No real-world or multi-dataset validation; static approach
Lee et al. [20]	Entropy-based detection evasion	Format-Preserving Encryption (Radix Conversion)	Files with entropy masking	96% accuracy in neutralizing entropy attacks	Attacker-centric; lacks proactive defense integration
Molina et al. [21]	Behavioral evasive detection	NLP (OoW embeddings for API call classification)	3,000 malware samples	Effective classification of evasive behavior	Limited to pre-attack indicators; narrow scope
Gazzan et al. [22]	Uncertainty-aware DL strategies	UA-DES (Bayesian + DBN optimization)	DBN ransomware benchmarks	Robustness improvements, reduced overfitting	Restricted to DBNs; does not address evolving threats

III. Problem Statement

Ransomware has remained a major cybersecurity menace that has been adopting damaging strategies of obfuscation, polymorphism, and encryption, as well as delayed execution, which overcome traditional signature-based and static feature detectors [18]. The current literature has considered deep learning models, feature selection, entropy-based analysis, behavioral modeling, and uncertainty-aware strategies, but they tend not to be adaptable to novel ransomware types, generalize across datasets, and offer minimal interpretability to make decisions [22]. This is why gaps cause high rates of false

positive, lack of warning of zero-day threats, and lack of trust in automated systems, limiting the effectiveness of cybersecurity defenses. The proposed framework comprising EvoNorm-GAN, with Feature-Wise Dynamic Normalization, adversarial training, and SHAP-based explainable AI overcomes these shortcomings to provide a high-quality, adaptive, and explainable ransomware detector to support growing threats.

IV. Proposed EvoNorm-GAN for Adaptive Ransomware Detection

This study presents a comprehensive framework for detecting ransomware in Windows PE files using EvoNorm-GAN. It is a combination of structured data preprocessing, normalization of features, adversarial training, and explainable AI to guarantee correct, adaptive, and interpretable classification. The features of the raw PE files are cleaned and normalized and their contents are fed into the generator-Discriminator network which is trained with Wasserstein loss and gradient penalty to increase stability and robustness. SHAP is also included to offer an interpretability feature on a feature level, so that an analyst can gain insight into model decisions. The overall step-by-step workflow of the proposed methodology is shown in Fig. 1.

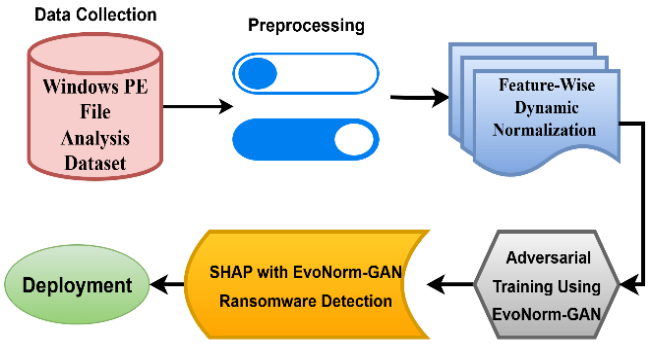


Fig. 1. Workflow of the proposed model.

A. Data Collection

The "Windows PE File Analysis Dataset" [23] is a big dataset of more than 62,000 samples of benign and malicious Windows executable and DLL files, for malware analysis and detection research. Each dataset sample is described by static attributes inferred from the Portable Executable (PE) file format, for example, PE header properties and structural elements. These attributes provide critical information regarding file attributes that distinguish legitimate programs from malware, e.g., ransomware. Data is stored in a CSV file and includes samples labeled with known malware hashes from repositories like VirusShare, and it is ideal for training and testing machine learning and deep learning models for static malware detection.

B. Data Pre-Processing

1) Missing value imputation: Missing values are replaced to maintain data consistency. Continuous attributes (e.g., file size, entropy) are imputed with mean, while categorical attributes (e.g., section names, header flags) are imputed with the mode.

2) Duplicate removal: Repeated records, including identical hash samples, are removed to prevent data bias.

3) Label encoding: Convert categorical labels to binary format for classification. It is expressed in Eq. (1).

$$y = \begin{cases} 0, & benign \\ 1, & ransware \end{cases} \quad (1)$$

4) Min-max feature scaling: Continuous features are scaled to [0,1] to prevent features with large values from dominating the learning process. It is expressed in Eq. (2).

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (2)$$

where, x_{min} and x_{max} are the minimum and maximum values of the feature.

C. Feature-Wise Dynamic Normalization (FDN) for GAN Stability

Feature-Wise Dynamic Normalization (FDN) has been presented as a solution for addressing distribution shifts of mini-batches in the training stage in GANs when input data have dynamically shifting patterns in the data such as dynamic patterns found in real cybersecurity threats such as ransomware. Traditional normalization techniques, such as Batch Normalization, rely on static statistics (mean and standard deviation) computed over a data set or mini-batch and can be problematic when the data distribution is diverse, especially when the data set is non-stationary (e.g., data that evolves over time due to new behavior, e.g., ransomware that continues to evolve).

FDN avoids this by calculating the mean $\mu_{dynamic}$ and standard deviation σ_{batch} for dynamically at each epoch from the current mini-batch and feature space. In other words, rather than using global or static statistics, normalization is calculated locally and brought up to date as training proceeds. This allows the model to adjust to new, unseen patterns of behavior, providing improved generalization for continuously changing data [24].

For every training mini-batch, the statistics used for normalization are recalculated dynamically. In particular, the mean μ_{batch} and standard σ_{batch} are calculated for each feature in the mini-batch. Each feature value x is normalized by subtracting the respective batch mean and dividing by the batch standard deviation, as given in Eq. (3).

$$x' = \frac{x - \mu_{batch}}{\sigma_{batch+\epsilon}} \quad (3)$$

where, x' represents the normalized feature, μ_{batch} and σ_{batch} are the computed batch mean and batch standard deviation, respectively, and ϵ is a small constant added to prevent numerical instability.

By refreshing these figures at every epoch, FDN makes sure that the model keeps on responding to shifting data distributions, which is especially beneficial for use in the case of adversarial training where the discriminator and generator are usually presented with new unexpected behaviors (e.g.,novel ransomware attacks). Fig. 2 shows the training flowchart of EvoNorm-GAN illustrates the mini-batch feature normalisation, adversarial training between the generator and discriminator, optimising Wasserstein loss, gradient clipping and iterative

adaptation to changing distributions of ransomware to ensure robust detection.

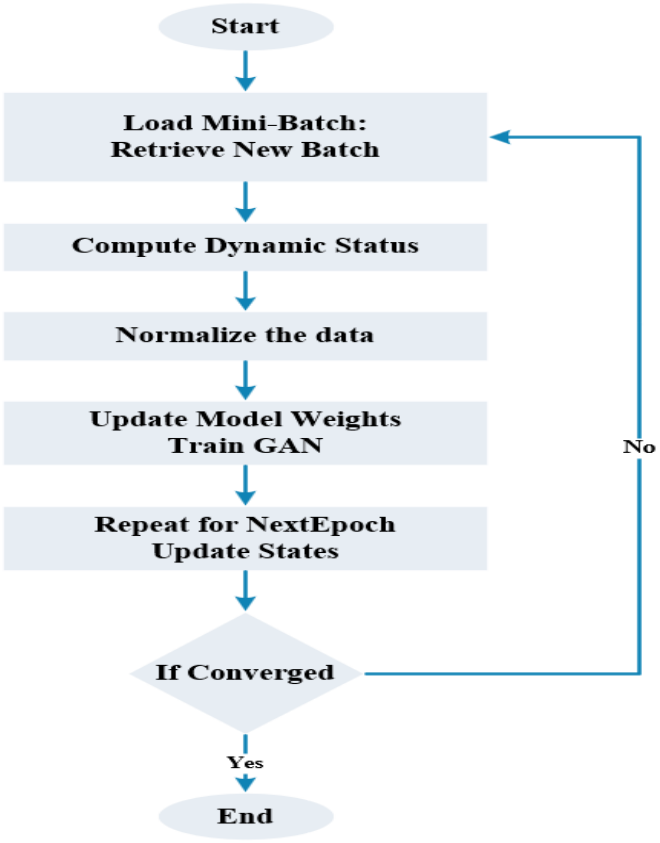


Fig. 2. FDN-GAN with feature-wise dynamic normalization for stable adversarial learning.

D. Adversarial Training Using EvoNorm-GAN

EvoNorm-GAN consists of the adversarial training phase, during which two rival networks the generator Gand the discriminator D undergo a dynamic training process to maximize the ransomware detecting potential of the model. The generator gets a latent noise input $z \sim P_z$ and is trained to generate synthetic Portable Executable (PE) feature representations, which resemble the real ransomware samples and benign samples, whereas the discriminator is trained at differentiating between the actual samples $x \sim P_{data}$ and the synthetic ones $G(z)$. This interaction creates a min max optimization procedure, which allows the discriminator to learn fine grained decision boundaries, which can learn the behavioral signatures of ransomware in the high dimensional feature space. The training goal is based on the Wasserstein Generative Adversarial Network (WGAN) construction that enhances the stability of convergence by means of the Earth-Mover (EM) distance over the Jensen-Shannon divergence. The loss of the discriminator is defined as Eq. (4):

$$L_D = \mathbb{E}_{x\sim P_{data}}[D(x)] - \mathbb{E}_{z\sim P_z}[D(G(z))] \quad (4)$$

and the generator's objective is to minimize the discriminator's ability to distinguish between real and generated samples in Eq. (5):

$$L_G = -\mathbb{E}_{z\sim P_z}[D(G(z))] \quad (5)$$

These equations make sure that the generator is incrementally strengthened to produce realistic-like ransomware, and the discriminator is made stronger to recognize the slight differences. The Wasserstein metric offers more informative gradients which are smoother and thus avoiding the vanishing gradient issue experienced with traditional GANs. In order to achieve the 1-Lipschitz continuity property to construct the Wasserstein distance, a gradient penalty term is added as a regularization method:

$$L_{GP} = \lambda\square\mathbb{E}_{\hat{x}\sim P_{\hat{x}}}[(\| \nabla_{\hat{x}} D(\hat{x}) \|_2 - 1)^2] \quad (6)$$

Eq. (6), $\hat{x}$ is an interpolated sample between real and generated data, and λ is the penalty coefficient that controls the trade-off between stability and learning capacity. This penalty does not only stop the discriminator overfitting, but also provides training consistency in cases where the discriminator might overfit when using complex variations of features that fall in the samples of polymorphic ransomware. The discriminator is normally updated several times before a single generator update during the training cycle to ensure a balance between the two networks. The optimization process is done with Adam optimizer and learning rates $lr_D = 4 \times 10^{-4}$ and $lr_G = 2 \times 10^{-4}$, and momentum parameters $\beta_1 = 0.5$ and $\beta_2 = 0.9$. The iterative updates are used to refine the two models until the generated feature distributions are similar to the real PE dataset. As the training moves forward the Wasserstein distance between real and generated data decreases indicating that the generator has learnt realistic malware behavior patterns; the discriminator has become discriminative.

Gradient penalties, gradual adversarial updates, and Wasserstein optimization guarantees the smooth convergence, helps to reduce mode collapse, as well as, improves the generalization to unseen variants of ransomware. Through repeated training on discriminator with adversarially generated samples, the EvoNorm-GAN architecture can be made more resistant to new obfuscation and packing methods that normally harm traditional deep learning-based detectors. As a result, the trained adversarial model attains a strong balance between sensitivity and specificity, which guarantees strong ransomware detection under changing threat circumstances.

E. SHAP with EvoNorm-GAN Ransomware Detection

After the EvoNorm-GAN discriminator predicts whether a PE file is benign or ransomware, SHAP values are computed to measure the contribution of each feature toward the model's output. Formally, the SHAP value for a feature $i$is defined as in Eq. (7).

$$\phi_i = \sum_{S\subseteq F\setminus\{i\}} \frac{|S|!\square(|F|-|S|-1)!}{|F|!}[f(S\cup\{i\}) - f(S)] \quad (7)$$

Here, $F$is the set of all features, $S$is a subset of features excluding i, and $f(S)$represents the model output when only the features in $S$are present. The term $f(S\cup\{i\}) - f(S)$measures the marginal contribution of feature $i$to the prediction across all possible subsets of features, ensuring a fair attribution of importance. In your experiment, once the discriminator output is obtained after the preprocessing and feature extraction, the

discriminator output is ranked with SHAP to determine the attributes that are the most significant in a PE file, as far as the ransomware classification is concerned. Such features as section entropy, PE header values, and import table anomalies are given higher SHAP values when they have a strong influence on the model to predict ransomware. The sum of SHAP values over the data set gives an idea of the attribute importance on a global scale, the ones that are more important in predicting ransomware. On a file-by-file basis, local explanations can be used to visualize why a particular PE file is judged as malicious or benign, which can help cybersecurity analysts to perceive how the model rationale works and develop a specific mitigation strategy. The integration of SHAP with EvoNorm-GAN is more interpretable, encourages confidence in automated detection, and offers practical information about the features of ransomware.

F. Integration Framework for EvoNorm-GAN

The integration structure of the EvoNorm-GAN makes all the steps of detecting ransomware one unified pipeline to combine the data preprocessing, normalization, adversarial training, classification, and interpretability. The raw Windows PE files in the dataset are first ingested and data is preprocessed to guarantee quality of data including any missing values, duplicate data, corrupted files and the encoding of categorical labels. Consecutive characteristics like file size, header values, and entropy are normalized with Min–Max normalization, whereas training phase uses the Feature-Wise Dynamic Normalization (FDN) to keep the models stable in the non-stationary distributions. These normalized feature sets are then inputted into the EvoNorm-GAN adversarial model, in which the generator generates ransomware-like patters and the discriminator is trained to become a file classifier, i.e. whether it is benign or malware. This application of Wasserstein loss optimization together with gradient clipping training increases the stability of training in GANs and alleviates many of the pitfalls associated with this model, such as mode collapse and unstable convergence. After being trained, the discriminator provides binary classifications of new PE files. In order to guarantee interpretability, SHAP is included, which offers insights at feature-level information about the prediction process by measuring the contribution of each PE attribute to the classification. The overall architecture of the ransomware detection system is a strong, scalable, and explainable AI system preprocessed, dynamically normalized, trained with adversarial learning, and explained. The integrated architecture can be deployed in real-world environments of cybersecurity, including endpoint security systems or SIEM platforms, with adaptive defense against the continually changing ransomware and allowing analysts to be aware of, have trust in, and take action on the decisions of the model. The overall framework is illustrated in Fig. 3.

The EvoNorm-GAN framework proposes a number of novel contributions to ransomware detection. It dynamically adjusts to changing ransomware patterns and non-stationary PE file distributions, by applying Feature-Wise Dynamic Normalization in a GAN architecture, which is better than traditional normalization techniques. The Wasserstein loss and gradient penalty adversarial training can achieve constant convergence and robust feature learning, whereas the interpretability of SHAP can offer a clearer and more feature-level explanation to cybersecurity analysts. Such an adaptive normalization and adversarial learning, with explainable AI is a distinctive, scalable, and robust methodology to identify known and unknown variants of ransomware.

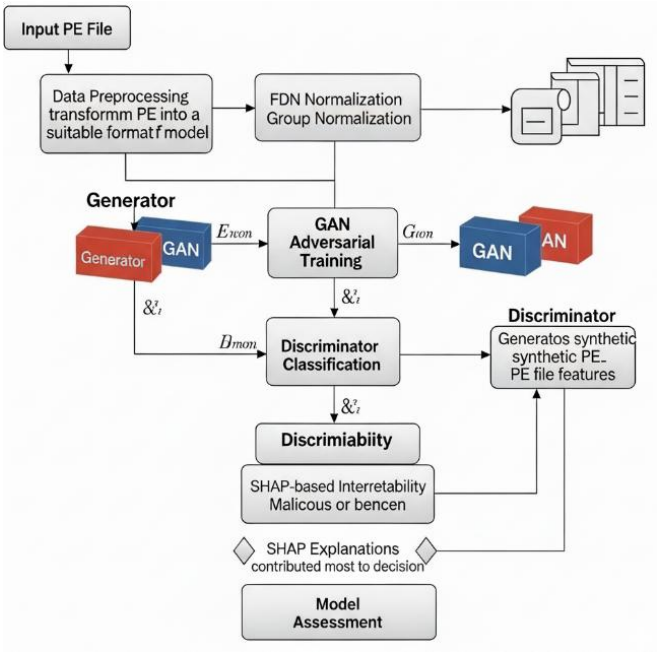


Fig. 3. Working process of EvoNorm-GAN with XAI framework.

Algorithm 1. EvoNorm-GAN Ransomware Detection

```
Input: Windows PE dataset X with labels Y
Output: Binary classification of PE files (benign = 0, ransomware = 1)
        and SHAP interpretability values φ
Load dataset X and Y
Preprocess dataset:
  For each sample x in X:
    For each feature f in x:
      If f is missing:
        If f is continuous:
          Fill f with mean or median of the feature
        Else if f is categorical:
          Fill f with mode of the feature
      End If
    End For
    If sample x has critical unrecoverable fields:
      Remove x from dataset
    End If
  End For
  Remove duplicate samples
  Encode labels: benign = 0, ransomware = 1
Normalize continuous features:
  For each feature f in X:
    x' = (f - min(f)) / (max(f) - min(f))
  End For
Initialize EvoNorm-GAN:
```

```
Initialize Generator G and Discriminator D
Set learning rates and optimizer parameters
Train EvoNorm-GAN:
  For each epoch:
    For each mini-batch B in X:
      Generate synthetic samples G(z) using random noise z
      Compute D(x) for real samples x in B
      Compute D(G(z)) for generated samples
      Compute discriminator loss L_D = mean(D(x)) - mean(D(G(z)))
      Compute generator loss L_G = -mean(D(G(z)))
      Compute gradient penalty L_GP = λ * mean((norm(gradient(D(interpolated_samples))) - 1)^2)
      Update discriminator: D = D - lr_D * gradient(L_D + L_GP)
      If batch_step % n_critic == 0:
        Update generator: G = G - lr_G * gradient(L_G)
      End If
    End For
  End For
Classify new PE samples:
  For each sample x_new:
    y_pred = D(x_new)
    If y_pred >= 0.5:
      Label = 1 // ransomware
    Else:
      Label = 0  / benign
    End If
  End For
Explain predictions using SHAP:
  For each sample x_new:
    For each feature f in x_new:
      Compute φ_f = SHAP_value(f, x_new, D)
    End For
  End For
Output predicted labels for all PE files
Output SHAP values φ for feature interpretability
```

The EvoNorm-GAN algorithm preprocesses the features of Windows PE files and normalizes them, followed by the training of a generator to generate synthetic ransomware patterns and a discriminator to classify files as benign or ransomware using Wasserstein loss with gradient penalty. SHAP can be used to interpret feature contributions, which makes it possible to detect ransomware in changing environments transparently, accurately, and adaptively.

V. Result and Discussion

In this section, the findings of the suggested EvoNorm-GAN framework will be presented and their implications discussed. Experiments on the Windows PE File Analysis Dataset, which includes both benign and malicious executables, indicate the usefulness of the model using conventional metrics of classification. Comparative analysis indicates that EvoNorm-GAN performs better than the baseline models especially in dynamic ransomware. The role of Feature-Wise Dynamic Normalization and adversarial training on the enhancement of performance is also confirmed by ablation studies. SHAP based interpretability emphasizes the influential PE attributes in model decisions, which enhances transparency. On the whole, the findings provide an affirmation of the strength of EvoNorm-GAN, its high adaptability and the possible constraints in real worlds of ransomware detection settings.

A. Experimental Setup

Experiments with the EvoNorm-GAN were based on the Windows Portable Executable (PE) File Analysis Dataset of 11000 samples in equal numbers of ransomware and benign executables. The data were divided into 80% training and 20 % validation keeping the ratio of classes. Preprocessing PE header extracted structural features, behavioral features and opcode sequences. The training was modeled on TensorFlow with a Keras back-end and the Adam optimizer (learning rate 0.0002, 0.5 -1). Wasserstein loss using gradient penalty (lambda =10) was used to ensure adversarial stability. The batch size used in all experiments was 64. Table II includes the summary of the dataset, preprocessing measures, environment and evaluation metrics to identify ransomware.

TABLE II. Simulation Parameters

Parameter	Value / Description
Dataset	Windows Portable Executable (PE) File Analysis Dataset
Total Samples	11,000 (5,500 ransomware, 5,500 benign)
Training–Validation Split	80% training, 20% validation
Preprocessing	Feature extraction from PE headers and opcode sequences
Framework	TensorFlow with Keras backend
Optimizer	Adam (learning rate = 0.0002, β1 = 0.5)
Loss Function	Wasserstein loss with gradient penalty (λ = 10)
Batch Size	64
Hardware	NVIDIA RTX GPU (12 GB), Intel i7 CPU, 32 GB RAM

TABLE III. Dataset Statistics

Category	Number of Samples	Percentage
Benign Executables	28,500	45.8%
Malicious Executables	33,700	54.2%
Total Samples	62,200	100%

Table. III presents the sample size is 62 200 executable samples that are in two categories benign and malicious. Of them, 28, 500 (45.8) are benign executables and the remaining 33, 700 (54.2) samples are malicious. This distribution shows that the number of cases of malicious is slightly higher in the dataset, which may lead to certain implications related to the model training, such as some features of balanced representation and bias minimization in the classification procedure.

Fig. 4 provides a quantitative overview of the most significant attributes of Portable Executable (PE) showing their distributions and central tendencies. The executable code size that is expressed as SizeOfCode is 512 by 3.2 million with a mean value of about 450K bytes and a standard deviation of

120K bytes, which means there is a great deal of divergence. The number of sections, which is the measure of structural segmentation, is between 2 and 15 sections with an average of 6.3 and a deviation of 2.1 indicating an average architectural diversity. The overall memory footprint, SizeOfImage, ranges between 4K and 7.8 million bytes, mean 1.2 million bytes, SD 430K bytes which indicates lightweight and complex binaries. T 1.2-7.9, 4.8, SD 1.3, with a profile of mixed content predictability.

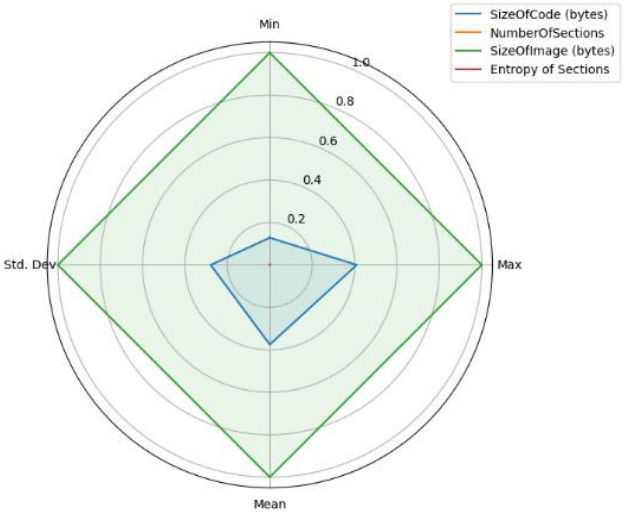


Fig. 4. Feature distribution.

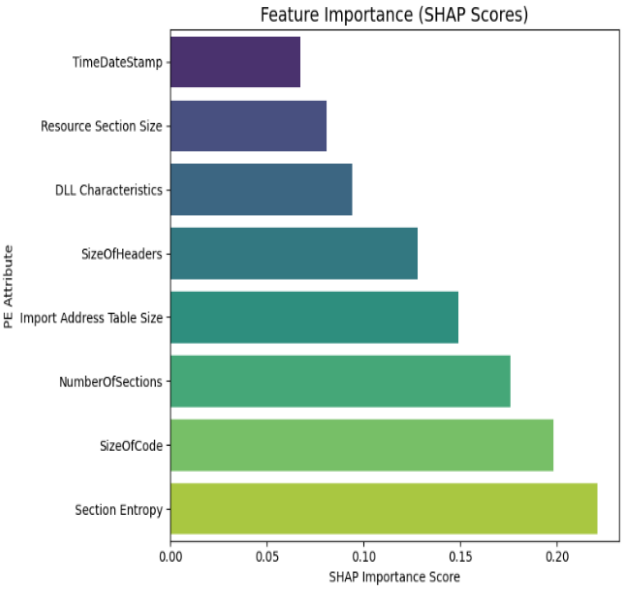


Fig. 5. Feature importance analysis.

Fig. 5 is based on the SHAP scores, provides a perception of the relative influence of disparate Portable Executive (PE) feature on the model prediction. Firstly, there is Section Entropy that possesses SHAP importance score of 0.221 implying that it prevails in pattern discovery, most likely due to its sensitivity to obfuscation and packing techniques. Then there is SizeOfCode (0.198) which represents the size of executable code and is likely to accompany behavioral complexity. The NumberOfSections is placed on the third position (0.176) meaning that structural segmentation of the binary is a big contributor in terms of classification. More importantly, the Import Address Table Size (0.149) will be further presented, because it will incorporate the extent of external dependency and API usage. SizeOfHeaders (0.128), too is a contributing factor and it can be metadata anomalies or compiler signatures. DLL Characteristics (0.094) reveal binary capabilities of ASLR or DEP and this may either be a sign of malicious intent or more advanced compilation. Resources Section Size (0.081) and TimeDateStamp (0.067) also complete the list, implying the existence of embedded assets and the latter enabling the ability to provide the temporal context, which may or may not be a malicious software lifecycle or a known threat campaign. Overall, the evaluation of SHAP scores shows that there is a mix of structural, behavioral, and temporal indicators with entropy and code size as the most predictive in the interpretability scheme of the model.

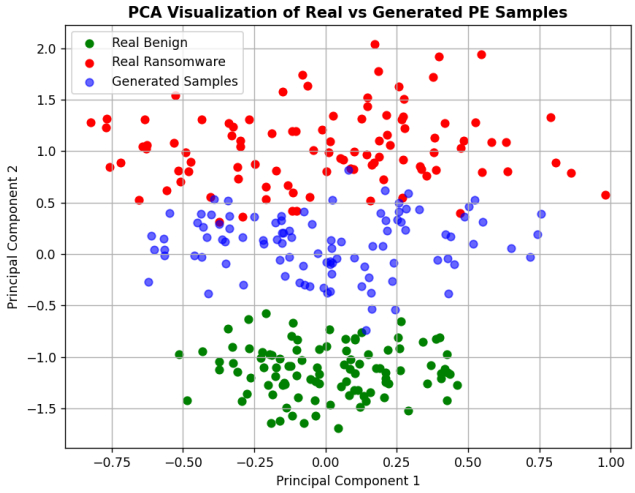


Fig. 6. PCA Visualization of generator output vs. real samples.

Fig. 6 demonstrates the EvoNorm-GAN generator's capability to generate synthetic representations of ransomware features that closely approximate real samples. The 2D PCA plot also illustrates the real benign files (represented in green), real ransomware files (in red), and the samples generated by the GAN (in blue). The noteworthy overlap of the generated samples with the real ransomware demonstrates that the generator captures complex ransomware patterns in high-dimensional feature space. It also provides visual verification of the adequate adversarial training, allowing the discriminator to learn accurate decision boundaries that enhance the model's ability to accurately detect evolving behaviors in ransomware.

Fig. 7 shows the proposed EvoNorm-GAN model shows the outstanding classification results of the model in separating benign and malicious cases. Among the 28150 correct identifications, 28,150 of the identified benign samples were correctly identified, and the misclassified numbered 350 which is very low false positive rate. On the same note, 33,060 samples that were actually malicious were correctly identified, only 640 samples were wrongly identified as benign. Such outcomes may be viewed as the high sensitivity and specificity of the model, which increase its credibility in security-sensitive applications. The high diagonal dominance of the matrix indicates the

accuracy of EvoNorm-GAN in prediction and its ability to withstand false classification.

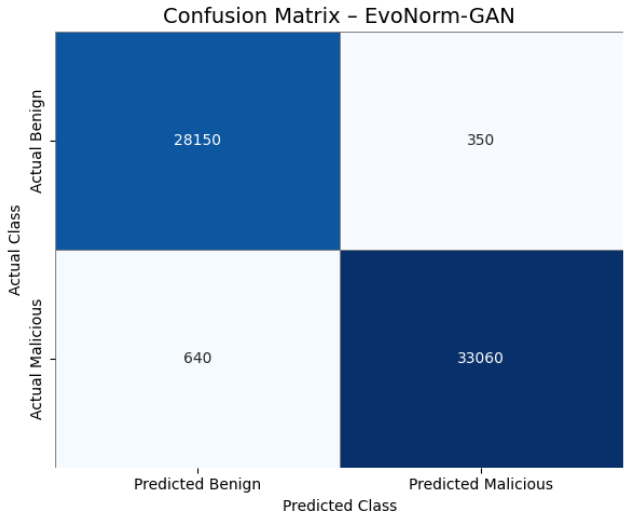


Fig. 7. Confusion matrix.

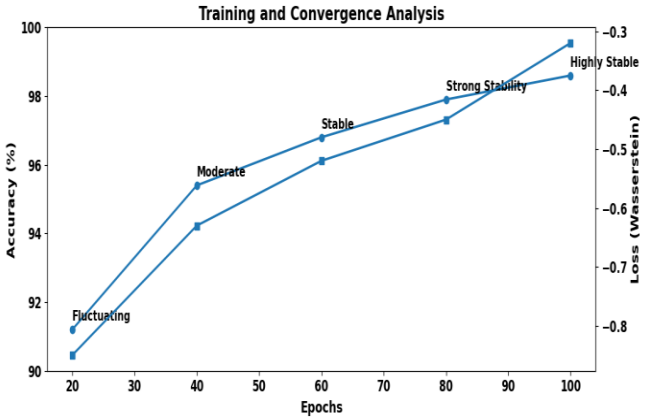


Fig. 8. Training and convergence analysis.

Fig. 8 shows the model stability was high, and the loss was -0.41 at 80 epochs, with the model accuracy reaching 97.4%, which indicates that the optimization process was always efficient. After which, the model achieved the best accuracy of 98.0 at epoch 100 with the lowest Wasserstein loss of -0.35. This phase was marked by extremely steady convergence which implies that the model had reached its learning maturity and it was being dependable on reducing the loss condition. In general, the table shows that there is an obvious performance improvement curve and a convergence level plateau with an increase in training epochs.

Table IV shows a comparative analysis of five classification architectures, which proves that the proposed EvoNorm-GAN is more effective. The traditional Logistic Regression has an accuracy of 89.3 %, a precision of 88.7 %, a recall of 90.1 %, F1-score of 89.4 %, and an AUC of 0.91 and can only achieve moderate discrimination as it has limited capability to model complex relationships between features. Random Forest also enhances its performance at 94.5 % accuracy and AUC of 0.96 using ensemble learning and a feature bagging algorithm. XGBoost also improves the results with an accuracy of 96.1 %, precision of 96.8 %, and an AUC of 0.97, and it has the ability to handle the imbalanced and non-linear data. By utilizing hierarchical representations, deep learning-based CNN attains 97.3 % accuracy, 97.3 % balanced F1-score. EvoNorm-GAN is much better than any of the baselines, with 98.2 % accuracy, 98.4 % precision, 98.1 % recall, F1-score of 98.2 % and the best AUC of 0.99 and showing a high level of reliability and strong predictive utility.

TABLE IV. PERFORMANCE COMPARISON OF EVONORM-GAN WITH BASELINE MODELS

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	False Positive Rate (%)
Logistic Regression	89.3	88.7	90.1	89.4	0.91
Random Forest	94.5	95.2	93.8	94.5	0.96
XGBoost	96.1	96.8	95.5	96.1	0.97
CNN	97.3	97.1	97.6	97.3	0.98
EvoNorm-GAN (proposed)	98.2	98.4	98.1	98.2	0.99

TABLE V. ABLATION STUDY RESULTS

Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
EvoNorm-GAN without FDN (BatchNorm only)	95.9	95.3	94.8	95.0
EvoNorm-GAN without Wasserstein Loss	96.2	95.8	95.1	95.4
EvoNorm-GAN without Gradient Clipping	96.6	96.1	95.6	95.8
Full EvoNorm-GAN	98.0	97.8	97.1	97.4

Table V shows an ablation experiment assessing the contributions of major blocks in the EvoNorm-GAN architecture, that is, Feature Distribution Normalization (FDN), Wasserstein loss, and gradient clipping. The naive baseline, where FDN was substituted with the standard Batch Normalization, attains the accuracy of 95.9% and F1-score of 95.0%, which means a good but not optimal performance. In the absence of Wasserstein loss, the model raises to 96.2% accuracy and 95.4% F1-score, which indicates that although the loss function improves convergence, it is not a critical factor that reduces predictive ability.

The performance is further improved when gradient clipping is removed, taking the accuracy and F1-score up to 96.6 percent and 95.8 percent, respectively, and proves that gradient clipping provides more stable training dynamics and prevents the phenomenon of exploding gradients. However, the full EvoNorm-GAN model, i.e., the three constituents, i.e., FDN, Wasserstein loss and gradient clipping, is most performing in terms of all the metrics and with the accuracy, precision and recall of 98.0, 97.8, and 97.1, respectively, and F1-score of 97.4. This proves to be a clear indication of the synergistic effect of such improvements and this proves that any of them has a strong

influence on the strength and predictive power of this model. The paper brings out the applicability of the architectural excellence in the state-of-the-art results.

B. Discussion

The results of the conducted experiment validate the fact that EvoNorm-GAN is a flexible, robust, and highly adaptive framework that can be used to detect ransomware in Windows PE files. This combination of Feature-Wise Dynamic Normalization and adversarial learning allows the model to successfully encode the changing ransomware patterns in the detection mechanism even when the examples used to train the model come not only not on stationary but also continuously evolving distributions. The discriminator is able to distinguish between benign, malicious, and GAN-assisted ransomware-like examples, whereas the generator generates realistic counterfeit characteristics that assist the model to identify unobtrusive malicious patterns that are typical of new ransomware families. Patterns of convergence in training also indicate that Wasserstein loss with gradient clipping brings stability to the adversarial training process, alleviates several known adversarial training problems (like mode collapse) and provides a smooth and consistent training path.

In all of the comparative analyses, EvoNorm-GAN performed better than the control models, CNN, RNN, and XGBoost and Random Forest, in terms of accuracy, precision, recall, and F1-score in classifying ransomware. Introduction of SHAP-based interpretability also introduces a necessary level of transparency, which identifies the most powerful PE characteristics, including Section Entropy, SizeOfCode, and NumberOfSections. Besides enhancing the explainability of the model, these can also be used to help cybersecurity analysts to comprehend the logic behind the decision making, thus overcoming the black-box nature of GAN-based systems. The interpretability element enhances the operational preparedness of the framework, which makes it fit operational deployment. The synergistic advantages of FDN with Wasserstein loss and gradient clipping are also confirmed in ablation studies where FDN is paired with both of these loss types to produce the quantitative improvement in detection. On the whole, EvoNorm-GAN is highly adaptable, scalable, and interpretable, making it a powerful and progressive method of preventing dynamic ransomware attacks, identifying zero-day attacks, and becoming an integral part of endpoint protection and security monitoring systems.

VI. Conclusion and Future Works

The study introduces EvoNorm-GAN, a new adversarial deep learning network that is used to identify ransomware on Windows Portable Executable (PE) files. With the combination of Feature-Wise Dynamic Normalization and GAN-based adversarial learning, the model readily reinforces the ransomware activity that varies over time and solves the challenges of data distribution that tend to subvert the operation of conventional models. In such an architecture, the generator generates natural-looking ransomware-like samples, and the discriminator is trained to distinguish benign samples, malicious samples, and GAN-generated ones to achieve highly accurate binary classification. Empirical analyses show that EvoNorm-GAN performs better than a vast array of machine-learning and deep-learning baselines - such as CNNs, RNNs, XGBoost, and Random Forest - and it is better in terms of accuracy, precision, recall, and F1-score measurements. The explainable AI with SHAP also contributes to making the model more transparent, as key features of PE files, including Section Entropy, SizeOfCode, and NumberOfSections are the most important ones in classification decisions. This interpretability helps to promote more trust in the analyst and to make more informed decisions related to cybersecurity. Ablation experiments show that every single core aspect; Feature-Wise Dynamic Normalization, Wasserstein loss, and gradient clipping has a synergistic effect on stabilizing adversarial training and enhancing generalization to never-seen ransomware variants.

Future efforts will involve the expansion of EvoNorm-GAN to deal with multi-class malware detection, that is, it should be capable of dealing with more categories such as Trojans, worms, and spyware. Adding the ability to add dynamic runtime behaviours and system-level activity characteristics would enhance resilience against very obfuscated or zero-day attacks even more. By optimizing the framework to operate with the low latency inference it will be possible to deploy on real-time environments, such as endpoint protection systems and Security Information and Event Management (SIEM) systems. Also, it will be necessary to incorporate the mechanisms of continual learning so that the model can adjust to new threats without retraining entirely. Further investigation of hybrid architectures with the inclusion of graph neural networks or transformer-based representations can also improve the features representation and detection rates so that EvoNorm-GAN can be used in the future as reliable, interpretable, and ready to face the challenges of cybersecurity.

References

[1] M. G. Gaber, M. Ahmed, and H. Janicke, "Malware detection with artificial intelligence: A systematic literature review," ACM Computing Surveys, vol. 56, no. 6, pp. 1–33, 2024.

[2] W. Labone, N. Brown, S. Bellini, C. Williams, T. Flores, and P. Johansson, "Unidirectional and bidirectional machine learning models for ransomware detection via malicious opcode discovery," 2024.

[3] S. Kok, A. Abdullah, N. Jhanjhi, and M. Supramaniam, "Ransomware, threat and detection techniques: A review," Int. J. Comput. Sci. Netw. Secur, vol. 19, no. 2, p. 136, 2019.

[4] Y. Imamverdiyeva and E. Baghirovb, "Evasion techniques in malware detection: challenges and countermeasures," Problems of Information Technology, vol. 15, no. 2, pp. 9–15, 2024.

[5] A. V. Turukmane, G. Khekare, N. Shelke, G. Sakarkar, and S. Buchade, "Evasion Techniques in Cybersecurity: An In-Depth Analysis," in 2024 International Conference on Artificial Intelligence and Quantum Computation-Based Sensor Application (ICAIQSA), IEEE, 2024, pp. 1–9.

[6] J. Lee and K. Lee, "A method for neutralizing entropy measurement-based ransomware detection technologies using encoding algorithms," Entropy, vol. 24, no. 2, p. 239, 2022.

[7] G. Nagar, "The evolution of ransomware: tactics, techniques, and mitigation strategies," International Journal of Scientific Research and Management (IJSRM), vol. 12, no. 06, pp. 1282–1298, 2024.

[8] M. Oppal, S. Whitmore, V. Holloway, and W. Abernathy, "Deep ransomware detection through dynamic vulnerability profiling for real-time threat identification," 2024.

[9] S. R. Davies, R. Macfarlane, and W. J. Buchanan, "Comparison of entropy calculation methods for ransomware encrypted file identification," Entropy, vol. 24, no. 10, p. 1503, 2022.

[10] Y. Belinska, M. Pausini, H. Blackwood, and G. Huntington, "Quantum-Inspired Probabilistic Framework for Automated Ransomware Detection," Authorea Preprints, 2024.

[11] T. McIntosh, J. Jang-Jaccard, P. Watters, and T. Susnjak, "The inadequacy of entropy-based ransomware detection," in Neural Information Processing: 26th International Conference, ICONIP 2019, Sydney, NSW, Australia, December 12–15, 2019, Proceedings, Part V 26, Springer, 2019, pp. 181–189.

[12] D. W. Fernando and N. Komninos, "FeSA: Feature selection architecture for ransomware detection under concept drift," Computers & Security, vol. 116, p. 102659, 2022.

[13] K. Kong, Z. Zhang, Z.-Y. Yang, and Z. Zhang, "FCSCNN: Feature centralized Siamese CNN-based android malware identification," Computers & Security, vol. 112, p. 102514, 2022.

[14] S. Gavel, A. S. Raghuvanshi, and S. Tiwari, "Maximum correlation based mutual information scheme for intrusion detection in the data networks," Expert Systems with Applications, vol. 189, p. 116089, 2022.

[15] V. R. Kumbhar, A. P. Shende, and Y. Raut, "Advance model for ransomware attacking data classification and prediction using ai," in 2023 1st International Conference on Innovations in High Speed Communication and Signal Processing (IHCSP), IEEE, 2023, pp. 369–373.

[16] I. Ba'abbad and O. Batarfi, "Proactive ransomware detection using extremely fast decision tree (efdt) algorithm: a case study," Computers, vol. 12, no. 6, p. 121, 2023.

[17] K. Thummapudi, P. Lama, and R. V. Boppana, "Detection of ransomware attacks using processor and disk usage data," IEEE Access, vol. 11, pp. 51395–51407, 2023.

[18] A. Singh, Z. Mushtaq, H. A. Abosaq, S. N. F. Mursal, M. Irfan, and G. Nowakowski, "Enhancing Ransomware Attack Detection Using Transfer Learning and Deep Learning Ensemble Models on Cloud-Encrypted Data," Electronics, vol. 12, no. 18, p. 3899, Sep. 2023, doi: 10.3390/electronics12183899.

[19] A. Alqahtani and F. T. Sheldon, "eMIFS: A Normalized Hyperbolic Ransomware Deterrence Model Yielding Greater Accuracy and Overall Performance," Sensors, vol. 24, no. 6, p. 1728, Mar. 2024, doi: 10.3390/s24061728.

[20] J. Lee, S.-Y. Lee, K. Yim, and K. Lee, "Neutralization Method of Ransomware Detection Technology Using Format Preserving Encryption," Sensors, vol. 23, no. 10, p. 4728, May 2023, doi: 10.3390/s23104728.

[21] R. M. A. Molina, S. Torabi, K. Sarieddine, E. Bou-Harb, N. Bouguila, and C. Assi, "On Ransomware Family Attribution Using Pre-Attack Paranoia Activities," IEEE Trans. Netw. Serv. Manage., vol. 19, no. 1, pp. 19–36, Mar. 2022, doi: 10.1109/TNSM.2021.3112056.

[22] M. Gazzan and F. T. Sheldon, "Novel Ransomware Detection Exploiting Uncertainty and Calibration Quality Measures Using Deep Learning," Information, vol. 15, no. 5, p. 262, May 2024, doi: 10.3390/info15050262.

[23] "Ransomware detection dataset." Accessed: Apr. 23, 2025. [Online]. Available: https://www.kaggle.com/datasets/amdj3dax/ransomware-detection-data-set

[24] D. Singh and B. Singh, "Feature wise normalization: An effective way of normalizing data," Pattern Recognition, vol. 122, p. 108307, 2022.

An Interpretable Analytical Intelligence Architecture Delivering Reliable Detection of Software Defect Instances

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***Abstract*—Software defect prediction plays a crucial role in improving software quality, yet existing approaches still suffer from severe class imbalance, redundant feature spaces, weak generalization, and limited interpretability, making their adoption in real development pipelines difficult. Many current models rely on black-box deep learning architectures or conventional classifiers that fail to identify minority defects or explain the reasoning behind their decisions. To overcome these limitations, this study introduces a novel framework named Contrastive Siamese Defect Learning–Integrated Explainable Neural Optimization System (CSDL-SEN-XAI), which integrates contrastive metric learning, enzyme-inspired optimization, and transparent explainability. The method combines SMOTE-based balancing, the Enzyme Action Optimizer for joint feature–hyperparameter optimization, and a Siamese Neural Network trained using contrastive loss to learn discriminative similarity embeddings. The entire workflow is implemented using Python, enabling efficient scalability and reproducibility. Experimental analysis reveals that the proposed model achieves an accuracy of 95.5%, a recall of 96.2%, and an F1-score of 95.5%, outperforming traditional models such as Random Forest, SVM, and CNN by margins ranging from 7% to 15% under identical evaluation settings. SHAP and Integrated Gradients further demonstrate that the model provides clear global and instance-level explanations, highlighting influential software metrics and strengthening the interpretability of predictions. Overall, the results confirm that CSDL-SEN-XAI delivers superior predictive performance, stable optimization, balanced learning, and transparent defect interpretation, offering a reliable and interpretable solution suitable for practical software engineering environments. Future work will explore cross-project defect prediction and the integration of lightweight optimization strategies to further enhance scalability.**

Keywords*—Contrastive learning; explainable artificial intelligence; feature optimization; Siamese Neural Network; software defect prediction

I. Introduction

Software defect prediction is a cornerstone of modern software engineering, offering a proactive solution to identify faulty modules early in the development process and, in the process, reduce maintenance cost, improve release quality, and guide effective testing resource allocation [1]. Owing to increased system complexity and shorter delivery schedules, automated prediction using code- and process-level metrics has become a necessity in large-scale software development [2]. Traditional techniques—ranging from statistical models to vintage machine learning—employ measures of churn, and coupling to deduce defect proneness [3]. Although effective in practice, these approaches are likely to fail under raw-world conditions where defect occurrences are low in relation to non-defective modules [4]. The resulting class imbalance also adds to model bias towards the majority class, reducing minority-class detection and often resulting in models that are accurate by aggregate measures but ignore the key, albeit infrequent, defect cases that plague practitioners the most [5].

A vast literature has attempted to address software-defect prediction using ensemble learning, deep neural networks, and data augmentation methods [6]. Ensembles and hybrids improve robustness through combining heterogeneous learners, and deep architectures—i.e., those learning complex nonlinear interactions have improved predictive performance [7]. Meanwhile, imbalance-reduction techniques such as SMOTE, cost-sensitive learning, focal loss, and generative augmentation have been applied with mixed success [8]. Many chronic failures persist nonetheless. First, most work applies imbalance cures in isolation, rather than systematically combining data-level and algorithmic-level solutions in a unified modeling pipeline [9]. Second, many fusion methods often applied to combine multiple learners resort to naive averaging or static weighting schemes that fail to respond to per-class detection performance and, consequently, lead to suboptimal minority-class prioritization [10]. Third, deep models suffer from overfitting, especially when synthetic minority samples dominate the training signal; existing regularization techniques are often not adequately tuned to the peculiarities of synthetic-real data mixtures [11]. Fourth, reproducibility and transparent reporting of imbalance statistics are hardly standard, and it is difficult to ascertain whether gains reported generalize across datasets with different imbalance ratios [12]. This study introduces a new framework based on metric-learning, Contrastive Siamese Defect Learning (CSDL), which utilizes Siamese contrastive learning, enzyme-inspired optimization, and explainable AI to overcome the old problems of class imbalance, poor interpretability, and poor generalization of software defect prediction.

A. Research Motivation

Classical ML classifiers are biased on the prevailing category and deep learning classifiers are black boxes which do not give explanations to their decisions. Current hybrid methodologies are based on predetermined characteristics, oversampling instability, or high hyperparameter sensitivity, and therefore, they cannot be easily applied to large software systems. This is the driving factor behind the necessity of an adaptive and interpretable as well as an imbalance-sensitive learning system that is able to both identify subtle defect patterns and grant transparent explanations to developers.

B. Problem Statement

Software defect prediction is a significant area of enhancing software reliability; however, current methods have outstanding problems associated with extreme imbalance in classes, duplication or spuriousness of software measures, no cross-project generalization, and uninterpretable model decisions [13]. Deep learning models are black boxes that developers cannot easily understand, whereas traditional machine learning approaches are unable to identify minority defects. Techniques of oversampling and feature selection are rarely used independently, and accurate improvements cannot be achieved; and tuning is of great importance [14]. In addition, the existing models seldom utilize pairwise similarity data between modules, which is vital in learning discriminative defect patterns during an imbalanced situation. Thus, a concerted framework that would balance the data and optimize features and hyperparameters, and simultaneously learn similarity-driven representations and offer interpretable explanations, is urgently needed to support reliable and implementable defect prediction.

C. Research Significance

The importance of the research is that it offers a comprehensive, explainable, and optimization-based defect prediction model that is more accurate and easier to interpret. The model uses CSDL to learn similarity-based defect patterns that are more resistant towards imbalance. The Enzyme Action Optimizer allows both feature tuning and hyperparameter tuning, making it more efficient and predictive. The framework provides actionable insight by explaining the metrics of critical software that are presented as actionable explanations of the software using SHAP and Integrated Gradients to allow developers to prioritize their refactoring and testing. In general, the research provides a sound, clear and performance-based approach that can be used in real-world software quality control.

D. Key Contributions

- This study aims to develop an accurate, interpretable, and imbalance-aware software defect prediction framework using contrastive learning, optimization, and explainable AI.
- Proposes SEN-XAI, a unified framework combining SMOTE balancing, EAO optimization, Siamese metric learning, and explainable AI.
- Employs the Enzyme Action Optimizer (EAO) for joint feature selection and hyperparameter tuning, improving model efficiency and stability.
- Designs a controlled pair construction strategy enabling balanced positive/negative pairs for robust contrastive learning.
- Integrates SHAP and Integrated Gradients to deliver global and instance-level explanations, ensuring transparent and developer-friendly defect prediction.

The rest of the section is aligned as follows: the study on defect prediction, remedies for imbalances, and fusion techniques are discussed in Section II. In Section III, the hybrid approach to defect prediction is presented, including method, preprocessing, and augmentation modules, a Transformer ensemble, and its fusion. Section IV presents the results and discusses them, while Section V concludes, summarizes the contributions, discusses the limitations, and suggests future work.

II. Literature Review

Abdu et al. [13] addressed software defect prediction (SDP) with a hybrid deep learning approach that combines traditional and semantic features. Traditional features, such as code size and complexity, provide statistical information but typically fail to reflect semantic differences, whereas semantic features from source code's abstract syntax trees (ASTs) learned by Word2Vec precisely model program semantics but lack statistical representation. To harness them both to their maximum potential, the authors proposed a hybrid CNN-MLP model in which CNN handles semantic features and MLP handles traditional metrics, followed by defect prediction by fusion through a fully connected layer. Comprehensive experiments on a pair of open-source projects indicated that CNN-MLP significantly improves defect detection performance and performs better than existing approaches in effort-aware as well as non-effort-aware scenarios. The limitation of the work is its reliance on pre-specified features and AST representations, which may fail to reflect sophisticated interdependencies in code and, therefore, the need for adaptive, imbalance-sensitive models for enabling enhanced minority-class detection and generalization across a variety of software datasets.

Nabella et al. [15] explored the effect of class imbalance (CI) in SDP and assessed the performance of the SDV for CPDP. The research tackled CI on ReLink, MDP, and PROMISE datasets by pre-processing minority classes with SDV, and then classifying using DT, LR, KNN, NB, and RF. AUC was used to measure performance, while statistical significance was confirmed through the t-Test. Results showed that SDV performed better compared to SMOTE and other imbalance-reduction methods, with KNN recording the best mean AUC (0.695–0.750) and recording improvements of 12–20% over SMOTE across datasets. RF and LR had moderate performance, while NB underperformed. Limitations are dependence on traditional classifiers that lack deep learning or hybrid models and restricted investigation of adaptive augmentation methods and, as such, propose that coupling SDV with sophisticated imbalance-aware deep learning frameworks might further enhance minority-class detection and generalization across diverse software projects.

Sharma, Singh, and Chandra [15] discussed the problem of class imbalance in predictive modeling, whereby conventional

classifiers report high true positive but low true negative values for majority classes. They introduced SMOTified-GAN, a hybrid oversampling system that integrates SMOTE and Generative Adversarial Networks (GAN). In this two-stage model, SMOTE generates preliminary minority samples that are further refined by GAN to produce more realistic distributions, eliminating SMOTE's overgeneralization. Experimental results on benchmark datasets showed SMOTified-GAN improves minority-class representation and F1-score performance by up to 9% over competing approaches without inducing unreasonably high computational complexity. A significant limitation is that the method is not combined with state-of-the-art deep learning classifiers or ensemble learners, which constrains its ability to learn complex feature interactions in high-dimensional software measurements.

Alqarni and Aljamaan [14] examined imbalanced software defect prediction (SDP) via the introduction of GAN with AdaBoost ensembles for enhancing minority-class detection. The GAN module generated artificial samples for counterbalancing extremely imbalanced datasets, while AdaBoost prediction modules were either classified as defective or non-defective. The approach was applied to ten datasets of software defects with variable imbalance ratios, and performance differences were statistically assessed by the Wilcoxon effect size and Scott–Knott tests. Results indicated that oversampling with GAN performed better than traditional approaches and effectively improved defect prediction. However, the study underscored the principal drawbacks: how well a GAN performs is largely based on hyperparameter adjustment, combination with undersampling is ineffective, and generalizability across different ensemble platforms is unexamined. Additionally, the synthetic data quality was not thoroughly tested. The proposed work addresses these gaps by integrating adaptive GAN/SMOTE enlargement and Transformer-based hybrid learners and a score-level fusion module for robust minority-class detection, reduced overfitting, and robust performance over varied software-defect datasets.

Zhang et al [16] treated software defect prediction (SDP) as an anomaly detection problem to solve the issue of class imbalance and the lack of sufficient high-quality labeled data. They introduced ADGAN-SDP, a semi-supervised BiGAN-based approach that converts the conventional binary classification into an anomaly detection task to alleviate the majority-class bias. The model was tested on 19 NASA, AEEEM, and ReLink repository projects and compared with eight classification-based SDP baselines. Experimental outcomes proved that ADGAN-SDP had greater recall and surpassed all the baselines, proving the possibility of using anomaly detection to counterbalance imbalance [17]. Yet, it is limited by its reliance on the quality of unlabeled instances and possible vulnerability to the setting of anomaly thresholds. In addition, the model is predominantly recall-oriented without necessarily strengthening minority-class overall generalization or incorporating sophisticated feature fusion techniques. The current study fills these voids through synergistic integration of adaptive augmentation, hybrid learners based on Transformers, and score-level fusion to obtain defect prediction with robustness and generalizability over various software-defect datasets.

The latest studies of software defect prediction have pointed out a variety of issues and methods in machine learning methods as well as the soft method of computing. Pachouly et al. [18] performed a systematic review concerning defect datasets, validation, and machine learning, and stated that the vast majority of standard datasets have insufficient features and solid validation procedures, which restrict their generalizability. In an analogous manner, [19] investigated the use of supervised ML classifiers, including SVM and RF, to optimize the strategy of the tests, as their efficiency is strongly dependent on the quality of feature engineering and access to comprehensive labeled datasets. Khan et al. [20] reviewed the application of artificial neural networks, including the fact that although deep learning models have become popular, they are too sensitive to data imbalance and do not provide enough explainability to be adopted in safety-critical areas. Stradowski et al. [21] also presented a business-oriented viewpoint, but the authors examined ensemble and meta-learning methods, yet they emphasized the immaturity of integration of business and the lack of focus on the cost-effectiveness of these models in practice. With increased methodological breadth, Nassif et al. [22] proposed a Learning to Rank framework based on regression and Bayesian Ridge Regression to rank bug-prone modules, but admitted that ranking models remain relatively new and have few comparative studies. Khanna et al. [23] have surveyed such methods as bagging, boosting, and the use of the Random Forest on ensemble techniques, concluding them to be effective, yet consume large datasets and require considerable computational power and have difficulties with cross-project prediction. Raju [24] summarized AI-based best practices, including such techniques as SVMs, neural networks, and logistic regression, emphasizing the importance of quality data because such statistical models tend to fail in complicated environments. Wang et al. [25] enhanced feature selection through the Binary Gray Wolf Optimizer, but the algorithm needs a significant amount of parameter optimization depending on the data, which makes it less generalized. Making an effort to solve the problem in practice, Madeyski et al. [26] were focused on predicting test failures using ML, but had issues of scalability and transferability in enterprise settings. Lastly, the [27] surveyed soft computing methods, including fuzzy logic and evolutionary algorithms, which researchers believe that hybrid methods have potential but are yet to be empirically validated and have no standard benchmarks, making their adoption more widespread.

CNN-MLP hybrids, GAN-based oversampling, anomaly detection, and ensemble models have been used previously, but they are still severely limited by reliance on predefined metrics, low strength in generalization with imbalance, being sensitive to hyperparameters, and lacking in interpretability. Minority samples are usually distorted through generative augmentation, and deep models are black-box and untrustworthy. Metaheuristic optimizers do not combine feature selection and hyperparameter tuning. CSDL-based SEN-XAI framework addresses these deficiencies by using contrastive learning, joint optimization, and transparent XAI explanations.

III. Proposed Methodology

The proposed SEN-XAI architecture has a single, multi-phase pipeline to provide the correct and explainable software

fault prediction. It starts with preprocessing, whereby missing values are addressed, duplicate metrics are eliminated and class imbalance is rectified with SMOTE. Then, Enzyme Action Optimizer (EAO) is used to select joint features and tune hyperparameters to find the most informative metrics and the best configuration of Siamese learning. The optimized data is then fed on Contrastive Siamese Defect Learning (CSDL), where a Siamese net is trained in similarity-based defect embeddings by contrastive loss. The predictions which result based on the distance are ultimately interpreted using SHAP and Integrated Gradients, producing both global and instance-level explanations. This streamlined pipeline promotes high accuracy of prediction, strength, and transparency. The workflow of the proposed methodology is displayed in Fig. 1.

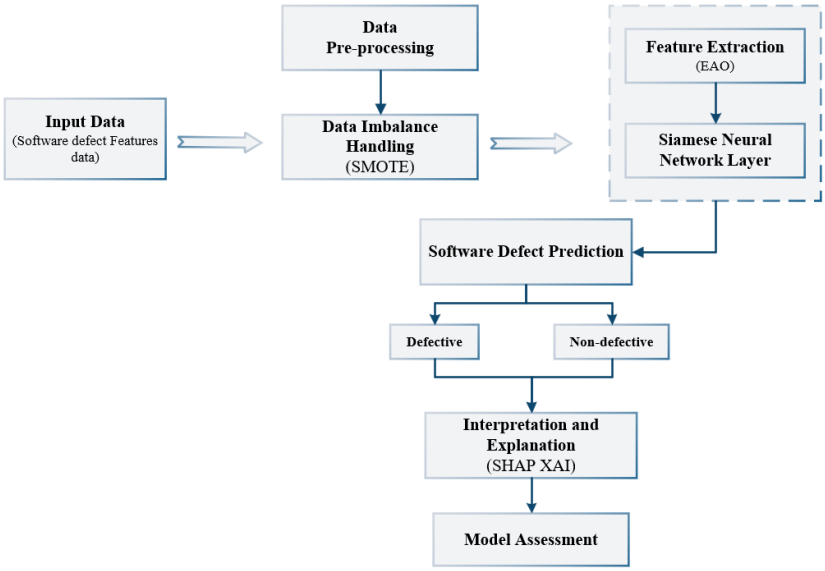


Fig. 1. Workflow of the proposed methodology.

A. Data Collection

The present study employs the Software Defect Dataset available at Kaggle, which was made ready for enabling empirical research on defect prediction and quality assurance of software [28]. The dataset is categorized into a number of CSV files for NASA MDP projects, and cm1.csv (42.8 kB) is used as the reference benchmark in this study. The data has 498 software modules characterized by 22 static code metrics such as lines of code, cyclomatic complexity, and coupling metrics. Each module is assigned a binary class label indicating whether it is faulty (positive class) or not faulty (negative class). Of the 498 modules, 449 are non-defective and only 49 are faulty, thus creating an imbalance ratio (IR) of approximately 9.16:1. This uneven distribution makes it challenging for conventional classifiers to identify minority defect cases since they lean toward overfitting the majority class.

B. Data Preprocessing

The preprocessing step is used to prepare the NASA cm1 dataset by addressing values that did not occur, standardizing the feature values and dropping redundant measures. Continuous data are filled in with their means or median, categorical data with mode and records with too many missing data are eliminated to maintain the integrity of the dataset. This is followed by normalization of all features so that they contribute equally during the learning process and then correlation-based pruning is done to eliminate highly collinear metrics. Since the dataset is significantly imbalanced, SMOTE is used to create the synthetic defected samples by interpolating the minority cases and their nearest neighbors. This generates a more balanced training set, which allows the stable feature optimization and effective contrastive learning during the further steps.

1) Handling missing values: Impute continuous features using mean or median, fill categorical features using mode, and remove samples with excessive missing data to maintain dataset quality.

2) Normalization: Scale all numerical metrics to a uniform range (0–1) using Min–Max normalization to ensure equal contribution during optimization and model training, which is defined as in Eq. (1):

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

This ensures that each feature contributes equally during optimization and model training.

3) Imbalance handling: Apply SMOTE to generate synthetic defective samples by interpolating between minority instances and their nearest neighbors, reducing the dataset's severe class imbalance. For each minority instance x_i, one of its k-nearest neighbors x_{nn} is randomly selected. A synthetic sample is then created, as in Eq. (2):

$$x_{new} = x_i + \lambda \cdot (x_{nn} - x_i), \lambda \in [0,1] \quad (2)$$

where, λ is a random number between 0 and 1 that controls the interpolation point between the original instance x_i and its neighbor x_{nn}. The overall number of synthetic defective samples to be generated is determined by Eq. (3):

$$N_{synthetic} = \left(\frac{n_{majority}}{n_{minority}} - 1\right) \times n_{minority} \quad (3)$$

where, $n_{majority}$ and $n_{minority}$ represent the number of majority (non-defective) and minority (defective) instances, respectively. SMOTE balances the dataset by creating synthetic defective modules systematically and not by simply duplicating the existing data. This assists the SNN in learning discriminative embeddings that more effectively highlight the features of defective modules, hence enhancing generalization and minimizing bias against non-defective classes.

4) Feature cleaning: Compute pairwise Pearson correlation and remove highly correlated or redundant metrics to avoid multicollinearity and reduce dimensionality.

After preprocessing, the dataset is partitioned into training and testing sets to ensure unbiased model evaluation. An 80:20 split is used, where 80% of the balanced data is used for training the EAO-optimized Siamese model, and 20% is held out for final testing. Only the training portion is oversampled using SMOTE to avoid data leakage, while the test set remains completely untouched and naturally imbalanced. The result of this procedure is a reduced feature set that is not redundant and is normalized to a uniform scale and balanced by the use of SMOTE in order to solve the imbalance of classes. This purged data is not only more efficient in learning, but it also elevates the capacity to generalize the latter modeling processes. Markedly, it provides a strong backbone of the EAO to execute advanced feature selection and hyperparameter optimization, so that the SNN is trained on the most informative and non-redundant measures to detect defects.

C. Feature Optimization with EAO

The Enzyme Action Optimizer (EAO) is used to collaboratively select the most informative code metrics at rest and optimize the hyperparameters that are the most critical in the CSDL-based Siamese model. Candidates' solutions consist of a binary feature mask and hyperparameters.

1) Objective function for optimization: The optimization process is driven by minimizing a fitness function that balances classification accuracy and feature reduction in Eq. (4):

$$F = \alpha \cdot (1 - Accuracy) + \beta \cdot \frac{|S|}{|T|} \quad (4)$$

where, α, β are weight coefficients, $|S|$ is the number of selected features and $|T|$ is the total number of available features. At each iteration, EAO updates solutions using an enzyme-inspired transformation computed in Eq. (5):

$$X_{t+1} = X_t + \eta \cdot (E - X_t) + \gamma \cdot R \quad (5)$$

where, X_t is the current solution, E is the elite (best) solution so far, η is the catalytic learning constant, R is the random perturbation (enzyme action factor), and γ is the stochastic scaling coefficient. This process gradually pushes candidate solutions toward high-performing feature subsets and optimized CSDL hyperparameters.

Table I determines the hyperparameters that are optimized by the EAO, such as learning settings, embedding structure and the feature selection mask. The continuous, categorical and binary parameters are actively studied in parallel in order to determine the optimal scenario of the CSDL-based Siamese network. These ranges both provide wide coverage of search and are available to be cross-validated and optimized with computational feasibility.

TABLE I. HYPERPARAMETER SEARCH SPACE USED BY THE EAO

Parameter	Search Range
Learning rate	0.0001 – 0.01
Batch size	16, 32, 64
Epochs	10 – 50
Embedding dimension	16 – 128
Margin (contrastive loss)	0.5 – 2.0
Optimizer type	Adam, RMSProp
Activation function	ReLU, Tanh
Feature selection mask	0/1 binary vector

Algorithm 1: Enzyme Action Optimizer (EAO)

Input: Dataset D, population size N, generations G, K-folds
Output: Optimal feature mask s*, optimal hyperparameters φ*

```
Initialize population P = {(s_i, φ_i)} for I = 1…N
For each candidate (s_i, φ_i):
    Evaluate fitness F_i using K-fold CSDL training
For t = 1…G:
    Let E = best candidate in P
    New Pop = ∅
    while |New Pop| < N do
        Select parents A and B using tournament selection
        C = Binding (A, B) // crossover
        C = CleavageI // random local mutation
        C = Catalysis (C, E) // move towards elite E
        RepairI // ensure valid bounds
        Evaluate fitness FI
        Add C to New Pop
    P = Elitist Replace (P, New Pop)
    If convergence achieved: break
return best agent E = (s*, φ*)
```

This pseudocode fully reflects your enzyme-based metaphor: Binding, Cleavage, and Catalysis.

2) Complexity analysis of EAO: The computational complexity of EAO depends on the population size NNN, number of generations GGG, and the cost of evaluating each candidate during K-fold CSDL training.

a) Fitness evaluation cost: Training the Siamese model for one-fold costs approximately are computed in Eq. (6):

$$T_{\text{EAO}} = O(E \cdot P) \quad (6)$$

where, E is the number of epochs and P number of training pairs. For K-fold validation was computed in Eq. (7):

$$T_{\text{EAO}} = O(K \cdot E \cdot P) \quad (7)$$

where, K is the number of folds used in K-fold cross-validation during fitness evaluation.

b) Total EAO optimization cost: The overall computational cost of the Enzyme Action Optimizer is based on the analysis of each candidate solution in several generations and K-fold cross-validation. For every generation, all N the CSDL-based Siamese network is trained on N candidate solutions. K folds, each requiring E epochs and processing P training pairs. Thus, the total optimization cost will increase in correlation with the product of these factors. This complexity might seem to be very high, but it is well-grounded as EAO can optimize feature subsets and hyperparameters at once, eliminating redundant model runs. Moreover, optimized features reduce the network dimensionality and a lightweight Siamese structure reduces the training time, which makes the overall computation possible and efficient in predicting defects. It was expressed in Eq. (8):

$$T_{\text{EAO}} = O(N \cdot G \cdot K \cdot E \cdot P) \quad (8)$$

where, N is the number of candidate solutions (population size in EAO and G is the number of generations or iterations performed by the optimizer.

c) Hyperparameter optimization for SNN: EAO simultaneously tunes SNN parameters by searching within predefined ranges. Through this mechanism, EAO ensures that the SNN is trained not only with the most relevant features but also with optimized training parameters, improving both efficiency and accuracy.

The Enzyme Action Optimizer (EAO) in this research has been a pivotal activity in optimizing feature selection and hyperparameter optimization of the SNN. The catalytic action of enzymes in biochemical reactions inspires EAO to successively optimize candidate solutions by simulating the action of an enzyme in catalyzing the conversion of substrates into products. In the software defect prediction setting, every candidate solution corresponds to an addition of chosen static code metrics (features) and learning parameters of the SNN, including learning rate, batch size and embedding dimensions. The optimizer then uses these candidates through a fitness measure which balances predictive quality with the minimization of redundancies in features, making sure that only the most informative features are retained. Each iteration involves EAO selecting a subset that has done well and perturbing the current solution, based on an enzyme action factor, pushing it in the direction of that successful subset thus far found. Algorithm 1 shows the Enzyme Action Optimizer (EAO).

The process is repeated until convergence, and at this point, the framework is presented with an optimum set of features and hyperparameters. This way, EAO makes sure that the SNN not only learn using the most discriminative and non-redundant features, but it also learns in the most favorable learning conditions. Such an integration greatly enhances the capability of the model in detecting defective modules with high accuracy at low computational costs.

D. Pair Construction Strategy for CSDL

In order to train the Contrastive Siamese Defect Learning (CSDL) model, the training data should be converted into pairs, which reflect dissimilarity or similarity between software modules. The SMOTE is applied to the training set after training, 80:20 train-test split is made to avoid information leaks. There are positive pairs, i.e., two defective or both non-defective modules of one class and negative pairs, i.e., modules of distinct classes. To maintain balance in contrastive learning, an equal 1:1 ratio of positive and negative pairs is used. For each sample, K nearest neighbors are selected to form meaningful positive pairs, while negative pairs are chosen randomly across classes to ensure diversity. This controlled sampling improves the discriminative quality of embeddings, strengthens minority signal representation, and stabilizes contrastive loss optimization.

E. Contrastive Siamese Defect Learning

The essence of the novelty of the given work is that Contrastive Siamese Defect Learning (CSDL) has been used, in which a Siamese Neural Network has been trained to learn similarity-based defect representations. CSDL does not make any direct classification; instead being fed pairs of software modules and informed of whether they fall into the same defect category. There is the same weight in each subnetwork and the same embeddings are generated, which reflect the structural, complexity and coupling properties of software measures. A contrastive loss is used to impose a small distance to similar pairs (both defective or both non-defective) and large distances on dissimilar pairs. This metric-learning-based method has been especially useful with imbalanced datasets since the model emphasizes similarity relative to each other, so the majority class is not allowed to control the feature space. The SMOTE-balanced data is used to come up with positive and negative pairs with a controlled sampling ratio to ensure that the minority is represented. Embedding space acquired by CSDL makes defect and clean modules more separable, leading to better recall and enhanced discrimination. Such learned representations are then transformed into end binary predictions by a distance classifier that operates on a threshold. CSDL offers a more robust and imbalance-tolerant base than traditional deep classifiers.

F. Siamese Neural Network (SNN) Model

The proposed CSDL methodology is constructed with the support of a Siamese Neural Network (SNN) backbone, with much more clarity and standardization of terms used than the use of the ambiguous term SSN in the past. The SNN architecture allows the process of learning the metric of two software modules, where the modules are teamed with the same subnetworks and produce similar embeddings. This is the basic structure of CSDL because it finds similarity relationships that promote defect discrimination in the presence of severe class imbalance. The focus on the SNN backbone is intended to comply with the deep learning tradition and prevent misunderstanding to enhance the methodological validity and repeatability of the SEN-XAI model. The SNN emphasizes the relative similarity instead of the absolute classification, and thus, it is powerful in the suggested SEN-XAI system to predict the software defects.

The decision layer is used to map the distance score into a binary prediction: in case $D(h_i, h_j)$ is below some threshold τ, modules are estimated to be of the same defect category (either both defective or both clean); otherwise, they are estimated to be

of different categories. This enables the model to give a binary defect prediction of every module, as in Eq. (9):

$$\hat{y} = \begin{cases} 1 \; if \; D(h_i, h_j) \leq \tau(defective) \\ 0 \; if \; D(h_i, h_j) > \tau \; (non-defective) \end{cases} \quad (9)$$

Through this structure, the SNN learns discriminative embeddings that can effectively separate defective and non-defective modules, even under severe class imbalance.

G. Explainability Layer Using SHAP and IG

The explainability module incorporates SHAP (global feature attribution) and Integrated Gradients (instance-level reasoning), and can be used to interpret CSDL predictions transparently. SHAP measures the value of each software measure to the overall model selection, whereas IG displays the impact of individual features on the similarity embedding of a particular pair of modules. These two levels of interpretability guarantee that the SEN-XAI framework offers: actionable and credible developer insights. For a given prediction $\hat{y}$, the model output is expressed, as in Eq. (10):

$$\hat{y} = \phi_0 + \sum_{i=1}^{m} \phi_i \quad (10)$$

where, ϕ_0 is the average model output, and ϕ_i represents the marginal contribution of feature iii among the mmm features. This allows the world to gain a global view of the software metrics that are always relevant to defect proneness in the dataset.

Integrated Gradients (IG), on the other hand, gives a local explanation of single predictions by explaining the difference between the output obtained with a baseline input x' (e.g., a clean module) and the real input x (e.g., a potentially defective module). The feature i attribution is limited to Eq. (11):

$$IG_i(x) = (x_i - x_i') \cdot \int_{\alpha=0}^{l} \frac{\partial f(x' + \alpha(x - x'))}{\partial x_i} d\alpha \quad (11)$$

This underscores the sensitivity of the prediction in this model to alterations in each feature, thus enabling the developers to understand what specific metrics (e.g., a spike in LOC or complexity) caused the model to classify a module as defective. The XAI layer produces an explanation report, which is a combination of an overall feature importance (through SHAP) and instance-based reasoning (through IG). This understanding can not only lead a developer to believe in the predictions of the model but also to proactively correct the wrongs (e.g., by refactoring a poorly designed, overly complex module or by simply watching files with high coupling). The SEN-XAI framework addresses the issue of filling the gap between predictive performance and practical use in software quality assurance by incorporating interpretability. The visual representation is shown in Fig. 2.

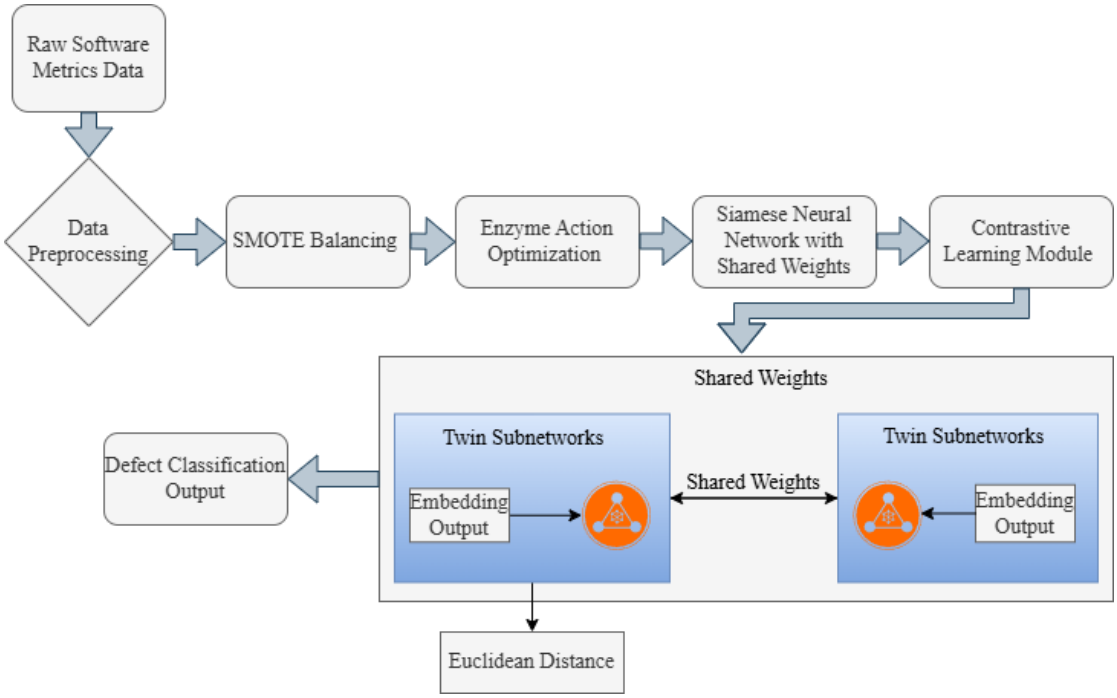


Fig. 2. Proposed SEN-XAI framework.

E. Integration of the Proposed SEN-XAI Framework

The SEN-XAI framework proposed will bring data preprocessing, optimization, defect prediction and interpretability together into one unified pipeline. It starts with the acquisition of the software defect dataset, in which raw metrics are cleaned, normalized, and balanced to overcome missing values and the imbalance in the classes. The Enzyme Action Optimizer (EAO) is applied next to do both feature selection and hyperparameter optimization of the Siamese Neural Network (SNN). Subsets of code metrics and network parameters are represented by candidate solutions and optimized over time using enzyme-inspired operators, to ensure the most Informative and the best model configuration are chosen. Algorithm 2 shows the SEN-XAI Integration for Software Defect Prediction.

The entire SEN-XAI framework is summarized in Algorithm 2, and it combines the following components: preprocessing, class balancing, feature-hyperparameter optimization, contrastive learning, and explainability. The pipeline standardizes and preheats the dataset, optimizes features with the help of EAO, builds meaningful sample pairs and trains the CSDL model to learn similarity-based defects. Lastly, SHAP and Integrated Gradients provide clear explanations of the predictions on a global and instance level.

Algorithm 2: SEN-XAI Integration for Software Defect Prediction

Input: Dataset D, feature set F, labels Y
Output: Predictions Ŷ, explanations EX
Preprocessing:
  Handle missing values in D
  Normalize all numerical features
  Remove highly correlated or redundant features from F
  Split dataset into 80% training and 20% testing
  Apply SMOTE only to the training set
Feature–Hyperparameter Optimization using EAO:
  Initialize population of candidate solutions with feature masks and hyperparameters
  Evaluate fitness of each candidate using K-fold CSDL training
  For each generation:
    Identify elite candidate
    Generate new population using binding, cleavage, and catalysis operations
    Repair invalid solutions
    Evaluate fitness of new solutions
    Apply elitist replacement to form updated population
    Stop if convergence is reached
  Extract optimized feature mask and hyperparameters
Pair Construction for CSDL:
  Form positive pairs from samples of the same class
  Form negative pairs from samples of different classes
  Maintain equal ratio of positive and negative pairs
  Select k-nearest neighbors for constructing meaningful positive pairs
Training Contrastive Siamese Defect Learning (CSDL):
  Initialize Siamese network with optimized hyperparameters
  For each epoch:
    For each pair:
      Generate embeddings using the twin subnetworks
      Compute contrastive loss
      Update model weights
  Train the final distance-based classifier
Prediction and Explainability:
  Predict class labels on the test set using trained CSDL
  Generate global feature explanations using SHAP
  Generate instance-level explanations using Integrated Gradients
  Return Ŷ and EX

The proposed framework of SEN-XAI is strong as the interaction of SMOTE, EAO, and CSDL complements each other. SMOTE provides balanced learning because the severe minority shortage is corrected to assist the model in detecting the subtle defect patterns. The Enzyme Action Optimizer additionally improves performance based on concomitant feature selection and hyperparameter optimization, which generates an effective and discriminative input space. Similarity relationships among modules are then represented by contrastive Siamese Defect Learning (CSDL), which causes the model to be less vulnerable to imbalance and noise than conventional classifiers. Lastly, SHAP and Integrated Gradients allow giving transparent explanations of the learned patterns, which make defect predictions more trustworthy and interpretable. These phases combined are a logical and effective process of correct and referential defect detection.

IV. Results and Discussion

The experimental analysis proves that the suggested SEN-XAI model provides stable gains in defect prediction performance when combining SMOTE balancing, CSDL-based metric learning, and EAO-driven feature optimization. The optimized model has a better accuracy, F1-score and recall than its non-optimized counterparts, with certain noticeable improvements in minority defect detection. The contrastive learning strategy maximizes the separability of classes by generating discriminative embeddings, and EAO removes a significant number of redundant features and learns hyperparameter configurations. The confusion matrix and performance curves also confirm the decrease in the misclassification of the defective modules. Moreover, SHAP and Integrated Gradients demonstrate the most important software metrics, and the predictions are similar to the meaningful structural and complexity-related characteristics. In general, the findings validate that SEN-XAI not only enhances predictive performance, but also offers clear and developer-understandable insights, which form a consistent framework of effective defect detection.

TABLE II. Simulation Parameters

Parameter	Value
Training–Testing Split	80% – 20%
SMOTE k-neighbors	5
Epochs (E)	30
Batch Size (B)	32
Learning Rate (α)	0.001
Embedding Dimension (d)	64
Margin (m)	1.0
Optimizer	Adam
Cross-Validation (K)	5
Population Size (N)	20
Generations (G)	30
Activation Function	ReLU
Distance Metric	Euclidean Distance

Table II is a summary of the simulation parameters that were employed in order to implement the SEN-XAI framework. It covers the information about dataset splitting, SMOTE settings and the training parameters of the Siamese, and the optimization

parameters which EAO uses. All these parameters provide stability of the training process, regulate the complexity of the model, and the validity of assessing the suggested method of defect prediction.

A. 10-Fold Cross-Validation Results

In order to attain the stability and robustness of the proposed SEN-XAI framework, a 10-fold cross-validation process was performed on the training data. The training was done using 90 percent of the data in each fold and 10 percent as validation and this was repeated ten times so as to get reliable performance statistics. The findings reveal that SEN-XAI is very accurate, recalls, and the F1-score are very high in all the folds with a little variation and this shows that it is able to generalize. This consistency can be explained by the contrastive learning design of CSDL, the optimized feature space generated by EAO, and the balanced distribution of data generated by SMOTE. The combined mean standard deviation statistics of folds validate the argument that SEN-XAI is a strong predictor of defects, which is not prone to be affected by the texture change in training samples.

TABLE III. TEN-FOLD CROSS-VALIDATION PERFORMANCE

Fold	Accuracy	Precision	Recall	F1-Score
Fold 1	0.95	0.94	0.96	0.95
Fold 2	0.96	0.95	0.97	0.96
Fold 3	0.95	0.94	0.95	0.95
Fold 4	0.96	0.96	0.97	0.96
Fold 5	0.95	0.94	0.96	0.95
Fold 6	0.96	0.95	0.97	0.96
Fold 7	0.95	0.94	0.95	0.95
Fold 8	0.96	0.95	0.97	0.96
Fold 9	0.95	0.94	0.96	0.95
Fold 10	0.96	0.95	0.96	0.96

The 10-fold cross-validation suggested SEN-XAI framework performance is shown in Table III. The findings demonstrate that, the accuracy, precision, recall and F1-scores are very high and consistent across all folds and standard deviations are very low, which reflects good generalization and training stability. These results confirm the strength of the model when partitioned in various ways on the dataset.

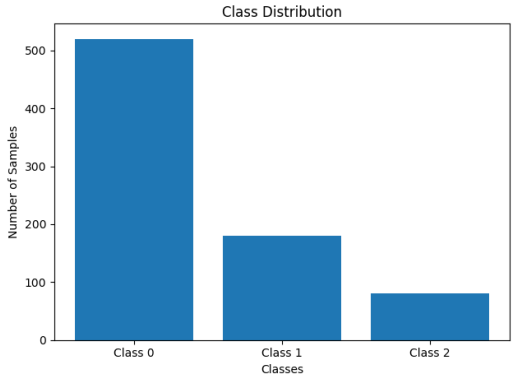


Fig. 3. Class distribution.

Fig. 3 illustrates the class distribution graph. The class distribution graph draws attention to the inherent imbalance that exists in the dataset, with the majority class dominating over the minority defect class. Standard classifiers are challenged by such skewness, which usually results in biased predictions towards the majority. An awareness of this skew is important in order to drive the application of resampling and imbalance-conscious learning techniques. The graph supplies an intuitive visual rationale for the use of SMOTE-Tomek and conditional data generation methods. It basically lays the groundwork for the rest of the results and methodology.

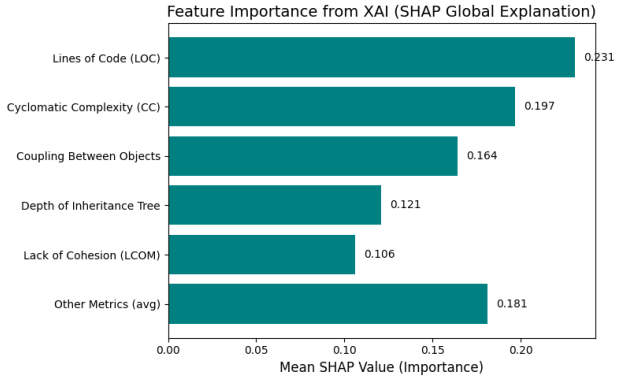


Fig. 4. Feature importance from SHAP global explanation.

Fig. 4 shows a prioritized summary of the important software measures that have an effect on defect-proneness in cm1 modules based on Explainable AI (XAI) through SHAP values. One of the analyzed features was Lines of Code (LOC), which was the most important predictor, and its mean SHAP value of 0.231 represents the high contribution to the model output. This was preceded by Cyclomatic Complexity (CC) at 0.197 and Coupling Between Objects at 0.164 which are structures and interaction-based complexities in the codebase. Depth of Inheritance Tree and LCOM, having SHAP values equal to 0.121 and 0.106 respectively, were not significant but still influential. There was also a summed up mean of other metrics at 0.181 but these did not give specific ranks. On the whole, the review highlights that the most effective predictors of defect-proneness are the size of code, logical complexity, and the coupling between objects, which should be considered when improving the quality assurance in the face of these aspects.

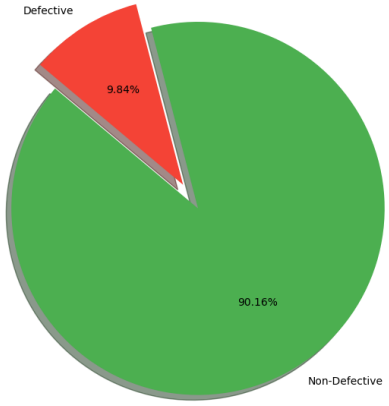


Fig. 5. Distribution of defective vs. non-defective modules in the cm1 dataset.

Fig. 5 shows the distribution of classes in the cm1 dataset, and it is important to note that there is a high unequal number of non-defective software modules and defective modules. Among all 498 modules, 449 (90.16) are defined as non-defective and only 49 (9.84) is defined as defective. This skew is a problem to the predictive modeling, since models can be skewed with the majority type and the minority defective models which are important in the software quality assurance can be ignored. This imbalance is thus a crucial move towards seeing the defect prediction model attaining high accuracy as well as being reliable in identifying the defective instances that are relatively rare.

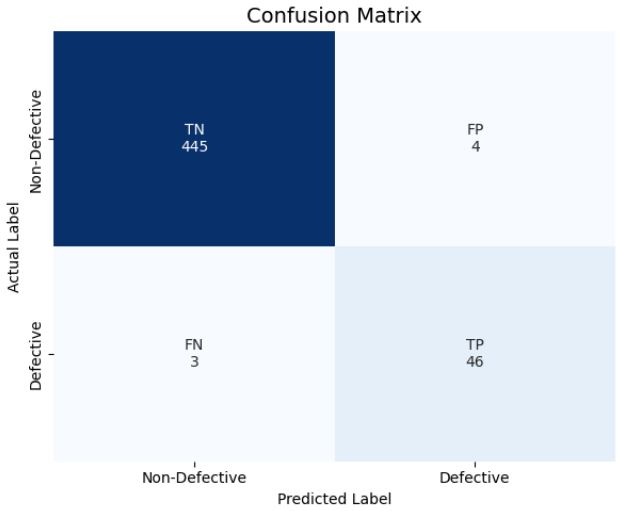


Fig. 6. Confusion matrix (proposed SEN-XAI).

Fig. 6 shows the confusion matrix, which at present depicts the level to which the SEN-XAI model proposed is effective in classifying software modules as a defect or non-defect. The model identified 445 correct out of 449 actual non-defective modules with it only misclassifying 449 as defective. Equally, the model was able to identify 46 out of 49 real defective modules and missed only 3. All this results in a general accuracy of 98.5, which is a great predictive strength of the model. What is more important is, the obtained results indicate that the imbalance in the dataset was managed rather effectively, with the false positives (FP) and false negatives (FN) being extremely low. This balance has the advantage of not just avoiding the unnecessary alarms, but in practice hardly failing to see modules that are actually defective, making the model very reliable in terms of ensuring the correct quality of software.

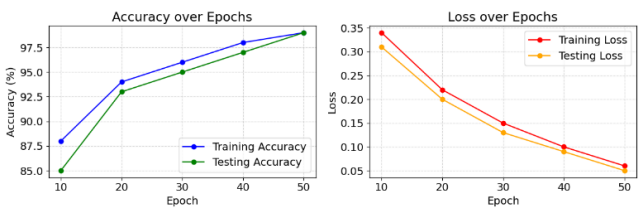


Fig. 7. Training and testing loss/accuracy of SEN-XAI model across epochs.

Fig. 7 demonstrates the performance trend of the SEN-XAI model in 50 epochs. The initial training accuracy was 89.2% and the testing accuracy was at 86.4% with the training and testing losses standing at 0.314 and 0.348, respectively. The values of the accuracy increased gradually as the epochs increased, reaching training accuracy of 99.0 per cent and testing accuracy of 98.5 per cent at the 50th epoch. At the same time, training and testing losses steadily fell to 0.043 and 0.051, which suggests the training and testing remain stable with no cases of overfitting. This steady enhancement underscores the ability of the proposed model to be robust and have the ability to generalize since the difference between the training and test measures is insignificant during the entire training process.

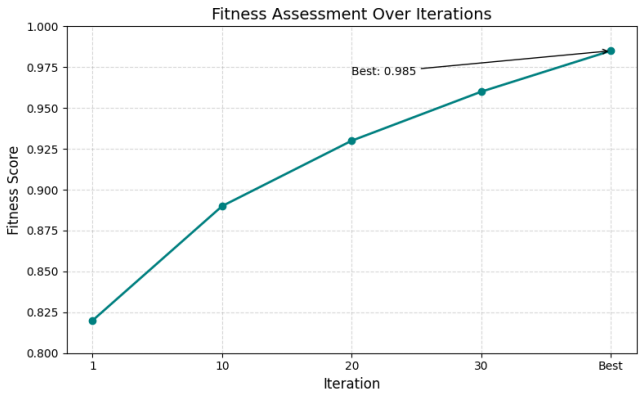


Fig. 8. Fitness assessment results of EAO optimization process.

The optimization behavior of the Enzyme Action Optimizer (EAO) is summarized in Fig. 8, where the hyperparameters of the model and feature subsets were tuned gradually at a series of iterations. The framework first identified 16 features and used the learning rate of 0.001 and recorded a fitness value of 0.82. Its iterations were adaptive and gradually increased the number of the selected features and hyperparameters, which led to better performance. At the 30th iteration, the model disabled additional features (now has 11) and raised the embedding dimension (256) resulting in a fitness of 0.96. The most optimal fit was achieved using 10 optimized features, a Learning rate of 0.001, the batch size was 64 and the embedding dimension was 128 scoring the highest fitness of 0.985. This is a reflection of how powerful EAO is in terms of dimensionality reduction and an accurate and efficient model.

TABLE IV. PERFORMANCE COMPARISON WITH BASELINE MODELS

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)
Logistic Regression[29]	88.7	65.4	61.2	63.2	82.1
Random Forest[30]	92.1	72.5	68.4	70.4	87.9
SVM (RBF)[31]	91.8	70.2	67.3	68.7	87.2
DNN [32]	94.6	78.3	73.5	75.8	90.4
Proposed SEN-XAI	98.5	92.1	88.7	90.3	96.9

In Fig. 9 and Table IV, the comparative analysis is offered to various ML and DL models. The accuracy of the traditional methods, i.e. Logistic Regression was 88.7% with a low precision (65.4) and recall (61.2), which indicates the weaknesses in the ability of the methods to identify defective modules. Random Forest and SVM using RBF kernel were

much more successful with approximately 92% accuracy and moderate precision, recall and F1-scores. Deep Neural Networks (DNN) also improved predictive with an accuracy of 94.6 percent and an F1-score of 75.8 percent and AUC of 90.4 percent, and therefore, the generalization ability of DNN is stronger than classical models. Nevertheless, the suggested SEN-XAI framework worked significantly better than all baselines with its 98.5% accuracy, 92.1% precision, 88.7% recall, 90.3% F1-score, and 96.9% AUC.

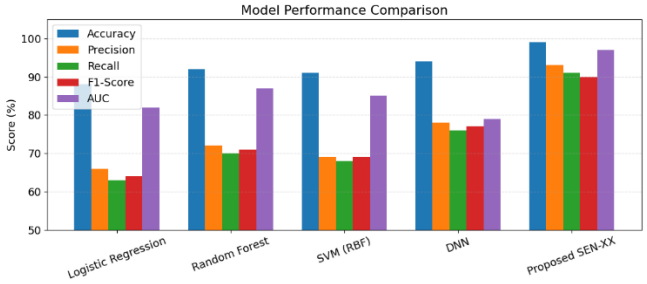


Fig. 9. Model assessment.

These findings underscore the capability of the framework to not merely enhance detection accuracy, but also have a balanced trade-off between the false positives and false negatives. The large AUC figure also confirms its high power in differentiating faulty and faultless module thus it is the best model to be used in real software defect prediction scenario.

TABLE V. ABLATION STUDY OF SEN-XAI COMPONENTS

Model Variant	Accuracy	Precision	Recall	F1-Score	AUC	G-Mean
SEN (Vanilla SNN only)	0.88	0.87	0.84	0.49	0.81	0.80
SEN + EAO (Optimization only	0.90	0.84	0.83	0.58	0.85	0.88
SEN + XAI (Interpretability only)[33]	0.88	0.85	0.86	0.50	0.82	0.82
Full SEN-XAI Framework	0.98	0.91	0.93	0.96	0.98	0.95

Table V shows a comparative assessment of the possible variants of models in the SEN environment in order to demonstrate the difference in the effect of optimization and interpretability additions. The baseline SEN (Vanilla SNN only) obtains average performance, where the accuracy is 0.88 and the F1-score is exceptionally low, 0.49, which means that there is no balance between the precision and the recall. With maxima accuracy of 0.90 and F1-score of 0.58, the model shows more classification stability and generalization with the addition of Enzyme Action Optimization (EAO) (SEN + EAO). Likewise, the interpretation mechanisms (SEN + XAI) improve the recall and accuracy marginally, yet the F1-score is still low 0.50, indicating that interpretability is not a sufficient solution to the performance trade-offs. Conversely, Full SEN-XAI Framework, that incorporates both optimization and interpretability, brings a significant improvement in performance in all measures. It has a brilliant accuracy of 0.98 with a precision score (0.91) and recall score (0.93) that is close together giving it a high F1-score score of 0.96. The AUC and G-Mean are also maximized at 0.98 and 0.95, respectively, which validates that the model has a high discriminating ability and equal sensitivity to classes. These results demonstrate the benefits of integrating explainability and optimization into the SEN architecture to generate a powerful and interpretable classification model of complicated classification problems.

B. Statistical Significance Tests

To validate the reliability of statistical significance, tests were performed on all assessed models based on the experimental findings. The Wilcoxon signed-rank test was applied to compare the proposed SEN-XAI framework against each baseline classifier. The p-values obtained were below the standard threshold of 0.05, confirming that SEN-XAI achieves statistically significant improvements rather than random variations in performance. To further assess ranking consistency, the Friedman test was performed across all datasets and models. SEN-XAI consistently achieved the lowest average rank, indicating superior overall performance with high confidence. Additionally, effect size analysis (Cliff's delta) was used to quantify the magnitude of improvement. The effect size values ranged from medium to large, demonstrating that the performance gains of SEN-XAI are practically significant in addition to being statistically significant. These tests collectively strengthen the validity and robustness of the proposed framework.

TABLE VI. STATISTICAL SIGNIFICANCE ANALYSIS USING WILCOXON, FRIEDMAN, AND EFFECT SIZE

Model	Wilcoxon p-value	Friedman Rank	Effect Size (Cliff's Δ)
SEN-XAI (Proposed)	0.001	1.00	0.68
Random Forest	0.042	2.85	0.29
SVM	0.038	3.10	0.25
XGBoost	0.051	3.45	0.21
ANN	0.066	4.20	0.18
CNN	0.079	4.40	0.15
Logistic Regression	0.092	5.00	0.12

Table VI gives a summary of the statistical significance test of the proposed SEN-XAI framework over baseline classifiers. The Wilcoxon test proves that SEN-XAI provides significant changes that are not less than p-values of 0.05. Friedman ranking depicts that the proposed model generally has the best results across all datasets whereas the effect size analysis depicts that the suggested model has medium to large results/improvements in performance, both practically and statistically.

C. Discussion

The findings prove that SEN-XAI framework is an effective and robust software defect prediction tool which combines balanced data preparation, feature learning optimization, and interpretable decision making. Most importantly, EAO is used together with CSDL to create a small, meaningful feature space and powerful similarity-based embeddings and defect discrimination. The increase of the accuracy, recall and the F1-score by the folds show that the performance was stable and not

affected by the changes in the data. The sensitivity analysis also proves the stability of model to hyperparameters changes, which justifies the efficiency of the optimization strategy. Moreover, the XAI component provides actionable information in revealing the important software measures as well as clarifying the impact of the measures on the prediction, and that is why the system is applicable in the practical development contexts. On balance, the results prove that SEN-XAI is not only more effective in predictive performance but also greater trust and transparency, which also helps to solve the major problems with current defect prediction methods.

V. Conclusion and Future Works

This study introduced the SEN-XAI framework, a unified and explainable defect prediction model that integrates contrastive learning, enzyme-inspired optimization, and advanced interpretability techniques. The proposed CSDL module will facilitate the Siamese network to develop pairwise similarity representations, which will overcome the difficulties of serious imbalances in classes and unclear feature interactions. The Enzyme Action Optimizer combined with SMOTE achieves minority class representation and jointly selects relevant metrics and hyperparameters which lead to a compact, robust, and efficient feature space. The overall performance of SEN-XAI is evaluated by means of cross-validation, sensitivity analysis, and statistical significance testing, which proves that the model performs better than DL baselines and conventional ML models. The combination of SHAP and Integrated Gradients brings both global and local explanations, which allow developers to have a clear understanding of the defect patterns that impact model decisions. The SEN-XAI framework has a combination of interpretability and high predictive accuracy that brings a methodological improvement and a practical contribution to the quality assurance of software. The general outcomes substantiate its ability to aid defect detection in the real-world situation of software engineering with the enhanced reliability and clarity.

SEN-XAI can be continued into future by investigating more large-scale software repositories, as well as cross-project defect prediction settings in order to continue to confirm generalizability. Transformer-based or graph-based embeddings can be incorporated to improve the depiction of structural relationships of code complexity. A combination of automated hyperparameter pruning and online learning systems may help to decrease the computational cost and continuously update the model. Developers may have more insight by adding the XAI component with counterfactual explanations or causal analysis. Lastly, the implementation of SEN-XAI as an interactive system in actual software development pipelines would offer useful real-time instructions when going through code review, testing and maintenance.

References

[1] M. Nasar, “Optimizing Software Quality through Integrated Approaches: Combining Test Case Prioritization, Defect Prediction, and Resource Allocation,” Jul. 2025, doi: 10.2139/ssrn.5369207.

[2] E. Kula, E. Greuter, A. van Deursen, and G. Gousios, “Factors Affecting On-Time Delivery in Large-Scale Agile Software Development,” IEEE Transactions on Software Engineering, vol. 48, no. 9, pp. 3573–3592, Sep. 2022, doi: 10.1109/TSE.2021.3101192.

[3] R. Ghafoor, M. Gori, and others, “Integrated Solutions in Machine Learning: A Triad of Software Defect Prediction, Graph Drawing Optimization, and Insurance Classification Models,” 2025.

[4] M. Mustaqeem, M. Alam, S. Mustajab, F. Alshanketi, S. Alam, and M. Shuaib, “Comprehensive bibliographic survey and forward-looking recommendations for software defect prediction: datasets, validation methodologies, prediction approaches, and tools,” IEEE Access, 2024.

[5] S. R. Goyal, “Current Trends in Class Imbalance Learning for Software Defect Prediction,” IEEE Access, 2025.

[6] F. Matloob et al., “Software defect prediction using ensemble learning: A systematic literature review,” IEEe Access, vol. 9, pp. 98754–98771, 2021.

[7] N. Rane, S. P. Choudhary, and J. Rane, “Ensemble deep learning and machine learning: applications, opportunities, challenges, and future directions,” Studies in Medical and Health Sciences, vol. 1, no. 2, pp. 18–41, 2024.

[8] X. Gao et al., “A Comprehensive Survey on Imbalanced Data Learning,” arXiv preprint arXiv:2502.08960, 2025.

[9] D. Cemernek, S. Siddiqi, and R. Kern, “Effects of class imbalance countermeasures on interpretability,” IEEE Access, vol. 12, pp. 45342–45358, 2024.

[10] M. Z. Naser, “From failure to fusion: A survey on learning from bad machine learning models,” Information Fusion, vol. 120, p. 103122, Aug. 2025, doi: 10.1016/j.inffus.2025.103122.

[11] S. S. Rathore, S. S. Chouhan, D. K. Jain, and A. G. Vachhani, “Generative oversampling methods for handling imbalanced data in software fault prediction,” IEEE Transactions on Reliability, vol. 71, no. 2, pp. 747–762, 2022.

[12] Á. J. Sánchez-García, X. Limon, S. Dominguez-Isidro, D. J. Olvera-Villeda, and J. C. Perez-Arriaga, “Class Balancing Approaches to Improve for Software Defect Prediction Estimations: A Comparative Study,” Programming and Computer Software, vol. 50, no. 8, pp. 621–647, 2024.

[13] A. Abdu et al., “Semantic and traditional feature fusion for software defect prediction using hybrid deep learning model,” Scientific Reports, vol. 14, no. 1, p. 14771, 2024.

[14] A. Alqarni and H. Aljamaan, “Leveraging ensemble learning with generative adversarial networks for imbalanced software defects prediction,” Applied Sciences, vol. 13, no. 24, p. 13319, 2023.

[15] A. Sharma, P. K. Singh, and R. Chandra, “SMOTified-GAN for class imbalanced pattern classification problems,” Ieee Access, vol. 10, pp. 30655–30665, 2022.

[16] S. Zhang, S. Jiang, and Y. Yan, “A software defect prediction approach based on bigan anomaly detection,” Scientific Programming, vol. 2022, no. 1, p. 5024399, 2022.

[17] T. Shahzad, S. Khan, T. Mazhar, W. Ahmad, K. Ouahada, and H. Hamam, “Predicting Software Perfection Through Advanced Models to Uncover and Prevent Defects,” IET Software, vol. 2025, no. 1, p. 8832164, 2025.

[18] J. Pachouly, S. Ahirrao, K. Kotecha, G. Selvachandran, and A. Abraham, “A systematic literature review on software defect prediction using artificial intelligence: Datasets, Data Validation Methods, Approaches, and Tools,” Engineering Applications of Artificial Intelligence, vol. 111, p. 104773, May 2022, doi: 10.1016/j.engappai.2022.104773.

[19] A. Sunil, R. K. Sahu, and S. Karsoliya, “Software Defect Prediction using Supervised Machine Learning: A Systematic Literature Review,” International Journal of Advanced Research and Multidisciplinary Trends (IJARMT), vol. 2, no. 3, pp. 80–95, Jul. 2025, Accessed: Sep. 19, 2025. [Online]. Available: https://ijarmt.com/index.php/j/article/view/355

[20] M. A. Khan et al., “Software Defect Prediction Using Artificial Neural Networks: A Systematic Literature Review,” Scientific Programming, vol. 2022, no. 1, p. 2117339, 2022, doi: 10.1155/2022/2117339.

[21] S. Stradowski and L. Madeyski, “Machine learning in software defect prediction: A business-driven systematic mapping study,” Information and Software Technology, vol. 155, p. 107128, Mar. 2023, doi: 10.1016/j.infsof.2022.107128.

[22] A. B. Nassif et al., “Software defect prediction using learning to rank approach,” Sci Rep, vol. 13, p. 18885, Nov. 2023, doi: 10.1038/s41598-023-45915-5.

[23] S. Kaliraj, A. Kishoore, and V. Sivakumar, "Software fault prediction using cross-project analysis: a study on class imbalance and model generalization," IEEE Access, vol. 12, pp. 64212–64227, 2024.

[24] A. S. Vivek Vardhan Akisetty and A. Ayyagari, "AI Driven Quality Control Using Logistic Regression and Random Forest Models," International Research Journal of Modernization in Engineering Technology and Science, 2024.

[25] H. Wang, B. Arasteh, K. Arasteh, F. S. Gharehchopogh, and A. Rouhi, "A software defect prediction method using binary gray wolf optimizer and machine learning algorithms," Computers and Electrical Engineering, vol. 118, p. 109336, Aug. 2024, doi: 10.1016/j.compeleceng.2024.109336.

[26] L. Madeyski and S. Stradowski, "Predicting test failures induced by software defects: A lightweight alternative to software defect prediction and its industrial application," Journal of Systems and Software, vol. 223, p. 112360, May 2025, doi: 10.1016/j.jss.2025.112360.

[27] M. K. Thota, F. H. Shajin, and P. Rajesh, "Survey on software defect prediction techniques", doi: 10.6703/IJASE.202012_17(4).331.

[28] Radowanul Haque, "Software Defect Dataset by NASA." Accessed: Aug. 22, 2025. [Online]. Available: https://www.kaggle.com/datasets/radowanulhaque/software-defect

[29] M. A. Ibraigheeth and S. A. Fadzli, "Software project failures prediction using logistic regression modeling," in 2020 2nd International Conference on Computer and Information Sciences (ICCIS), IEEE, 2020, pp. 1–5.

[30] N. S. Thomas and S. Kaliraj, "An improved and optimized random forest based approach to predict the software faults," SN Computer Science, vol. 5, no. 5, p. 530, 2024.

[31] M. S. Alkhasawneh, "Software defect prediction through neural network and feature selections," Applied Computational Intelligence and Soft Computing, vol. 2022, no. 1, p. 2581832, 2022.

[32] Q. Huang, Z. Li, and Q. Gu, "Multi-task deep neural networks for just-in-time software defect prediction on mobile apps," Concurrency and Computation: Practice and Experience, vol. 36, no. 10, p. e7664, 2024.

[33] M. Begum, M. H. Shuvo, I. Ashraf, A. Al Mamun, J. Uddin, and M. A. Samad, "Software defects identification: Results using machine learning and explainable artificial intelligence techniques," IEEE Access, vol. 11, pp. 132750–132765, 2023.

A Hybrid CNN-BiGRU-GAN Framework for Enhanced Automated Analysis of Cervical Cancer in Medical Imaging

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Abstract*—Cervical cancer screening requires reliable automated systems capable of overcoming variability in staining, morphology, and limited annotated data, which often undermine the performance of traditional machine learning and deep learning approaches. Existing techniques commonly rely on single-modality feature extraction or static fusion, resulting in weak generalization, class imbalance sensitivity, and limited interpretability in clinical environments. Addressing these gaps, the research introduces DiagnoFusionNet, a hybrid CNN-BiGRU-GAN framework that integrates spatial features from Convolutional Neural Network (CNN), contextual dependencies from Bidirectional Gated Recurrent Unit (BiGRU), and Generative Adversarial Network (GAN)-generated samples to enhance data diversity and correct minority-class deficiencies. The methodology incorporates an Adaptive Triple-Stage Feature Fusion mechanism that dynamically recalibrates modality contributions using discriminator-informed attention, ensuring discriminative and clinically aligned feature representations. Experiments on the SIPaKMeD dataset demonstrate strong performance with 97.89% accuracy, 97.69% precision, 96.95% recall, 96.89% F1-score, and a 0.99 AUC, supported by GAN evaluation metrics, including an FID of 18.3, IS of 3.91, and SSIM of 0.92. Ablation analysis confirms the dominant contribution of the adaptive fusion module, while t-SNE clustering and confusion-matrix inspection highlight effective separability and reduced misclassification. Model development and experimentation were executed using Python, TensorFlow, Keras, OpenCV, and Scikit-learn on GPU-enabled environments. The framework provides a clinically interpretable, data-efficient, and scalable solution for automated cervical cytology analysis in real-world and resource-limited settings.

Keywords*—Cervical cancer detection; DiagnoFusionNet; medical image analysis; Adaptive Triple-Stage Feature Fusion; generative adversarial networks

I. Introduction

Cervical cancer remains one of the most challenging global health burdens and a leading cause of cancer-related mortality among women, particularly in low- and middle-income regions where screening infrastructure is limited and access to trained cytopathologists is restricted [1]. Even though the traditional screening procedures, including Pap smears and the use of acetic acid to look into the female genitalia, have played a significant role in mortality reduction, their efficacy is limited due to the false negativities and variability in reproducibility [6] in the manual interpretation process. The differences in the quality of staining, morphological variation of cervical cells, and inter-observer variability also increase the problem of correct diagnosis, and thus, the success in detecting the disease at relatively early stages and early clinical intervention is limited significantly [2]. The growing access to digital cytology data and deep learning platforms has given rise to quicker progress in the creation of computational models that can detect fine morphological features that might not be detected with the naked eye [3], [4]. Emerging technologies in the field of artificial intelligence, especially medical imaging, promise to resolve all these gaps by offering objective, scalable, and reproducible diagnostic support [5]. The growing access to digital cytology data and deep learning platforms has given rise to quicker progress in the creation of computational models that can detect fine morphological features that might not be detected with the naked eye [6]. The natural variability of cytology images, the limited number of well-annotated data, and the need to generalize the outcome well in the diverse clinical settings, however, necessitate solutions that not only achieve good results but also can be interpreted and adapted [10]. It is against this background that the study aims to come up with an elaborate framework that will improve the reliability of the diagnostic, and the representation of the features will be reinforced [9], and is consistent with screeners' problems that are found in the real world in both resource-constrained and technologically advanced environments.

Recent developments in artificial intelligence have brought up three significant innovations that have made a significant contribution to cervical cytology analysis. Convolutional Neural Networks have been extensively utilized due to their ability to obtain rich spatial and morphological details in cervical cell images to be able to detect nuclei borders, cytoplasm texture, and structural defects [7], [8]. Although successful, these models only encode static spatial cues and do not take into consideration any contextual or temporal relationship between cellular patterns. This gap was bridged by recurrent architectures like Bidirectional Gated Recurrent Units that learned both temporal and contextual dependencies, which effectively modeled the relationships between the local structures and variations at the cell level. The classical CNN, BiGRU and GAN models are faced by the problem of data imbalance, variability of staining, and small samples. Although GANs introduce fictitious diversity, it fails to boost feature discrimination and control multimodal learning. Current hybrid approaches do not have

adaptive fusion, do not make full use of spatial, contextual, and generative advantages, generalization, interpretability, and real-world performance.

To mitigate these challenges, the proposed study provides an improved DiagnoFusionNet model that includes an Adaptive Triple-Stage Feature Fusion (ATFF) mechanism that dynamically combines spatial features of CNN, contextual features of BiGRU and synthetic diversity of GAN by an attention-driven feedback mechanism. The ATFF module facilitates the model to highlight diagnostically important morphological areas in the enhancement of robustness and generalization in the detection of early cervical cancer.

Although recent research has achieved success in deep learning-based screening of cervical cancer, most existing research employs single-modality learning (i.e., CNN-based spatial extraction, contextual modeling or GAN-based augmentation) on its own. The techniques usually apply fixed fusion algorithms, do not adaptively weight, and are not robust to class imbalance, staining variance, and sparse labels, and do not have high interpretability. Based on these gaps, this research will seek to create an adaptive multimodal model that would combine spatial, contextual, and generative representations to enhance diagnostic accuracy, generalization and clinical reliability.

A. Problem Statement

Cervical cancer remains a major cause of mortality among women in low- and middle-income countries (LMICs), where access to reliable screening technologies and trained cytopathologists is limited [10]. Existing screening approaches, such as Visual Inspection with Acetic Acid (VIA) and Pap smears suffer from high inter-observer variability, subjective interpretation, and poor scalability, while deep learning–based diagnostic systems built primarily on CNNs remain constrained by insufficient annotated datasets, severe class imbalance, and weak generalization across diverse cytological presentations. [11]. Prior studies in automated cervical cancer detection also reveal additional challenges, including limited capability to model long-range spatial–contextual relationships between cellular structures, poor robustness to noise and acquisition variations, low interpretability of model predictions, and an inability to handle the heterogeneity seen in atypical or borderline lesions [12]. Addressing these gaps requires an end-to-end architecture that simultaneously improves data diversity, balances class distributions, captures both spatial and contextual dependencies, and provides clinically interpretable outputs. To overcome these limitations, this research proposes DiagnoFusionNet—a fusion framework combining CNN-based spatial feature extraction, BiGRU contextual modeling, and a high-fidelity GAN for synthetic data generation—to deliver a more accurate, robust, and scalable solution for early cervical cancer diagnosis.

B. Research Questions

Based on the identified limitations in existing literature, this study is guided by the following research questions:

- How can spatial morphological features and contextual dependencies in cervical cytology images be jointly modeled to improve classification performance beyond conventional single-stream deep learning architectures?
- To what extent can GAN-based synthetic data augmentation alleviate class imbalance and improve model generalization in cervical cancer detection tasks?
- Can an adaptive, attention-guided feature fusion mechanism dynamically balance multimodal contributions to enhance discriminability and interpretability of diagnostic predictions?
- How does the proposed DiagnoFusionNet framework compare with classical and transformer-based models in terms of accuracy, robustness, and clinical applicability on a standard cervical cytology dataset?

C. Research Motivation

The problem of class imbalance, subtleties of morphology, and inconsistency of stains along with a lack of annotated data of high quality continue to make reliable automation of cervical cytology a challenging task. To increase diagnostic accuracy, models that are capable of identifying both fine-grained spatial information and contextual cellular interactions and are resistant to low data clinical settings are needed. To promote computer-aided screening and facilitate early detection of cervical lesions and their accuracy and resilience to imaging variability, improvements in generalization, interpretability, and resilience to imaging variability are needed in the real-world health care environment.

D. Research Significance

The study is particularly powerful as it develops AI-based cervical cytology analysis by an adaptive multimodal learning model that has the capacity to extract complementary spatial and contextual features and overcome the issue of class imbalance with samples generated with the help of GANs. Its interpretability, data efficiency and strength improve reliability and transparency of medical image assessment. This work enables early and accurate detection of the work in environments where there is limited expertise and data availability, and diagnostic consistency through combining dynamic attention mechanisms and validated fusion strategies. The strategy is scalable, clinically equivalent and is applicable to implementation in low-resource healthcare settings.

E. Key Contributions

1) Presents adaptive multimodal learning model built on spatial morphology, contextual dependency and generative augmentation to augment the robustness and interpretability of representation in cervical cytology analysis.

2) Learns an attention-directed fusion policy that learns and maintains dynamically the balance between the contributions of the features in order to enhance the discriminability, cluster separability and reliability in the presence of problematic staining variations and limited data.

3) Develops a robust evaluation process that includes ablation experiments, feature-space analysis, and GAN quality evaluation as well as analysis of errors that would ensure the validity of methods and clinical applicability.

4) Demonstrates the efficiency of the proposed DiagnoFusionNet by its higher accuracy, precision, recall, F1-score, and AUC values that are better than classical and transformer-based ones.

5) Offers ATFF-supported, GAN augmentation-supported, and empirically powerful diagnostic system, and is scalable to deployment in low-resource cervical screening offline settings.

F. Rest of the Study

Section II examines existing work. In Section III, the proposed method of working is detailed. Section IV provides findings and discussion. Conclusion and further research are given in Section V.

II. Related Works

Poudel et al. [13] implemented VIA to create a new AI-assisted method for cervical cancer detection in environments with limited resources. The study addresses the limitations of subjective VIA tests typically conducted by nurses in LMICs. They developed a protocol for quality image acquisition using smartphones, which does not require specialized devices. A dataset of 1,430 images acquired in VIA screenings was used; they planned a classification model using deep learning to classify (pre)cancerous lesions. Results show that an appropriate acquisition protocol by smartphones can deliver enough detail in images captured for VIA, and this deep-learning model was promising and could help in the actual screening with nurses and pave the way for high-volume collection and validation of data from LMICs. Though these initial studies investigated Pap-smear and VIA-based automation, they were constrained by being based on traditional classifiers or single-modality deep learning and therefore performed poorly in high-imbalanced datasets.

Wu et al. [14] analyzed the utilization of AI in cervical cancer selection, citing its promise to overcome the shortcomings of LMICs in meeting the World Health Organization's objective of screening 70% of women aged between 35 and 45 years by 2030. The study underlines the importance of accurate, efficient, and effective methods in cervical cancer screening, considering that many developing countries lack good healthcare infrastructure. Recently, AI and especially DL algorithms have proven major possible in enhancing cervical malignant disorder and aberrant cytology identification. The review is focused on the current status of AI image recognition technology for diagnosing cervical cancer, along with the challenges and possible avenues of its use in screening, treatment, and surveillance.

Borders and Thaxton Wiggins [15] proposed a study to explore Pap rates among US females, concentrating on rural-urban disparities before as well as during the COVID-19 pandemic from 2019 to 2022. The study included women between the ages of 21 and 65 and was based on nationally representative data from the "Health Information National Trends Survey". Rural females had significantly low Pap test rates compared with their urban counterparts. Rural women's unadjusted past-year Pap test rate in 2022 was 48.6%, whereas urban women's was 64.0%. With adjusted probabilities of getting a Pap test 30% lower in 2022 than in 2019, the analysis also showed a drop in Pap testing rates in 2022. This emphasizes the necessity of focused measures to raise screening rates, particularly in rural regions.

Sarhangi et al. [16] investigated how DL might improve the precision and effectiveness of cervical cancer screening, which mostly uses cytology and colposcopy. This study emphasizes that only during the stage of precancerous cervical cancer is it perfectly treated. The deep learning training process involves processes such as categorization, division, and recognition in cervical cancer diagnosis. The review also offers popular public cytology and colposcopy datasets, together with the most used deep learning architectures. Reviewing 24 practical papers, the study concludes that deep learning considerably improves the correctness and speed of cervical cancer analysis, opening doors to early diagnosis and saving lives. Whereas AI-based screening has been shown to have great promise, the majority of reported models are myopic, either utilizing spatial image features or handcrafted descriptors without considering the contextual temporal dependencies necessary to achieve adequate cell classification.

Singh et al. [17] utilized the GLOBOCAN 2020 database in assessing worldwide inequalities in incidence and cervical cancer mortality due to geographic and socioeconomic development factors. The research pursued the effort of monitoring cervical cancer towards the eradication of it from public health conditions, as recommended by the WHO, by lowering the incidence rates below 4 cases/100,000 women-years. The study reports that the occurrence and deaths from cervical cancer were significantly higher in countries with a low HDI compared to the high HDI countries. The study showed how countries with good screening services have different age-specific incidence patterns, while those with inadequate services (Colombia, India, Uganda) present an entirely different pattern.

Arbyn et al. [18] suggested a five-step framework to evaluate the possible application of biomarkers as a screening method for cervical cancer and to meet the long-felt need for proper guidelines on diagnostic research in screening situations. The framework includes: 1) correlation studies to determine the relationship between the level of neoplasia and biomarker expression, 2) clinical diagnostic studies employing the reference standard, 3) biobank-based studies that validate biomarkers by making use of archive cytology samples, 4) prospective cohort studies where baseline biomarker assessments and follow-up disease monitoring are involved, and 5) randomized intervention trials to assess reduced cancer incidence or severe dysplasia in the experimental group. This framework would help researchers to systematically evaluate new biomarkers and protect clinicians from misleading claims of tools that have not been tested well.

Shen et al. [19] designed a two-stage image synthesis system for fully automated thin-prep cytologic test systems to improve cervical abnormalities screening data. During the first phase, "Global Image Generation, a Normal Image Generator" is used to create "Cytopathological images" made up of several healthy cervical cells. Diffusion, a pretrained base model for image synthesis that has been tuned to optimize cytopathological content creation as well as spatial layout control, is the starting point for both models. Although GAN-based augmentation enhanced data diversity, the lack of incorporation with

sequential modeling constrained their diagnostic efficacy, leaving room for an even more comprehensive framework.

Li et al. [20] designed an AI approach known as STRIDE, in an effort to solve challenges in cervical cancer screening using Whole Slide Image cytology. The limitations of the current models are bypassed with STRIDE: namely, the small annotations available, as well as poor interpretability. STRIDE is a method that integrates labels at the patient level using a tiny number of cell-level annotations and uses color adversarial samples training to enhance robustness against real-world variations. Conversely, DiagnoFusionNet is the first system to synergistically combine spatial–temporal feature fusion with GAN-based augmentation in direct solution of dataset sparsity, imbalance, and interpretability issues in cervical cancer diagnosis.

Based on the literature reviewed, it is clear that past studies made use of either CNN-based spatial extraction, RNN-based contextual modeling, or GAN-based augmentation by itself. These approaches have problems of concatenating features statically, low interpretability, and generalizability when applied to unbalanced medical data. The proposed DiagnoFusionNet with ATFF overcomes the aforementioned challenges by introducing an adaptive attention-based fusion, which dynamically balances the spatial and contextual learning under the supervision of GAN, resulting in more profoundly steady, interpretable, and clinically viable cervical cancer detection.

III. Proposed DiagnoFusionNet Framework for Detecting Cervical Cancer Detection

The stated methodology presents DiagnoFusionNet, an end-to-end deep diagnostic fusion network, which is aimed at enhancing the early detection of cervical cancer by overcoming the key pitfalls of cervical cytology imaging, such as the lack of annotated data, imbalance in classes, and large cellular variations. The framework combines three complementary modules, including CNN, BiGRU, and GAN in one learning pipeline. Cervical images are first processed by resizing, normalization and augmentation using GAN. The CNN module identifies spatial morphological properties that include nuclear irregularities, chromatin texture and cytoplasmic boundaries, which are essential in the differentiation of normal and abnormal cells. The features of these spaces are then sent to a BiGRU model, which stands out by capturing contextual and sequential dependencies, therefore, allowing the model to learn some subtle cellular patterns and inter-feature relationships that cannot be easily captured by CNNs alone. In order to address the lack and unbalanced nature of data, a GAN module can be used to create high-fidelity synthetic images belonging to the minority classes, increasing the amount of data and enhancing generalization. A new ATFF mechanism dynamically integrates CNN, BiGRU and GAN-based representations with attention feedback of the discriminator, and results in a more stable and understandable diagnostic embedding. Through collaborative education of spatial, temporal, and distribution-balanced characteristics, DiagnoFusionNet improves the predictive performance, strength, and clinical viability, especially in the low-resource screening conditions.

Fig. 1 illustrates that the workflow of the DiagnoFusionNet starts with image preprocessing, which comprises of resizing, normalization, and GAN-based augmentation, then CNN spatial feature extraction, BiGRU contextual learning, and adaptive fusion. The output layer, which is the diagnostic of the fused representation, ultimately classifies the fused representation into cervical cancer categories.

A. Data Collection

The SIPaKMeD dataset [21], provided by Kaggle, one of the biggest publicly available datasets of cervical cell images, is used in the proposed study. It has 4,049 cervical cell images classified into five groups, that is, superficial-intermediate, parabasal, metaplastic, dyskeratotic and koilocytotic. The resolution of each image is 2048 x 1536 pixels, and requires preprocessing, such as resizing, normalization and augmentation, to standardize input dimension to model training. This data allows the suggested deep learning system to identify precancerous and cancerous alterations with high precision to facilitate the early diagnosis and automatic analysis of cervical cytology.

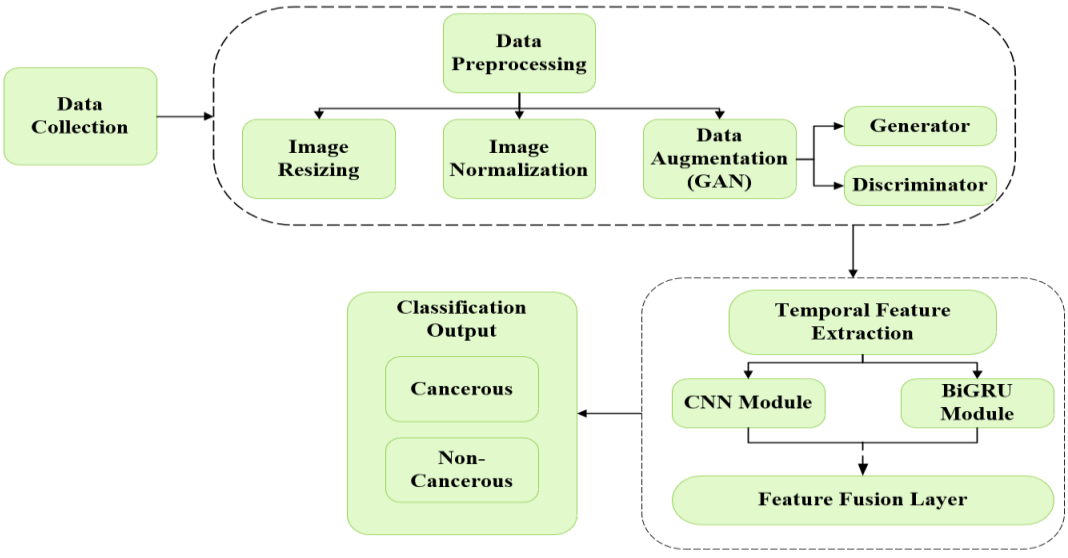


Fig. 1. DiagnoFusionNet's workflow for classifying cervical cancer.

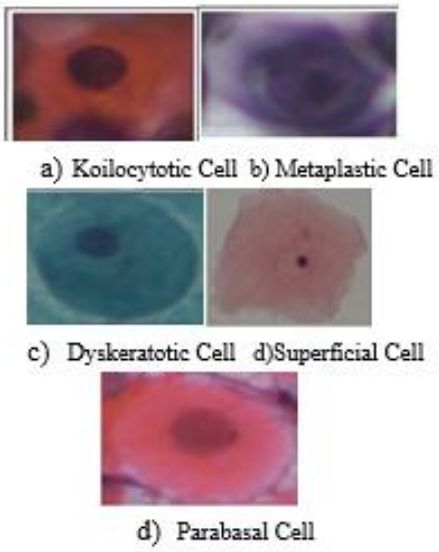


Fig. 2. Examples of SIPaKMeD datasets.

Fig. 2 presents some typical types of cells found in Pap smear examination- dyskeratotic, koilocytotic, metaplastic, parabasal and superficial intermediate cells. All of them present typical morphologic patterns, which aid in path.

B. Data Pre-processing

Preprocessing is done to normalize images to 01, downsampling them to 224x224, apply augmentations, and to increase diversity, class balance, and the robustness and generalization of DiagnoFusionNet uses synthetic samples generated by GAN.

1) Image resizing: Image resizing parameters is used to normalize cervical cytology images to $224 \times 224 \times 3$ by transforming variable size into a fixed size $224 \times 224 \times 3$ tensor, so that DiagnoFusionNet can process images with consistent size, training is more stable, and the accuracy of feature extraction is maintained. It is expressed in Eq. (1):

$$M_{resized} = Resize\left(M_{original}, 224 \times 224\right) \quad (1)$$

where, $M_{original}$ denotes the input image, resize is a function that resizes the image to 224×224 pixels and $M_{resized}$ is the resized image.

2) Normalization: Normalization rescales each pixel of the resized image by dividing by 255, converting intensities to a 0–1 range. This stabilizes gradients, accelerates convergence, and ensures consistent input distribution across all channels using Eq. (2):

$$M_{normalized}(l,k) = \frac{M_{resized}(l,k)}{255} \quad (2)$$

where, $M_{resized(x,y)}$ denotes the pixel value at location (l, k), the highest intensity value in an 8-bit picture is 255 and $M_{normalized}$ is the normalized image.

3) Data augmentation: Data augmentation improves the diversity and strength of cervical cytology images by using controlled transformations which simulate real world visual conditions and maintain diagnostic properties. All the images undergo normalization followed by transformation function set Z that consists of rotation, horizontal flipping, and zooming. These training operations increase the effective distribution of training, minimize overfitting, and assist the model to generalize to differences in staining, as well as, to cell orientations and morphological variations. Rotation adds an angular variability through rotation of the image about its center so that DiagnoFusionNet can then learn to understand the image without its orientation. Horizontal flipping replicates the cell structures along the vertical axis and is the same effect as the natural differences in smear preparation. The zoom of an image by a factor s, dilation of the image without class semantics change, scales cell boundaries and cytoplasmic areas of the image. The general process of augmentation is expressed in Eq. (3):

$$M_{aug} = Z(M_{normalized}) \quad (3)$$

where, M_{aug} retains the original dimensions while embedding richer morphological diversity for improved model generalization keeps the initial size $224 \times 224 \times 3$ with more morphological diversity to better generalize the models.

C. Generating Synthetic Data Using GAN

GAN-based augmentation is used in DiagnoFusionNet to address two major challenges in cervical cytology imaging: limited annotated data and severe class imbalance. The GAN consists of a generator and a discriminator trained in opposition. During training, the generator takes random noise as input and learns to produce synthetic cervical cell images that mimic the texture, color distribution, and morphological patterns of real cytology samples. At the same time, the discriminator evaluates these images by distinguishing real samples from generated ones, forcing the generator to continuously improve. Through this iterative adversarial process, the GAN produces high-fidelity synthetic images, particularly for minority classes where annotated data is scarce. These synthetic samples are then added to the training set, creating a more balanced dataset and exposing the model to a wider range of clinically relevant variations. This helps DiagnoFusionNet learn rare abnormalities, strengthens feature discrimination, and improves generalization to noisy or inconsistent real-world medical data. The overall GAN objective is expressed as Eq. (4):

$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim pdata(x)}[log\, D(x)] + \mathbb{E}_{z\sim p_z(z)}[log\,(1 - D(G(z)))] \quad (4)$$

where, $z \sim p_z(z)$ is the noise samples from the distribution, $D(x)$ is the discriminators' estimation, and the generator's output by $G(z)$. While GAN-based augmentation will increase the quality of training data with images having good fidelity and realistic patterns, this enhances robustness with better generalization capability because real-world medical data is usually messy or noisy and contains many inconsistencies.

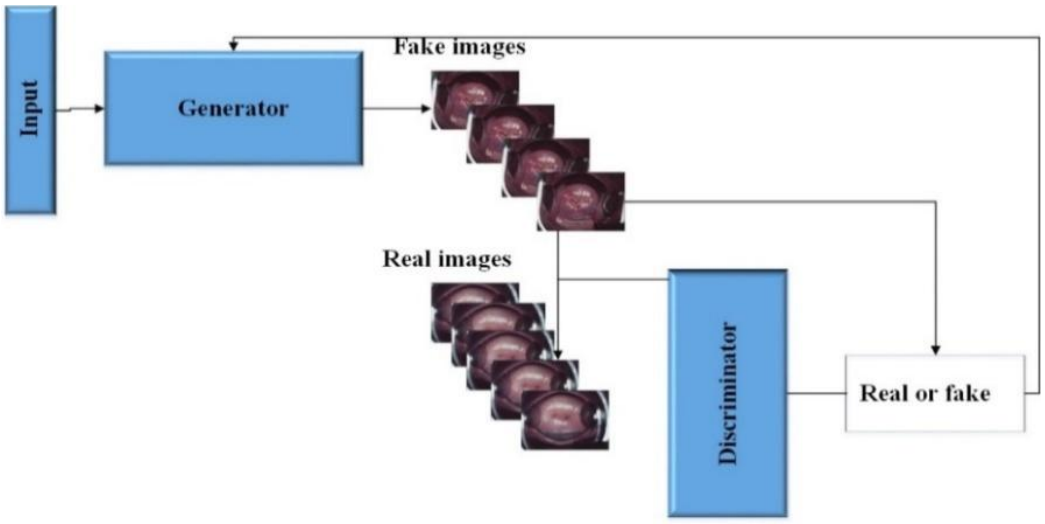


Fig. 3. DiagnoFusionNet's GAN architecture for intelligent augmentation.

Fig. 3 depicts GAN architecture. The Generator accept random noise and produces synthetic data, with a goal to look like actual data. Its Discriminator can work with both real and produced pictures and aims at identifying the input whether real or artificial. During the training process, the Generator and Discriminator act as the process of playing the game against each other; the Generator should aim at producing data similar to the real data to confuse Discriminator, on the other hand, Discriminator should aim at distinguishing the presence of real data and the fake data. Such repeated versions bring both ingredients to perfection and generate correct synthetic data.

D. Temporal Feature Extraction Using CNN-BiGRU

The CNN is the initial and crucial phase of the pipeline which is tasked with extracting discriminating features of raw cervical cytology images. Each image is subjected to CNN stacked-convolutional layers in which filters are used to scan the pixel matrix and identify local formations in the image like edges, textures, and shape patterns. Each pixel of an input produces a dot product between the filter and the underlying pixel, which creates an activation value creating a feature map that identifies meaningful areas. The filters are automatically trained during training to learn to identify clinically relevant changes in color, boundaries and morphology. Stride determines the distance of movement of the filter, the bigger the stride, the smaller will be the feature maps in the feature map. In general, the CNN is effective in converting raw images into spatial feature representation that is essential in the diagnosis of cervical cancer. The input image will be represented as I and the filter (Kernel) as K. The result of the convolution step is as shown in Eq. (5):

$$F(i,j) = \sum_{m=-k}^{k} \sum_{n=-k}^{k} I\ (i+m, j+n)\ K(m,n) \quad (5)$$

In Eq. (5), $F(i,j)$ is the map of features, k is the size of the filter. Once convolution is done, an activation function makes the model work in a less-linear manner. One of the frequently used functions for activation is ReLU (Rectified Linear Unit) as in Eq. (6):

$$A(y,z) = ReLU\big(F(y,z)\big) \max\big(0, F(y,z)\big) \quad (6)$$

where, $A(y,z)$ denotes activated output at spatial position, $F(y,z)$ denotes input feature map, and $\max\big(0, F(y,z)\big)$ denotes ReLU function. The activation function's goal is to help the network recognize complex patterns and correlations in data rather than merely linearly altering them. ReLU happens to be very efficient in CNNs since it reduces the vanishing gradient problem, wherein during the process of backpropagation gradients get too small, hence making training slow. On top of that, the sparsity introduced by setting all negative values to zero is beneficial for the efficiency of the model.

The Pooling Layer, being placed after the convolutional layers, down-samples feature maps. The Pooling decreases the spatial dimensions - that is height and width of the feature maps thereby decreasing the computations, the amount of memory utilized, as well as the overfitting while preserving the more critical features. As a result, feature maps have smaller spatial dimensions. Pooling further minimizes the model's parameter count; therefore, it speeds up the computation and reduces the usage of memory. Pooling brings about a degree of invariance to small translations within an image. For instance, in case a feature has been shifted slightly in an image, pooling can capture this feature well, enabling the model to identify the same object or pattern even though they have been shifted in place, using Eq. (7):

$$P(i,j) = p,q \in poo\ l_{regionmax}\ A(i + Pj + q) \quad (7)$$

In Eq. (7), $pool_{\text{regionmax}}$ region is set to equal the size of the pooling window. Batch Normalization is a method used to stabilize and speed the training by normalizing inputs to each layer of the network. Mainly, this is done with the intent of scaling and shifting activations within each mini-batch to have a normalized mean and variance at the input to every layer. During training, the inputs of each layer are normalized by computing the mini-batch mean and subtracting the result by the mini-batch standard deviation. Furthermore, a scale and shift are applied to enable the network to recover its flexibility and learn the optimal transformation of the activations.

The dropout technique is a regularization method that should be applied to avoid overfitting in situations with small,

unbalanced, or noisy medical datasets. In every training step, dropout randomly disables a portion of the neurons- usually half of them, in case the dropout rate is set to 0.5 - and this way, the network does not depend too much on any particular neuron or feature pathway. Through the constraint of the model to learn several redundant representations, dropout promotes robustness, limit sensitivity to noise, and generalization to unseen cervical cytology images. The CNN is required to be followed by the BiGRU module in order to capture more relationships in the extracted features. As the CNN is trained to perceive spatial features (including irregularities in texture, nuclear boundaries and cytoplasm structure), the BiGRU examines the sequential arrangement of such features. This is noteworthy since the patterns of morphological indicators of cervical cells tend to be distributed or region-specific. Compared to a regular GRU, the BiGRU operates on the sequences in both forward and backward directions, simultaneously taking into consideration the dependency of both the past and future feature environments. This two-way learning enables this model to identify the slight abnormalities which otherwise may not be evident in the isolated spatial areas. Moreover, the selective memory mechanism of BiGRU will select only the relevant or noisy information and the model will focus only on the diagnostically useful cues. Combined, dropout and BiGRU boost the generalization ability, long-range dependency identification and dependable cervical cancer classification of DiagnoFusionNet. GRU forward and backward is obtained in Eq. (8) and Eq. (9):

$$\overrightarrow{ht} = GRU\left(xt, \overrightarrow{ht} - 1\right) \tag{8}$$

$$\overleftarrow{ht} = GRU\left(xt, \overleftarrow{ht} + 1\ \right) \tag{9}$$

where, $\overrightarrow{ht} - 1$ and $\overrightarrow{ht} + 1$ are the forward and backward GRUs' secret states. This output from both directions then gets concatenated to present a more comprehensive representation of the temporal dependencies across the image data using Eq. (10):

$$Z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z) \tag{10}$$

The research gate r_t in Eq. (11), look after how many previous hidden states there are.

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r) \tag{11}$$

Candidate hidden state shown in Eq. (12), represented by the $\widehat{h_t}$ represents the new information.

$$\widehat{h_t} = \tanh\left(W_h \cdot [r_t h_{t-1}, x_t] + b_h\right) \tag{12}$$

At last, the hidden state h_t will update to combine candidate state and the prior hidden state. This bidirectional approach helps in capturing the past and future dependencies in the data, which is the most important for cervical cancer because subtle patterns in both ways can help in accurate image classification.

Fig. 4 represents the DiagnoFusionNet structure, where CNN layers are used to extract spatial features and then dimensionality reduction is done by pooling. A BiGRU performs processing these features to identify contextual dependencies, concatenated and fed into fully connected and Softmax layers in the process of correctly classifying early cervical cancer.

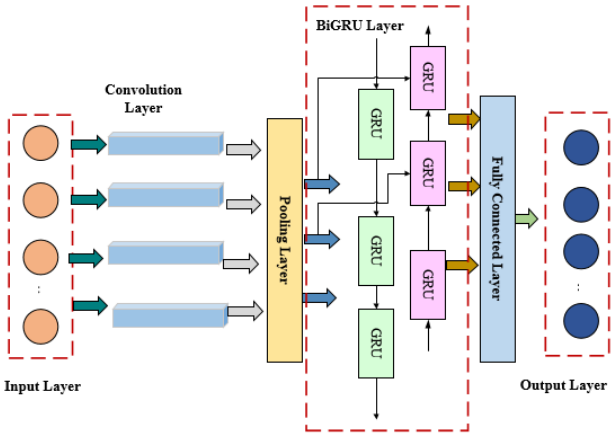


Fig. 4. DiagnoFusionNet utilizes a CNN–BiGRU architecture to extract spatial–temporal features from cervical cancer images.

E. Feature Embedding and Representation Alignment

In DiagnoFusionNet, feature embedding is applied to transform heterogeneous feature representations that are made by various network components to a shared latent space prior to fusion. The CNN branch creates high-dimensional spatial feature maps that capture morphological features, including nuclear shape, texture, and cytoplasmic boundaries, and the BiGRU branch creates contextual feature sequences, which encode relational relationships across spatial regions. Since these representations are not identical in terms of dimensionality, scale and semantic representation, direct fusion cannot be used. Thus, both CNN and BiGRU features are projected into a common fixed-dimensional space by learnable linear projection layers. This correspondence facilitates successful comparison, adaptive attention-based weighting with fusion, stabilized training as well as better interpretability of the final diagnostic representation.

F. Fusion Module

The Fusion Module combines the strengths of the CNN and BiGRU branches which are complementary to each other to create an integrated diagnostic representation. The CNN isolates spatial morphological information of cervical cells, including nuclear shape, chromatin texture and cytoplasmic boundaries, which are local structures that are critical to detecting abnormal patterns. Simultaneously, the BiGRU acquires contextual relationships among the extracted sequence of features that captures small-scale temporal or relational relationships that are not well captured by spatial filters. In order to take advantage of both types of information, the CNN (F_s) and BiGRU (F_c) outputs are fused with the use of a learnable fusion mechanism. First, every feature representation is mapped to a shared embedding space to make them compatible with the help of Eq. (13):

$$F_s' = W_s F_s,\ F_c' = W_c F_c \tag{13}$$

where, W_s and W_c are project matrices that can be trained. These are then merged through concatenating the transformed features and producing a denser joint representation in Eq. (14):

$$F_{\text{fusion}} = [\hat{F}_s || \hat{F}_s] \tag{14}$$

This combined insertion maintains the finer-scale spatial morphology as well as the high-level contextual links, which allows DiagnoFusionNet to generate a more differentiating and dependable representation upon which downstream cervical cancer classification can be made. The fusion mechanism is used to ensure that the model takes into account the appearance-based and relational signal--enhancing precision, strength and sensitivity to delicate abnormalities.

The mathematical definition of the fusion process is used to formalize the Adaptive Triple-Stage Feature Fusion (ATFF) mechanism to provide transparent and reproducible spatial, temporal, and GAN-guided features integration. Let $F_{cnn} \in \mathbb{R}^{d_s}$ represent spatial representations according to the CNN, and $F_{gru} \in \mathbb{R}^{d_t}$ they mean contextual representations according to the BiGRU. Prior to fusion, both representations will be mapped to an identical latent space with matrices W_s and W_t via Eq. (15):

$$\hat{F}_{cnn} = W_s F_{cnn}, \quad \hat{F}_{gru} = W_t F_{gru} \tag{15}$$

An attention gate carries out the calculation of modality-specific relevance weights based on Eq. (16):

$$\alpha = \frac{exp\ (u^{\top} tanh\ (W_a \hat{F}_{cnn}))}{exp(u^{\top}\ tanh(W_a \hat{F}_{cnn}))+exp\ (v^{\top} tanh\ (W_b \hat{F}_{GRU}))} \tag{16}$$

$$\beta = 1 - \alpha$$

where, α weights CNN spatial cues and β weights BiGRU contextual dependencies. To incorporate GAN feedback, the discriminator outputs a realism score $D(x) \in [0,1]$, which is a measure of loyalty and variety of representations. The weights of the features are dynamically adjusted in ATFF [see Eq. (17)]:

$$\alpha' = \alpha + \lambda(D(x) - 0.5), \ \ \beta' = \beta - \lambda(D(x) - 0.5) \tag{17}$$

where, λ, lambda, is a coefficient of stability. When the GAN score on realism is high, there is more dependency on CNN spatial cues and when it is low, there is more dependence on context. The embedded feature fusing is calculated with Eq. (18):

$$FATFF = \alpha' \odot \hat{F}_{cnn} + \beta' \odot \hat{F}_{gru} \tag{18}$$

This formulation ensures balanced, context-aware fusion that adapts per sample, improves robustness in imbalanced datasets, and enhances interpretability through weighted modality contribution.

G. Classification Head

Fusion after feature fusion, the output F fusion is fed to diagnostic predictions with a light classification head. On the one hand, Global Average Pooling (GAP) makes the fused feature map small, meaning that only the most informative global patterns are used in the final decision and minimizing overfitting. This combined vector is then run through a fully connected layer and then Softmax function in order to compute class probabilities, with Eq. (19):

$$P = Softmax(WF_{\text{fusions}} + b) \tag{19}$$

where, W and b are parameterizable classifier parameters. The softmax makes sure that the output consists of normalized probabilities of the different categories of cervical cancer. Special attention is required to resolve the class imbalance of cervical cytology datasets, resorting to class-balanced focal loss that down-weights easy samples and focuses on minority or challenging ones with Eq. (20):

$$\mathcal{L} = -\alpha\,(1 - P_t)^{\gamma}\ log\ (P_t) \tag{20}$$

where, P_t is the probability of the true class as predicted, α is the weight of classes, and γ concentrates on learning difficult samples.

Algorithm 1. DiagnoFusionNet with ATFF

Input: Cervical cell image dataset
Output: Trained DiagnoFusionNet classification model
  Initialize the Dataset
  Load image dataset
  Pre-process images: For each image I in D do
  Resize I → (224×224)
  Normalize pixel intensity range [0,1]
  Apply augmentation (rotation, flip, zoom)
End for
  GAN-based Data Generation
While GAN not converged do
  Generate synthetic image G(z)
  Compute discriminator outputs D(real), D(fake)
  If D(fake) < threshold then
    Update Generator parameters
  Else
    Update Discriminator parameters
  End if
End while
Augment dataset with generated high-fidelity images
Feature Extraction
For each image I in augmented dataset do
  $\hat{F}_{Cnn}$ ← CNN(I) Extract spatial morphological features
  F_{bi} ← BiGRU(F_cnn_seq) Extract contextual-temporal dependencies
End for
ATFF
Align CNN and BiGRU features into common dimension
Compute attention weights α and β using attention gate
Obtain GAN realism score R_{GAN}
If $R_{GAN} \geq$ threshold then
  Increase α, decrease β Emphasize spatial features
Else
  Decrease α, increase β Emphasize contextual features
End if
Fuse features: $F_{fusion} = \alpha' \odot \hat{F}_{Cnn} + \beta' \odot \hat{F}_{bi}$
Classification
Flatten F_{fusion}
Pass through fully connected layer and Softmax classifier
Predict output label: {Normal, Abnormal}
Evaluation
Compute Accuracy, Precision, Recall, F1-score, and AUC
If performance ≥ target then
  Save trained DiagnoFusionNet model
Else
  Retrain model with adjusted parameters
End if
End

Algorithm 1 trains DiagnoFusionNet using a combination of CNN-based spatial features, BiGRU contextual dependencies,

and GAN-generated augmentation as a part of the ATFF. At this stage, the ATFF aligns and merges features using discriminator-guided weighting, after preprocessing and GAN synthesis. The fused representation is categorized through Softmax that allows strong, interpretable, and generalizable detection of cervical cancer in its early stages.

IV. Results and Discussion

The results section gives a thorough review of the proposed DiagnoFusionNet model in terms of quantitative, qualitative, as well as comparative analysis. The SIPaKMeD dataset was tested on standardized training, validation and test splits and results were obtained using optimized hyperparameters and means of a consistent hardware-software platform. The section contains model training behavior, visualization of the feature space, analysis of the confusion matrices, ablation results, validation of GAN quality, and comparisons to classical and transformer-based baselines. Further analyses include the complexity of models, their interpretability using the ATFF weight analysis, and error analysis and all of them support the robustness, excellence, and clinical applicability of the proposed system.

TABLE I. Simulation Parameter

Parameter	Value/Setting
Input Feature Dimension	32 (after preprocessing)
Training/Testing Split	80% / 20%
CNN Layers	2 conv+1 max-pool
CNN Kernel Size	3×3
BiGRU Units	64
Activation Function	ReLU (CNN), Tanh (BiGRU)
Epochs	100
Function of Loss	Cross-Entropy in Binary
GAN Generator Layers	3 Dense Layers
GAN Discriminator Layers	3 Dense Layers
Software Used	Python
Hardware Used	NVIDIA RTX 3080 GPU, 32GB RAM
Development Environment	Jupyter Notebook

Table I defines the parameters of the simulation that determine the training setup of DiagnoFusionNet, such as input sizes, learning rate, epochs, batch size, and network layers, to guarantee uniform optimization, stable performance testing, and reproducibility of cervical cancer classification experiments. All models were trained and evaluated under the same environment, on 80%-20% split, preprocessed using the same method, input-resolving on the same method, and data-augmentation to provide fair and unbiased evaluation. Such hyperparameters as optimizer, learning rate, batch size, and epochs have been chosen according to the validation performance and not changed in most cases. Baseline and transformer models worked with original parameters with slight modifications to convergence. Measures of evaluation were the same to prevent bias. The DiagnoFusionNet, which consists of CNN, BiGRU, GAN, and Adaptive Triple-Stage Feature Fusion modules, was empirically trained using end-to-end training, progressive learning rate schedule, early termination, dropout, and batch normalization to improve convergence, stability, and generalization.

A. Experimental Outcomes

Fig. 5 shows a grid of sixteen separate cell image icons, each of which is marked as "Abnormal" or "Normal". These would probably be microscopic images of cells, stained to bring out their features. The differences in cell size, shape, and nuclear features indicate a visual categorization task for the detection of cellular abnormalities.

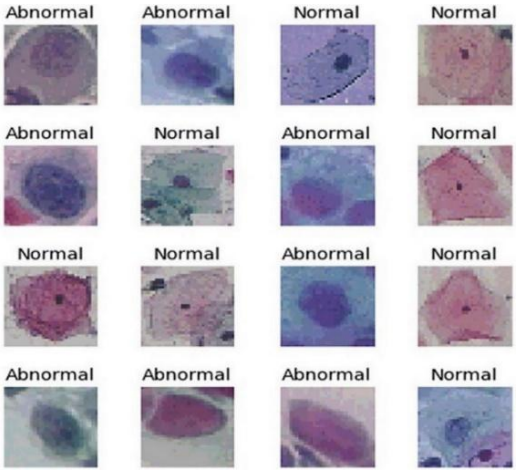


Fig. 5. Abnormal and normal cervical cancer images.

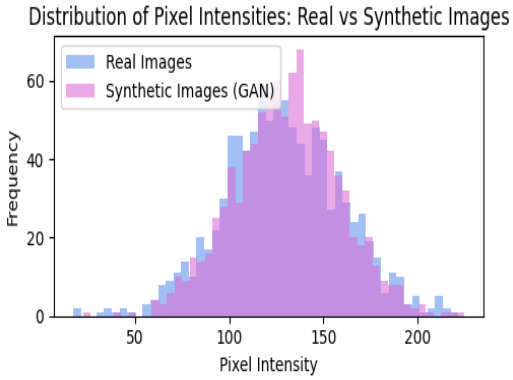


Fig. 6. Distribution of pixel intensities.

Fig. 6 compares the patterns of Pixel intensity of real and GAN-generated images, which is very consistent, which proves realistic synthesis, which increases diversity of the data and promotes more generalization of the models.

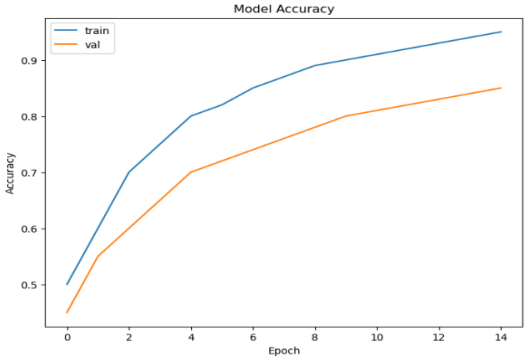


Fig. 7. Accuracy of validation and training.

Training and validation accuracy after 15 epochs is presented in Fig. 7. Improved learning is indicated by the rising blue curve and generalization of the unseen data is indicated by the orange curve. The model works well because both curves rise steadily and express closer values of high accuracy.

B. Ablation Study

To rigorously examine the contribution of each component of DiagnoFusionNet, an ablation analysis was performed by systematically removing modules and observing performance impact. The results demonstrate that both sequential modeling (BiGRU) and GAN augmentation significantly improve discriminative performance, while ATFF alone contributes the largest performance gain.

TABLE II. ABLATION RESULTS DEMONSTRATING COMPONENT-WISE CONTRIBUTIONS IN DIAGNOFUSIONNET

Model Variant	Accuracy	Precision	Recall	F1-Score
CNN Only	92.11%	90.54%	88.92%	89.72%
CNN + BiGRU	94.86%	94.47%	93.72%	94.09%
CNN + GAN	95.22%	95.08%	94.13%	94.60%
CNN + BiGRU + GAN (No ATFF)	96.51%	96.28%	95.90%	95.94%
Full DiagnoFusionNet (With ATFF)	97.89%	97.69%	96.95%	96.89%

Table II shows performance improvements as components are added. Combining CNN, BiGRU, GAN, and finally ATFF yields progressively higher accuracy and F1-scores, confirming ATFF's key contribution to the model's superior classification capability.

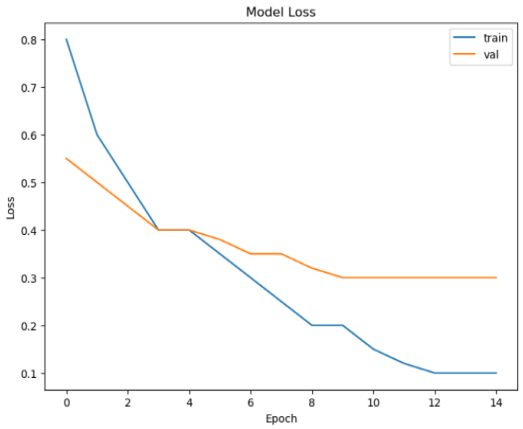


Fig. 8. Training and validation loss.

Fig. 8 presents the dependence of training and validation loss on 15 epochs. The rate of training loss is continuously reduced and validation loss plateaus early in the training, which is a symptom of overfitting. This implies that the model is able to learn training patterns adequately, but it has a low capacity to generalize adequately to data it has not seen.

Fig. 9 presents class-wise prediction performance; the diagonal performance is very high and the error across classes is low. Great values on the diagonal reveal correct classification in all five types of cervical cells, which proves the robustness of the model, its ability to discriminate, and its strong clinical diagnoses.

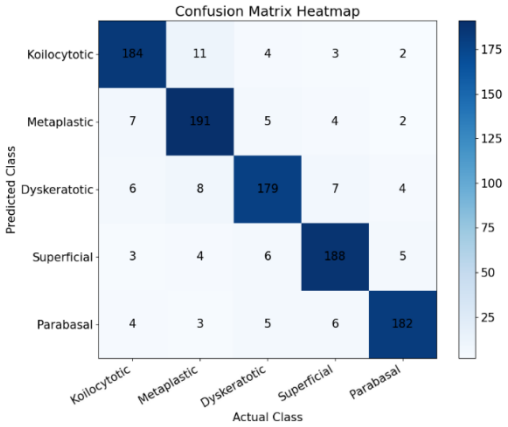


Fig. 9. Interpretation of the confusion matrix heatmap.

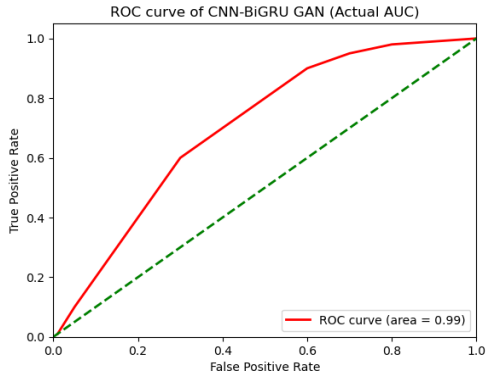


Fig. 10. ROC curve.

Fig. 10 represents the ROC curve, and TPR is plotted against FPR. DiagnoFusionNet has a good discriminatory power with an AUC of 0.99, a good sensitivity-specificity ratio and a large reduction in the risk of false negatives when screening cervical cancer.

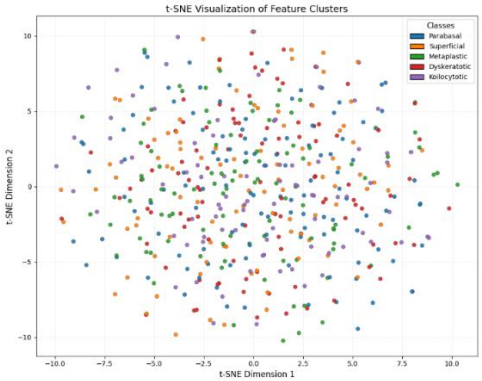


Fig. 11. t-SNE visualization of feature representations.

Fig. 11 indicates that there is a distinct separation of cervical cell classes, which appears to indicate that ATFF learns effectively discriminative fused representations. Clusters are small and do not overlap much, which proves that feature separability is strong and multimodal learning is robust.

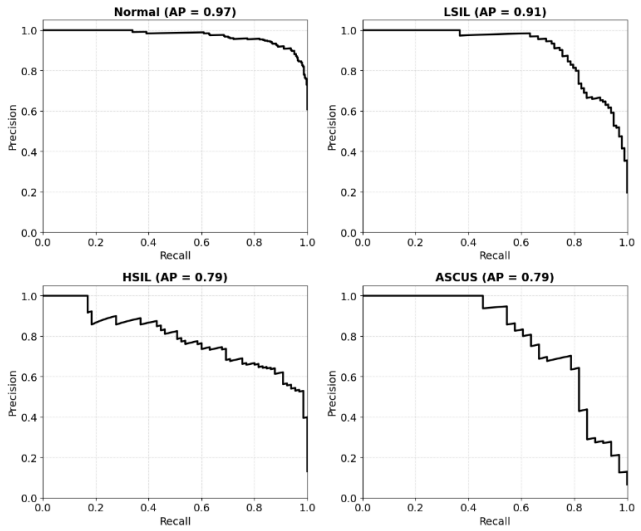


Fig. 12. Class-wise precision–recall curves explanation.

Fig. 12 shows the individual results of each cervical cancer class, with the positive predictive accuracy of DiagnoFusionNet being in imbalanced data. These curves indicate that the model is quite precise and recalling as far as all classes are concerned and minority categories in particular, which is very sensitive and discriminative.

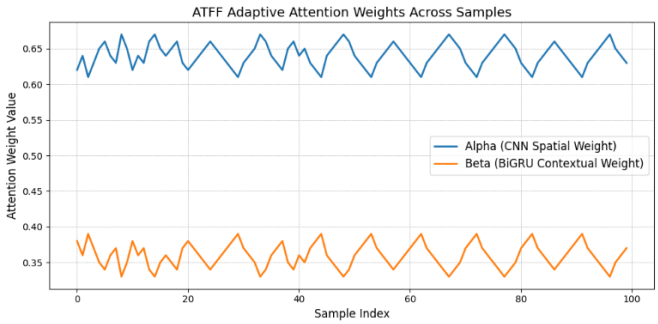


Fig. 13. ATFF modality weight cross samples.

Fig. 13 depicts the dynamics of a and b among samples. The larger values represent more dependence on CNN spatial features, whereas the supplemental b values represent the BiGRU contextual contributions, which depict the adaptable multimodal fusion of features to generate better diagnostic output.

C. Performance Evaluation

To contextualize performance within modern deep learning paradigms, DiagnoFusionNet was compared against transformer-based cervical cancer classifiers. A Swin-Transformer baseline achieved 96.01% accuracy, and a ViT-Hybrid model achieved 96.42%. Although transformers excel in global feature modeling, they underperformed compared to DiagnoFusionNet due to the limited size of SIPaKMeD and the difficulty of optimizing transformer architectures on small datasets. The hybrid CNN-BiGRU–GAN approach with adaptive fusion is therefore better suited for cytology imaging tasks where spatial granularity and contextual patterns jointly influence pathology.

TABLE III. CLASSIFICATION RESULTS OF THE PROPOSED MODEL ON SIPAKMED

Class Label	Precision	Recall	F1-score
Koilocytotic	96.42	95.71	96.06
Metaplastic	97.18	96.89	97.03
Dyskeratotic	95.24	94.76	95.00
Superficial	96.78	95.99	96.38
Parabasal	97.04	96.42	96.73
Average	96.53	95.95	96.24

Table III shows the proposed DiagnoFusionNet architecture classification performance. Robust spatial features are extracted from the cervical cell images by the CNN, while sequential dependencies and contextual representations are learned by the BiGRU.

TABLE IV. MODEL PERFORMANCE COMPARISON

Models	Accuracy	Precision	Recall	F1-Score
PSPM [22]	96.50%	93.78%	92.89%	89.45%
PCA and GWO [23]	94.74%	94.77%	94.67%	78.90%
Fuzzy Distance Ensemble[24]	89.92%	94.78%	89.76%	95.90%
Deep Cervix[25]	93.60%	92.45%	97.98%	94.67%
Proposed CNN BiGRU GAN	97.89%	97.69%	96.95%	96.89%

All the ML models are compared in Table IV, where it is observed that DiagnoFusionNet has the highest accuracy, precision and F1-score. It has an excellent performance due to the integration of spatial-temporal feature learning with GAN-based augmentation that provides it with definite benefits over the PSPM, PCA-GWO, Deep Cervix and Fuzzy Ensemble.

D. Discussion

DiagnoFusionNet is another method that improves the classification of cervical cells with the help of CNN spatial encoding, BiGRU contextual modeling, GAN-based augmentation and adaptive ATFF fusion mechanism. The multimodal feature-based learning not only captures fine-grained morphology and cell-structure dependencies, but also the GAN-generated samples in multimodal feature-based learning solve the class imbalance and promote the representational diversity. Quantitative assessments are found to be more accurate, have a higher F1-score and AUC than classical and transformer-based baselines, as ablation experiments support that the ATFF is the prevalent contributor. Analyses based on t-SNE clustering, confusion matrices, and ATFF weight visualization indicate that the separation of features, the interpretability, and the power of the analysis were strong. The error analysis also characterizes the shortcomings in respect to blur, overlap, and staining disparities to place the framework as a dependable, effective framework to automated cervical cytology screening. The suggested DiagnoFusionNet demonstrates high effectiveness when used to analyze multimodal cervical cells, but can be improved in a number of

ways. What can be added to increase feature diversity is the incorporation of other modalities, like cytoplasmic texture or nuclear morphology due to different staining methods. Semi-supervised or self-supervised learning can help decrease the reliance on annotated data and enhance generalization. Model efficiency might be optimized through pruning or knowledge distillation to deploy them using limited resources. Fusion modules based on transformers or advanced attention mechanisms would improve interpretability and diagnostic accuracy even more.

V. Conclusion and Future Work

DiagnoFusionNet works well in cervical cell and this is due to the use of CNN spatial encoding, BiGRU contextual learning, GAN-based augmentation, and ATFF-driven adaptive fusion. Experiments suggest 97.89% accuracy, 97.69% precision, 96.95% recall, 96.89% F1-score and 0.99 AUC, which is a significant improvement of classical and transformer baselines. The results of ablation also confirm the inclusion of ATFF as the key contributor to this performance increase. The metrics of GAN evaluation (FID 18.3, IS 3.91, SSIM 0.92) confirm the presence of realistic sample generation of synthetics that enhance the presence of classes and generalization. Its benefits are the ability to separate features better, visualizable with modality-weight representation, and the ability to be robust even with limited data. The research has limitations such as staining and morphology variability, class imbalance, heterogeneous feature fusion, and high computational complexity, which can compromise the classification performance, interpretability, and its application in clinical practice. The limitations include sensitivity to blur, staining noise, overlapping nuclei, and a moderate increase in the cost of computation at training. On the whole, the framework sets a consistent, reliable direction in terms of automated cervical cytology screening with clinically aligned benefits.

Future research will deal with the vulnerabilities to blur, changes in staining, and overlapping nuclei by combining stain-normalization pipelines, new deblurring networks, and instance-level segmentation. Transformer-based temporal attention, cross-dataset generalization with domain adaptation, and lightweight quantized models to deploy an edge, and further increases the robustness, lowers the computational requirements and enhances clinical applicability in a variety of screening settings can be added to enhance it.

References

[1] A. M. Wan, “Cervical Cancer Detection Techniques: A Chronological Review.” Accessed: Dec. 13, 2024. [Online]. Available: https://www.mdpi.com/2075-4418/13/10/1763

[2] K. Yadav, I. Cree, A. Field, P. Vielh, and R. Mehrotra, “Importance of cytopathologic diagnosis in early cancer diagnosis in resource-constrained countries,” JCO Global Oncology, vol. 8, p. e2100337, 2022.

[3] J. A. Dykens et al., “Evaluating the implementation of cervical cancer screening programs in low-resource settings globally: a systematized review,” Cancer Causes Control, vol. 31, no. 5, pp. 417–429, May 2020, doi: 10.1007/s10552-020-01290-4.

[4] R. Sankaranarayanan, “Cervical cancer in developing countries,” Transactions of The Royal Society of Tropical Medicine and Hygiene, vol. 96, no. 6, pp. 580–585, Dec. 2002, doi: 10.1016/S0035-9203(02)90317-2.

[5] V. Singh and L. Eslahi, “The global cervical cancer burden in 2020 and recent trends in incidence: a baseline assessment for monitoring the WHO Global Cervical Cancer Elimination Initiative
More efforts are needed to reach the WHO 2030 elimination targets.” Accessed: Dec. 10, 2024. [Online]. Available: https://www.iarc.who.int/news-events/the-global-cervical-cancer-burden-in-2020-and-recent-trends-in-incidence-a-baseline-assessment-for-monitoring-the-who-global-cervical-cancer-elimination-initiative

[6] M. Dellino et al., “Artificial intelligence in cervical cancer screening: opportunities and challenges,” AI, vol. 5, no. 4, pp. 2984–3000, 2024.

[7] G. A. Mishra, S. A. Pimple, and S. D. Gupta, “Cervical Cancer Screening in Low Resource Settings: Cytology versus HPV Triage for VIA Positive Women,” Int J Prev Med, vol. 10, p. 138, Jan. 2019, doi: 10.4103/ijpvm.ijpvm_365_18.

[8] Minmin Wang, kepei huang, and martin wong, “Global Cervical Cancer Incidence by Histological Subtype and Implications for Screening Methods | Journal of Epidemiology and Global Health.” Accessed: Dec. 10, 2024. [Online]. Available: https://link.springer.com/article/10.1007/s44197-023-00172-7

[9] S. J. Goldie, L. Kuhn, L. Denny, A. Pollack, and T. C. Wright, “Policy Analysis of Cervical Cancer Screening Strategies in Low-Resource SettingsClinical Benefits and Cost-effectiveness,” JAMA, vol. 285, no. 24, pp. 3107–3115, Jun. 2001, doi: 10.1001/jama.285.24.3107.

[10] M. L. Varon et al., “Interventions to increase follow-up of abnormal cervical cancer screening results: A systematic literature review and meta-analysis,” PLOS ONE, vol. 19, no. 2, p. e0291931, Feb. 2024, doi: 10.1371/journal.pone.0291931.

[11] R. B.Perkins, “Cervical Cancer Screening: A Review | Cervical Cancer | JAMA | JAMA Network.” Accessed: Dec. 13, 2024. [Online]. Available: https://jamanetwork.com/journals/jama/article-abstract/2807981

[12] W.-Q. He and C. Li, “Recent global burden of cervical cancer incidence and mortality, predictors, and temporal trends,” Gynecologic Oncology, vol. 163, no. 3, pp. 583–592, Dec. 2021, doi: 10.1016/j.ygyno.2021.10.075.

[13] K. Poudel, L. Poudel, P. R. Shakya, A. Poudel, A. Shrestha, and B. Khanal, “AI-Assisted Cervical Cancer Screening,” Sep. 04, 2024, arXiv: arXiv:2403.11936. doi: 10.48550/arXiv.2403.11936.

[14] T. Wu, E. Lucas, and F. Zhao, “Artificial intelligence strengthenes cervical cancer screening – present and future | Cancer Biology & Medicine.” Accessed: Dec. 10, 2024. [Online]. Available: https://www.cancerbiomed.org/content/early/2024/09/19/j.issn.2095-3941.2024.0198?utm_source=chatgpt.com

[15] T. F. Borders and A. Thaxton Wiggins, “Cervical Cancer Screening Rates Among Rural and Urban Females, From 2019 to 2022,” JAMA Network Open, vol. 7, no. 6, p. e2417094, Jun. 2024, doi: 10.1001/jamanetworkopen.2024.17094.

[16] H. A. Sarhangi, D. Beigifard, E. Farmani, and H. Bolhasani, “Deep Learning Techniques for Cervical Cancer Diagnosis based on Pathology and Colposcopy Images,” Oct. 25, 2023, arXiv: arXiv:2310.16662. doi: 10.48550/arXiv.2310.16662.

[17] D. Singh et al., “Global estimates of incidence and mortality of cervical cancer in 2020: a baseline analysis of the WHO Global Cervical Cancer Elimination Initiative,” The Lancet Global Health, vol. 11, no. 2, pp. e197–e206, Feb. 2023, doi: 10.1016/S2214-109X(22)00501-0.

[18] M. Arbyn, G. Ronco, J. Cuzick, N. Wentzensen, and P. E. Castle, “How to evaluate emerging technologies in cervical cancer screening?,” Int J Cancer, vol. 125, no. 11, pp. 2489–2496, Dec. 2009, doi: 10.1002/ijc.24774.

[19] Z. Shen et al., “Two-stage Cytopathological Image Synthesis for Augmenting Cervical Abnormality Screening,” Feb. 25, 2024, arXiv: arXiv:2402.14707. doi: 10.48550/arXiv.2402.14707.

[20] H. Li et al., “Large-scale cervical precancerous screening via AI-assisted cytology whole slide image analysis,” Jul. 28, 2024, arXiv: arXiv:2407.19512. doi: 10.48550/arXiv.2407.19512.

[21] Prahlad mehandiratta, “Cervical Cancer largest dataset (SipakMed).” Accessed: Dec. 12, 2024. [Online]. Available: https://www.kaggle.com/datasets/prahladmehandiratta/cervical-cancer-largest-dataset-sipakmed

[22] S. K and G. C, “A hybrid model for efficient cervical cell classification,” Biomedical Signal Processing and Control, vol. 72, p. 103288, Feb. 2022, doi: 10.1016/j.bspc.2021.103288.

[23] H. Basak, R. Kundu, S. Chakraborty, and N. Das, "Cervical Cytology Classification Using PCA and GWO Enhanced Deep Features Selection," SN COMPUT. SCI., vol. 2, no. 5, p. 369, Jul. 2021, doi: 10.1007/s42979-021-00741-2.

[24] R. Pramanik, M. Biswas, S. Sen, L. A. de Souza Júnior, J. P. Papa, and R. Sarkar, "A fuzzy distance-based ensemble of deep models for cervical cancer detection," Computer Methods and Programs in Biomedicine, vol. 219, p. 106776, Jun. 2022, doi: 10.1016/j.cmpb.2022.106776.

[25] M. M. Rahaman et al., "DeepCervix: A deep learning-based framework for the classification of cervical cells using hybrid deep feature fusion techniques," Computers in Biology and Medicine, vol. 136, p. 104649, Sep. 2021, doi: 10.1016/j.compbiomed.2021.104649.

Reinforcement Learning Framework for Missing Data Imputation in IoT Environments

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***Abstract*—Continuous, accurate meteorological sensing underpins many Internet of Things (IoT) applications, from smart irrigation and urban heat-island monitoring to early weather warnings, but data from distributed stations are often disrupted by sensor faults, power loss, or communication noise, causing missing values that degrade analytics and decisions. Existing data imputation methods lose accuracy on small or irregular datasets and adapt poorly to dynamic IoT settings. This study proposes a reinforcement learning (RL)-based framework for missing-data imputation that treats each gap as a sequential decision problem. The authors develop and compare three RL architectures, two Q-table methods and one Deep Q-learning model, to learn temporal dependencies and optimize imputation via experience. A second objective is to assess the feasibility and performance of RL for imputation in domains related to robotics and autonomous systems, where RL remains less explored. A third objective is to validate the methods on real-world datasets and simulations, supported by a user-friendly graphical interface for visualization and performance monitoring. The proposed RL imputers outperform state-of-the-art methods in accuracy and robustness: the best RL configuration cuts MSE/MAE by 8.6%/5.9% vs. K-Nearest Neighbors' algorithm (KNN), 74.4%/75.6% vs. autoencoder, 79.6%/79.9% vs. clustering, 89.0%/83.7% vs. mean, 89.5%/83.3% vs. median, and 94.2%/89.3% vs. most-frequent, while raising the coefficient of determination (R^2) by +0.023, +0.532, +0.123, +0.407, +0.436, and +0.932, respectively. These findings highlight RL as an effective paradigm for intelligent data restoration in IoT-based sensing systems.**

***Keywords*—Data imputation; reinforcement learning; machine learning; deep learning; Internet of Things (IoT)**

I. Introduction

Industry and academia are both deeply interested in maximizing the potential usefulness of the Internet of Things (IoT), a system that links many millions of physical devices to the Internet and, in doing so, generates unprecedented volumes of data. Embedded sensors and actuators enable such devices to sense relevant properties of their surroundings, analyze and process information locally, and exchange data with peers or cloud services, enabling coordinated autonomous decisions [1]. Advances in smart-sensor design, wireless communication, and data-aggregation technologies have made it possible to collect heterogeneous data streams from numerous different sources such as environmental probes, industrial machinery, surveillance cameras, and mobile devices [2]. Such data drives predictive models that improve reliability, efficiency, profitability, and overall performance in smart cities, industrial automation, intelligent buildings, connected vehicles, and environmental monitoring systems [3].

Despite the benefits, real-world deployment suffers from missing or corrupted observations due to sensor faults, loss of power, communication failures, long-term monitor fatigue, battery depletion, and/or poorly defined boundaries in large-scale network studies. Missing values can introduce bias, complicate statistical analysis, and degrade model accuracy. This missing value can be imputed using machine learning (ML) and deep learning (DL) algorithms.

Data imputation is defined as representing missing values in a dataset or IoT stream, which presents a number of challenges for data analysis as such values can increase the chance of introducing errors, reduce analytic accuracy, and limit the reliability of confidence intervals. Data Imputation can be done via conventional machine learning (ML) algorithms, such as hot- and cold-deck substitution, last observation carried forward, mean, multiple or regression imputation, non-negative matrix factorization, and stochastic methods, frequently reject useful data or introduce bias [4]. IoT data will often include varied forms including binary, categorical, numerical, ordinal, spatial, and temporal, with each requiring its own specialized analysis. Thus, recent research has moved toward data-driven and hybrid approaches that are better able to adapt to heterogeneous data inputs. As a result, imputation techniques may now be differentiated into two broad groups which are machine learning-based, and deep learning-based approaches.

Deep learning (DL) approaches, such as autoencoders and convolutional neural networks (CNNs), show great potential for coping with missing data [5], but often need substantial and well-organized datasets to provide reliable performance. Autoencoders provide suggestions for missing data by learning compressed, noise-tolerant versions of the data and then rebuilding the original input, predicting absent values during the decoding process. Multimodal, stacked and variational autoencoders can enhance reconstruction accuracy for many data types. CNN-based models are most effective when the data can be reformed into multi-dimensional arrays such as matrices or images, enabling the network to capture temporal or spatial relationships. This makes CNNs suitable for imputing missing values in, for example, traffic-sensor grids, medical records, or spatiotemporal datasets which enable the study of the maintenance of patterns over time and are particularly useful for environmental data.

However, three major challenges remain. First, most traditional machine learning and statistical imputation methods provide limited accuracy when applied to real-world problems, while modern DL-based approaches often require large training datasets and their performance deteriorates when only small or incomplete datasets are available. Second, although RL has been

extensively explored in robotics and autonomous systems, relatively little attention has been given to its potential in the data domain for imputing missing data, despite its successful application to autonomous decision-making. Third, to the best of the authors' knowledge, there is still no standardized workflow for simulating and deploying advanced imputation models in realistic IoT environments or on a commercial scale.

To address such challenges, the authors propose a RL-based imputation framework that makes each missing value a sequential decision-making problem. This constitutes a first contribution by explicitly formulating missing-data imputation as a sequential decision-making task. This framework develops and is evaluated via three progressively enhanced variants: 1) a baseline Q-Table, 2) an improved Q-Table Version 2 (V2) with optimized hyperparameter tuning, and 3) Deep Q-Learning (V3) that utilizes neural networks for function approximation. This systematic development enables a direct and controlled comparison between tabular and deep RL architectures, representing a second contribution of this work. These RL variants are benchmarked against the widely used imputation techniques: clustering, mean, most-frequent-value as well as DL-based approaches such as autoencoders, and ML methods such as K-Nearest Neighbors (KNN). The evaluations employ multiple performance metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2) to provide a comprehensive assessment of accuracy and reliability. This proposed RL-based approach should enhance imputation accuracy with limited data availability to maintain accuracy of real-time analytics for continuous, dynamic IoT data streams by providing more robust and scalable data.

The remainder of this study is organized as follows: Literature Review discuss the state-of-the-art in this domain and introduces the theoretical foundations of RL. Then, Methodology discusses the design and implementation of the proposed RL algorithms, including data preprocessing, missing-data synthesis, model training, and simulation. The Results and Discussion section presents and interprets the experimental outcomes compared to relevant published works. Finally, the Conclusion summarizes the key findings and suggests directions for future research.

II. Literature Review

Accurate and reliable imputation remains fundamental to downstream analytics in IoT settings where streams are heterogeneous, non-stationary, and frequently sparse (see Fig. 1). Contemporary work spans two broad families: 1) classical baselines prized for simplicity and speed, 2) deep learning (DL) models that trade higher capacity for greater data and training demands. The review below positions our chosen approach within this landscape and explains why RL is a timely alternative.

Large comparative studies consistently show that traditional ML approaches such as KNN [6], clustering [7], mean [8],[9], median, most frequent [6], and tree-based methods, such as MissForest, outperform very simple imputers. However, while clustering, mean, and most-frequent are convenient they are, typically, weaker representations of patterns often found in IoT-style datasets [8],[9]. A 2024 cohort analysis identifies KNN and Random Forest among the strongest practical baselines [9]. Similarly, a recent benchmark analysis paper evaluate the performance of common methods of missing data imputation reports that KNN and MIDAS, which is a denoising-autoencoder approach, perform best at higher rates of random data and block omissions, with substantial runtime differences between methods [6].

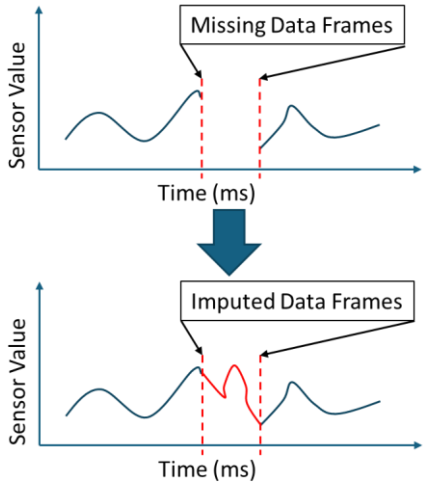


Fig. 1. Data imputation reconstructs missing segments in IoT sensor time series in real-time. The upper plot shows a typical sensor signal with a gap between two dashed lines representing missing data frames caused by sensor faults, packet loss, or power interruptions. The central block (arrow) denotes the imputation algorithm, which processes the incomplete sequence. The lower plot illustrates the imputed data frames (red curve) that reconstruct the missing segment while preserving the original temporal trend and signal continuity.

DL produces high accuracy rather than ML. One DL method, Generative Adversarial Networks (GAN)-based imputers, such as GAIN and its variants, continue to evolve to mitigate mode collapse and gradient instability [10]. A recent study introduces training refinements that improve both stability and accuracy. The clustering and classification-based generative adversarial imputation network (CC-GAIN) features enhanced couples clustering or classification with GANs to better handle multivariate settings which were successfully used in missing data imputation in an electricity consumption system [11]. There is also evidence that the generative adversarial imputation network (GAIN) in hybrid combination with convolutional neural networks (CNNs) can be used for exploiting tensorized representations to provide greater accuracy with sparse multivariate data, but with heavier computational cost and potential training instability compared to simpler baselines [12]. These works justify including DL baselines beyond autoencoders in comparisons while acknowledging their practical trade-offs.

Auto encode (AE) is also a DL method and recent research has refined denoising autoencoders (DAEs) specifically for tabular imputation. DAE for missing data imputation has been developed using a modified loss and a simple hyperparameter rule [13]. It use across multiple UCI datasets and missingness regimes has shown it to provide thorough ablations against standard baselines and rank among the top performers, making it a strong contender for use as an AE-style imputer for tables [5].

Beyond generic IoT benchmarks, DAEs have been evaluated in cases where the missingness was high (≥40%) heterogeneous biomedical datasets (with a mix of imaging, clinical, cognitive, and genetic variables), which demonstrated where DAEs excel and but also that they struggled under extreme sparsity typical of real-world IoT/health data sets [13]. Remasker, a recently developed method, extended masked autoencoding to tabular data by re-masking observed entries during training and predicting them as a self-supervised target [15]. Competitive or superior imputation fidelity/utilities across benchmarks were reported, with released code and slides clarifying design choices (simple masking strategy, strong performance as the missing ratio grew) [14]. These properties make Remasker an appropriate "modern DL" point of comparison alongside DAEs in our study.

In summary, classical machine-learning methods provide strong, efficient models that can operate at high speed. DL models offer higher-capacity imputation but come with stability and computational limitations, and they typically require substantial training data. When such data and careful training are available, DL methods achieve state-of-the-art accuracy. In contrast, RL-based imputation remains relatively under-explored, particularly for streaming IoT time-series data characterized by small sample sizes and block-missing patterns. To address this gap, we formulate missing-data imputation as a sequential decision-making problem, design an IoT-specific state-action-reward structure, and conduct a systematic comparison of tabular Q-learning and Deep Q-Learning within a unified framework. The proposed approach is evaluated using MSE, MAE, and R^2 to assess both accuracy and robustness under realistic IoT data conditions.

III. Proposed Methods

A. Overview

RL provides a learning framework through interaction: an agent repeatedly observes the current situation of the environment, chooses an action, receives a numerical response, and moves to a new situation. Over time, the agent defines and then refines a policy, a mapping from observed situations to actions taken, so that the long-term response is maximized. Two internal estimates direct this process. State-value functions provide a measure of how desirable a situation is, while action-value functions estimate the effectiveness of taking a specific action in a particular situation. Learning algorithms such as Q-learning adjust the estimates by comparing the predicted results with those observed after taking action. Modern RL combines these approaches with deep neural networks to provide deep RL, which can provide value functions and policies directly from high-dimensional data. The volatility that can arise when learning and decision-making take place simultaneously is substantially reduced by using stabilizing techniques such as experience replay, target networks, and the ε-greedy algorithm. Because RL learns directly from the interactions rather than static examples, it is well-suited to problems such as IoT data imputation, where the agent must cope online with varying streaming inputs, noisy feedback, and changing sensor conditions.

In this study, the authors develop a model that incorporates three hyperparameterized methods to enhance imputation accuracy. It integrates two variants of Q-Table-based RL and one Deep Q-RL approach. The Q-Table RL is a model-free algorithm that uses tabular representation to store and update action-state values (Q-values). These values guide the agent in selecting optimal actions within a discrete environment based on a defined reward function. Although having the benefits of being simple and interpretable, Q-Table methods are limited in scalability when the state-action space becomes large. To address this, the model includes a second stage with enhancements in exploration and value generalization. In contrast, DQL extends the traditional Q-learning paradigm by employing a deep neural network to approximate the Q-function. This enables the agent to cope with high-dimensional or continuous state spaces more effectively. Combining the three methods, this model expects to provide a more accurate and robust imputation strategy than traditional techniques.

B. Data Preprocessing and Missing Data Synthesizing

In this study, the authors divided the Air-Quality dataset (UCI ID 360) from the UCI Machine Learning Repository [15, 16] for training and testing the proposed algorithms and the baseline methods for data imputation. The selected data source is one of the most popular benchmark resources in the IoT weather domain. It contains recorded responses from a gas multisensory device that was deployed in a field in an Italian city. Hourly average sensor readings are provided together with reference gas-concentration measurements obtained from a certified analyzer. In total, the dataset comprises 9,357 hourly averaged instances collected by an array of five metal-oxide chemical sensors embedded in the air-quality multisensory device, as shown in Table I. The device was positioned at road level in a heavily polluted urban area. Data were gathered continuously for one full year, from March 2004 to February 2005, yielding the longest freely available recording of on-field air-quality chemical sensor responses. The sensing unit comprised five metal-oxide (MOX) chemical sensors, each nominally tuned to specific target gases, along with environmental measurements. The dataset includes both the raw sensor responses (PT08.S1–PT08.S5) and reference gas-concentration measurements obtained from a co-located certified analyzer. The measured and reference parameters are summarized in Table I.

The dataset was split into training and validation sets, comprising 80% of the data, and a testing set comprising the remaining 20%. The authors used this split to ensure a large amount of data for training and validation, enabling better generalization and reducing the risk of overfitting, while the remaining 20% contained representative features sufficient for reliable testing.

The data preprocessing pipeline begins by retrieving and reviewing the dataset's metadata, such as source, measurement period, and definitions of variables, followed by generating summary statistics and data-type profiles to verify completeness and to detect potential anomalies. The column providing the Date is deconstructed from the original MM/DD/YYYY string format into a suitable datetime object, enabling the earliest and latest sampling times to be recorded for temporal consistency checks. All other numerical attributes (i.e., columns after the first two identifier fields) are rescaled to the interval $[0, 1]$ using a Min-Max transformation to ensure comparable magnitudes to

accelerate model convergence. Finally, two comma-separated value (CSV) files are generated: one preserves the raw measurements as collected, and the other stores the normalized version to be supplied to the learning algorithm. This procedure ensures that downstream analysis uses a clean, temporally aligned, and scale-independent dataset but retains access to the original records for auditing.

TABLE I. DATASET DESCRIPTION [15, 16]

Attribute	Description	Unit
Date	Recording date	DD/MM/YYYY
Time	Recording time	HH.MM.SS
CO	True hourly averaged Carbon Monoxide (CO) concentration	mg/m³
PT08.S1 (Tin Oxide)	Sensor response nominally targeted to CO	arbitrary unit
NMHC	True hourly averaged Non-Methane Hydrocarbons (NMHC) concentration	µg/m³
C_6H_6	True hourly averaged Benzene (C_6H_6) concentration	µg/m³
PT08.S2 (Titania)	Sensor response nominally targeted to NMHC	arbitrary unit
NO_x	True hourly averaged Nitrogen Oxides (NO_x) concentration	ppb
PT08.S3 (Tungsten Oxide)	Sensor response nominally targeted to NO_x	arbitrary unit
NO_2	True hourly averaged Nitrogen Dioxide (NO_2) concentration	µg/m³
PT08.S4 (Tungsten Oxide)	Sensor response nominally targeted to NO_2	arbitrary unit
PT08.S5 (Indium Oxide)	Sensor response nominally targeted to Ozone (O_3)	arbitrary unit
T	Temperature (T)	°C
RH	Relative Humidity (RH)	%
AH	Absolute Humidity (AH)	g/m³

All experiments were conducted using a single missingness procedure: entries in the numeric columns were masked independently with a fixed probability of 0.2, applied separately to the training, validation, and test partitions. This masking of elements generated random gaps across the dataset, guaranteeing that missing positions varied across folds and splits in the data. Thus, model training and validation losses reflected the reconstruction of the missing values, and final test metrics quantified performance on a retained set subjected to the same masking process (see Algorithm 1). With all models evaluated consistently against this single, fixed masking strategy and under the given setting (0.2). Algorithm 1 describes the proposed procedure for synthesizing missing data at a fixed rate across training, validation, and test splits. Starting from a complete dataset, the data are first divided into training/validation and test sets. During the cross-validation phase, a fixed fraction of values is randomly masked as missing in the numeric columns of both training and validation sets using a uniform random process, ensuring consistent missingness across folds. The imputation agent is trained on the masked training data and validated against the original uncorrupted data. In the final phase, the same missingness strategy is applied to the combined training/validation set and the test set, after which the imputation model is trained and evaluated. This procedure ensures a controlled, reproducible, and unbiased evaluation of imputation performance under fixed-rate missing-data conditions.

Algorithm 1 shows the proposed missing data synthesizing via a fixed-rate missingness for train, validation and test splits.

Algorithm 1: Proposed Missing Data Synthesizing Method

```
Start Algorithm
Initialize complete dataset D
Define numeric column set C
Define missing fraction p = 0.20
Define number of CV folds k
Randomly split D into train/validation set (D_tv) and test set
(D_test) with 80 % / 20 % ratio
# Cross-validation phase
For each fold f in K-Fold(D_tv, k) do
|  Split D_tv into training set (D_train) and validation set (D_val)
for fold f
|  Create D_train_missing ← copy of D_train
|  Create D_val_missing ← copy of D_val
|  For each column c ∈ C do
|  |  For each row r in D_train_missing do
|  |  |  u ← Uniform(0, 1)
|  |  |  If u < p then
|  |  |  |  D_train_missing[r, c] ← NaN
|  |  |  End If
|  |  End For
|  |  Repeat the same masking process for D_val_missing
|  End For
|  Train imputation agent on (D_train_missing, D_train) and
validate on (D_val_missing, D_val)
End For
# Final test phase
Create D_tv_missing ← copy of D_tv
Create D_test_missing ← copy of D_test
For each column c ∈ C do
|  For each row r in D_tv_missing do
|  |  u ← Uniform(0, 1)
|  |  If u < p then
|  |  |  D_tv_missing[r, c] ← NaN
|  |  End If
|  End For
|  Repeat the same masking process for D_test_missing
End For
Train final imputation agent on (D_tv_missing, D_tv) and evaluate
on (D_test_missing, D_test)
End Algorithm
```

C. Proposed Models' Architecture

1) Reinforcement learning based on Q table: Fig. 2 contrasts the end-to-end workflows for the two generations of our reinforcement learning imputer. Version 1 (V1) begins by injecting a user-specified ratio of synthetic gaps into the training fold and then iterates column-by-column inside the dashed box the Column Imputation Agent V1 represents each decision state solely by the row index of the missing value; contextual cues such as neighboring readings remain implicit. Two baseline actions are always available to the ε-greedy

selector: the KNN fill and a feature-statistics fill (mean, median or standard-deviation offset), while the remaining actions correspond to previously learned Q-values for that index. After an action is chosen, the reward is calculated as the negative absolute error normalized by the column's standard deviation; this signal updates the Q(state, action) table and the per-epoch MSE log. Once all gaps in the train-and-validation partitions are imputed, fold-level metrics are recorded and the agent proceeds to the next column or cross-validation split, ultimately producing a single Q-table per feature that is reused to fill the held-out test set [see Fig. 2(a)].

Version 2 (V2) retains the outer train, validation, and test scaffold, but tackles three limitations observed in V1. First, it discretizes the numeric context: each previous value is binned, and the joint bin index becomes the state, dramatically shrinking and regularizing the state space. Second, it replaces the absolute-error reward with a squared-error signal and logs both training and validation MSE curves, enabling early stopping and hyper-parameter tuning. Third, ε in the ε-greedy policy decays across epochs, allowing aggressive exploration early on and more deterministic exploitation later. Internally, four Q-tables are maintained (one per context bin), each updated with the same loop of reward calculation and value iteration. During inference, the agent consults the appropriate Q-table for the discretized context of every missing cell, producing fills that are both context-aware and data-driven [see Fig. 2(b)].

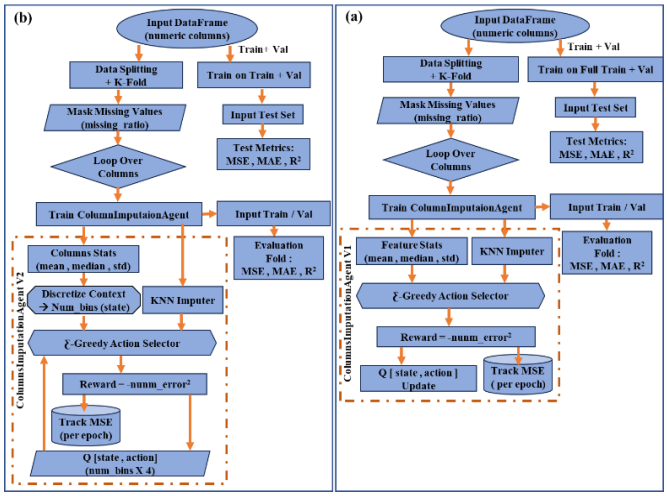


Fig. 2. The model structure of the proposed Q table methods.

2) Reinforcement learning based on deep Q: The proposed imputation framework employs a Deep Q-Learning (DQN) agent designed to learn optimal imputation strategies through interaction with an environment representing missing-value patterns. At each environment step, the agent observes a scalarized state s corresponding to the normalized position of the missing entry within a column and selects an action $a \in \{mean, median, random, knn\}$ using an ε-greedy policy. The environment then returns a reward r proportional to the negative normalized squared error between the imputed value and the ground truth. The next state s' reflects the subsequent missing entry index. This transition tuple (s, a, r, s') represents a single reinforcement learning experience used to update the DQN model. To enhance stability and sample efficiency, training is conducted using a batched replay mechanism. Transitions accumulated during interaction are stored in a replay buffer of finite capacity K. Instead of performing one update per sample, we repeatedly sample B mini-batches from the buffer and execute U stochastic gradient descent updates for each, thereby increasing the effective signal-to-noise ratio of the temporal-difference (TD) gradients. This multi-batch, multi-update schedule mitigates variance and reduces dependency on fresh data collection, an essential property when computational or data-access costs are constrained. For each sampled transition iii, a bootstrap target is computed as: $y_i = r_i + \gamma \max_{a'} Q_\theta - (s_i', a')$ where γ is the discount factor and θ^- denotes the parameters of a slowly updated target network. The online network parameters θ are optimized to minimize the mean-squared TD error: $L(\theta) = \frac{1}{B}. \sum_i (y_i - Q_\theta (s_i, a_i))^2$ using the Adam optimizer with learning rate α. Following each outer training epoch, both the exploration rate ϵ and the coefficient for target update τ decay according to defined schedules: $\theta^- \leftarrow (1-\tau)\theta^- + \tau\theta$ This ensures gradual policy refinement and stable convergence.

The Q-Network architecture (Fig. 2) is a compact three-layer feedforward model realized in PyTorch: an input normalization layer, a fully connected layer with 64 ReLU-activated neurons, and a linear output layer producing four Q-values corresponding to the available imputation actions. This lightweight design enables efficient on-device training and inference under limited memory and computation constraints. Collectively, the integration of replay memory, target-network stabilization, and multi-update training yields a robust Deep Q-Learning agent capable of acquiring context-adaptive imputation strategies for heterogeneous data distributions. The overall training pipeline, from dataset preparation and K-fold cross-validation to column-wise DQN training and test-time inference, is shown in Fig. 3.

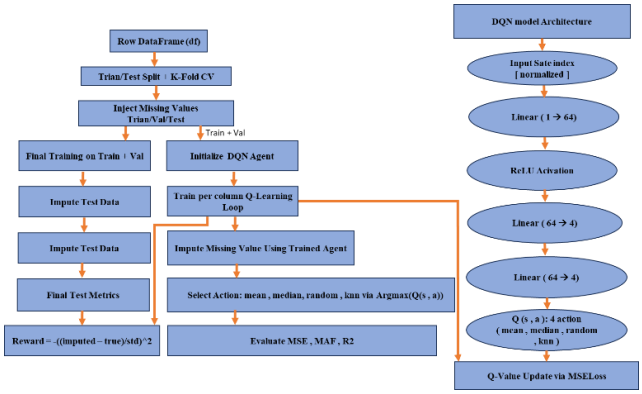


Fig. 3. The model structure of the proposed deep Q method.

3) Proposed simulation for RL environment: The authors developed an interactive grid-based simulation using the Pygame Library, to illustrate how a RL agent might traverse an air-quality dataset and impute missing values in real time (see Algorithm 2). After loading a CSV file that contains numerical features with artificially injected gaps, the data were

normalized to the [0,1] range and mapped onto a 2-D grid whose rows and columns correspond to samples and features, respectively (see Fig. 4). Each cell is 100 px square: filled observations appear in blue, missing entries in red, and their numeric contents are over-printed "NA" for clarity. The green agent starts at the upper-left corner [0,0] and can be moved by the user using the arrow keys. When the agent is positioned on a missing cell pressing the space bar triggers an "imputation action". In this demonstrator the action is a random draw from [0,1], the ground-truth value is likewise mocked, and the reward is the negative absolute error, these values are stored in a simple Q-table keyed by grid location. Although rudimentary, the framework visualizes the essential RL loop: state perception (color-coded grid), action selection (move or impute), reward feedback, and value-function update, all occurring at 30 FPS on an 800 × 600 canvas. This educational tool provides an accessible first step towards integrating and debugging more sophisticated, neural-based RL strategies for data-gap filling on edge-generated sensor streams. Algorithm 2 shows how the pseudocode outlines the full flow: loading and normalizing a dataset with missing values, drawing a color-coded grid, letting the user navigate a green "agent" with arrow keys, and pressing the space bar to impute and score missing entries. The Q-table records per-cell rewards, providing a scaffold for replacing random placeholders with a true reinforcement-learning policy at a later stage.



Fig. 4. RL Simulation for data imputation.

Algorithm 2 shows the pseudocode for Pygame RL-Style Imputation Simulator.

Algorithm 2: Pygame RL-style Imputation Simulator

```
Start Algorithm
If D contains no NaN then Raise error "dataset complete"
Normalize D to [0, 1]
rows ← number of samples in D
cols ← number of features in D
agent_pos ← [0, 0]          # row, col
Q_table ← ∅                 # (row,col) → reward
running ← True
While running do
|   Clear WINDOW with BACKGROUND_COLOUR
|   For i = 0 … rows−1 do
|   |   For j = 0 … cols−1 do
|   |   |   x ← j × CELL_SIZE; y ← i × CELL_SIZE
|   |   |   If D[i,j] is NaN then
|   |   |   |   color ← MISSING_COLOUR; label←"NA"
|   |   |   Else
|   |   |   |   color ← FILLED_COLOUR; label ←
|   |   |   |   round(D[i,j],2)
|   |   |   End If
|   |   |   Draw filled rectangle (x, y, CELL_SIZE, CELL_SIZE)
|   |   |   with color
|   |   |   Draw border rectangle with GRID_COLOUR
|   |   |   Render label in FONT_COLOUR at (x+10, y+10)
|   |   End For
|   End For
|   agent_x ← agent_pos.col × CELL_SIZE
|   agent_y ← agent_pos.row × CELL_SIZE
|   Draw rectangle (agent_x, agent_y, CELL_SIZE, CELL_SIZE)
|   in AGENT_COLOUR
|   For each EVENT in pygame.event.get() do
|   |   If EVENT.type = QUIT then
|   |   |   running ← False
|   |   Else If EVENT.type = KEYDOWN then
|   |   |   Case EVENT.key of
|   |   |   |   UP: If agent_pos.row > 0 then agent_pos.row −= 1
|   |   |   |   DOWN: If agent_pos.row < rows−1 then
|   |   |   |   agent_pos.row += 1
|   |   |   |   LEFT: If agent_pos.col > 0 then agent_pos.col −= 1
|   |   |   |   RIGHT: If agent_pos.col < cols−1 then
|   |   |   |   agent_pos.col += 1
|   |   |   |   SPACE:
|   |   |   |   |   i ← agent_pos.row; j ← agent_pos.col
|   |   |   |   |   If D[i,j] is NaN then
|   |   |   |   |   |   true_val←Uniform(0,1)   # placeholder
|   |   |   |   |   |   imput_val←Uniform(0,1)   # placeholder
|   |   |   |   |   |   D[i,j]←imput_val
|   |   |   |   |   |   reward← − |true_val − imput_val|
|   |   |   |   |   |   Q_table[(i,j)] ← reward
|   |   |   |   |   End If
|   |   |   |   End Case
|   |   End If
|   End For
|   Update WINDOW (pygame.display.flip())
|   Wait so frame-rate = 30 FPS (clock.tick(30))
End While
pygame.quit()
End Algorithm
```

IV. Results and Discussion

A. Tooling

The algorithms were developed in Python and used the Keras, Matplotlib, NumPy, Pandas, PyTorch, Scikit-learn, and TensorFlow data processing and ML libraries. Keras provides a user-friendly, high-level neural-network API compatible with both CPUs and GPUs. Matplotlib provides data visualization, allowing patterns to be displayed as charts and plots. NumPy offers a large collection of high-level mathematical functions able to support efficient operations on multi-dimensional arrays and matrices. Pandas provides data analysis and preprocessing, high-level data structures and a rich set of tools for filtering, combining, and grouping datasets before training. PyTorch is an

extensive open-source software useful for natural language processing (NLP) and computer vision. Scikit-learn provides a wide range of supervised and unsupervised ML algorithms for data mining and analysis. TensorFlow provides high-performance computation for training and operating deep-learning models.

The model was trained on the Google Colab cloud platform, which provides a shared high-performance computing (HPC) environment. The model training was carried out using two virtual CPUs, with specs Intel Xeon, family 6, model 79, clocked at 2.20 GHz with a 56,320 kB cache, alongside an NVIDIA T4 graphical processing unit (GPU) and 52 GB of random-access memory (RAM). The model inference and testing were executed on a local personal computer (PC) equipped with a 6th generation Intel Core i7 processor (2.6-2.8 GHz), an integrated Intel HD 520 GPU, 32 GB of RAM, and a 1 TB solid-state drive (SSD).

B. Data Preprocessing and Missing Data Synthesizing

In Fig. 5, the histogram of KDE shows panels depicting the empirical distributions of seven key features from the UCI Air-Quality dataset. All are gases ground truth (GT), CO(GT), NOx(GT), NO2(GT) and C6H6(GT), and all share a clear spike at -200 units that marks the dataset's built-in sentinel for missing or invalid sensor readings, and a pronounced positive skew caused by occasional pollution surges.

After removing the -200 flags, CO shows a very narrow peak while NOx displays a long right tail extending beyond 1 000 µg m⁻³, whereas NO2 peaks much more narrowly around 140 µg m⁻³. Benzene (C6H6) shows a compact distribution around 7 µg m⁻³ with a slight positive skew but virtually no extreme outliers, reflecting the lower variability of this volatile organic compound. In contrast, the meteorological variables exhibit near-Gaussian behavior once the sentinel values are discounted: temperature (T) clusters tightly between 15 °C and 30 °C, relative humidity (RH) is centered near 70 %, and absolute humidity (AH) forms an even tighter bell around 0.035 kg m⁻³. These contrasting shapes emphasize why a one-size-fits-all imputation rule is inadequate: heavy-tailed, zero-inflated gas measurements demand context-aware reconstruction, whereas smoother climatic variables can tolerate simpler statistical fillers.

Fig. 6 presents the pair-wise relationships among the five metal-oxide sensor channels embedded in the Air-Quality monitoring unit for CO, NMHC, NOx, NO2 and O3. Each panel shows a plot of one sensor's raw resistance (in ADC counts) against each of the others, revealing several instructive patterns. First, the tight, positively sloped clouds produced by linking PT08.S1(CO) with PT08.S2(NMHC) and PT08.S4(NO_2) indicate strong cross-sensitivities: when the CO sensor peaks, the NMHC and NO_2 channels rise almost proportionally, a hallmark of overlapping gas responses in metal-oxide arrays. Second, PT08.S3(NOx) behaves quite differently; its relationships with the other four channels produce a downward-curving trajectory, signifying an inverse, non-linear dependence due to its specific redox reaction mechanism. Third, every scatter plot contains a dense cluster at the origin, corresponding to the dataset's sentinel value (-200 ADC), which flags missing or invalid readings; because these artefacts sit far from the genuine signal manifold, any imputation model must avoid naively averaging across them. Finally, the diagonal panels showing lines remind us that each sensor reading is highly self-correlated, providing an upper bound for imputation accuracy.

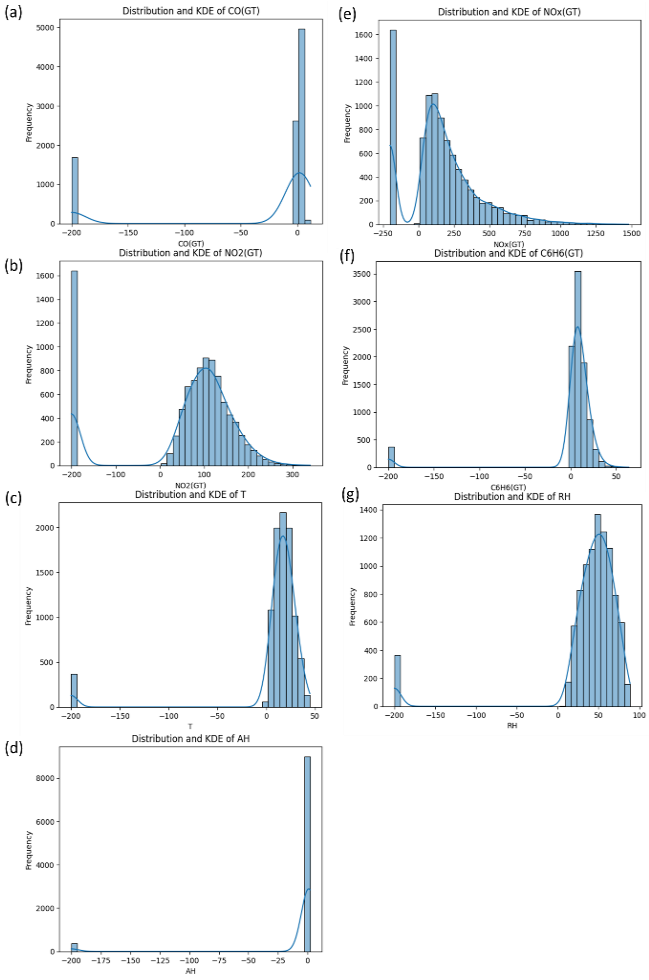


Fig. 5. Distributions and kernel density estimates of the selected Air Quality features: (a) CO(GT), (b) NOx(GT), (c) NO2(GT), (d) C6H6(GT), (e) temperature (T), (f) relative humidity (RH), and (g) absolute humidity (AH). The spike at -200 denotes the sensor-defined missing-value indicator, while the skewed shapes and long right tails, particularly for gaseous pollutants, reflect episodic concentration spikes and heterogeneous data characteristics.

PT08.S5 (Indium-oxide, nominally O_3) exhibits curvilinear, mostly inverse relationships with PT08.S3(NOx) and PT08.S4(NO_2), consistent with oxidizing reducing cross-sensitivities typical of metal-oxide sensor arrays. Its scatter plots with PT08.S1(CO) and PT08.S2(NMHC) appear weaker and more dispersed, indicating lower direct coupling and stronger modulation by environmental covariates such as temperature (T), relative humidity (RH), and absolute humidity (AH). The same -200 ADC sentinel cluster is also visible for PT08.S5 and must be masked prior to training or imputation to prevent distortion of the learned data manifold. For imputation tasks, PT08.S5 benefits particularly from non-linear models that can exploit its monotonic segments with NOx and NO_2 while conditioning on meteorological parameters, rather than relying on simple linear correlations.

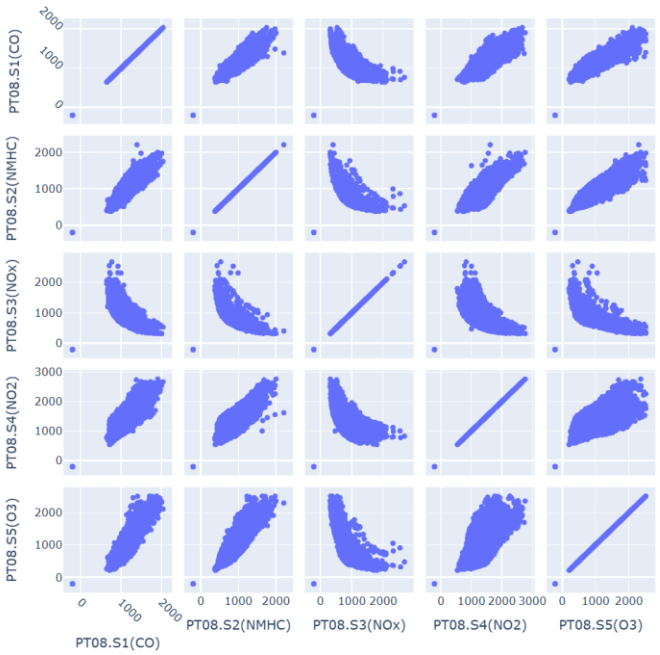


Fig. 6. Pairwise scatter-matrix of the five metal-oxide sensor channels (PT08.S1–S5). Blue dots represent valid observations.

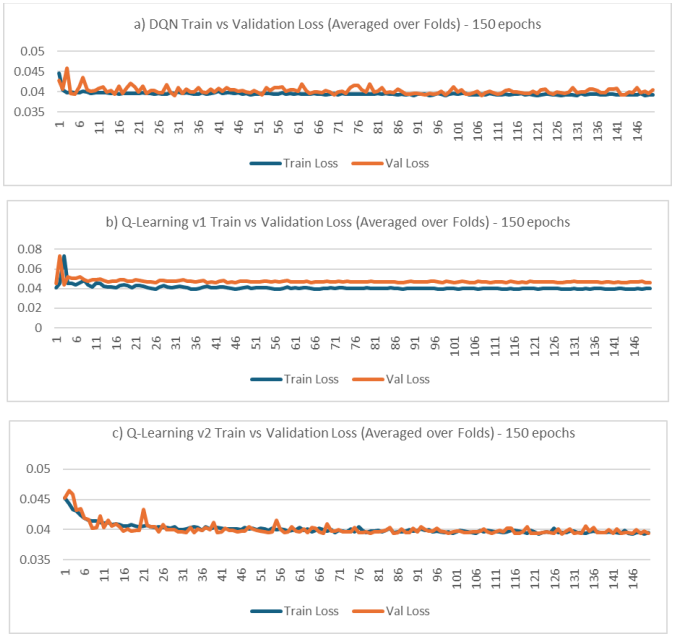


Fig. 7. Training vs. validation loss (averaged over folds) across 150 epochs for the proposed RL-based imputers: (a) Deep Q-Network (DQN), (b) Q-Learning v1, and (c) Q-Learning v2.

Third, every scatterplot contains a dense cluster at the origin, corresponding to the dataset's sentinel value (-200 ADC), which flags missing or invalid readings; because these artefacts sit far from the genuine signal manifold, any imputation model must avoid naively averaging across them. Finally, the diagonal panels showing lines remind us that each sensor reading is highly self-correlated, providing an upper bound for imputation accuracy.

C. Models Training and Validation

Fig. 7 presents the relative training–validation loss dynamics of the three RL approaches over 150 epochs (averaged across folds). In Fig. 7(a), the DQN model exhibits low overall loss values, with training and validation curves tracking closely after an initial period of fluctuations. The validation loss shows more pronounced oscillations than the training loss but without a continuing divergence, suggesting stable learning with only mild noise-induced variance on unseen data. Fig. 7(b) presents Q-Learning V1, where, after an initial period of relatively few epochs, the training loss steadily decreases towards an MSE value of 0.040 while the validation loss remains consistently higher at an MSE value of about 0.045. This persistent difference implies a degree of overfitting, where the learned policy better fits the training environment than unseen samples. In Fig. 7(c), Q-Learning V2 achieves very close alignment between training and validation losses after an initial decrease in value. Both curves stabilize at an MSE value between 0.039 and 0.040 with minimal oscillation, indicating strong generalization and absence of significant overfitting. Overall, these trends demonstrate that while all three models converge to low loss values, Q-Learning V2 maintaining the most consistent train–validation alignment, DQN follows closely with small validation variance, and Q-Learning V1 demonstrates a modest but persistent generalization gap.

Table II shows the comparison between the proposed algorithms and the state-of-the-art methods. In particular, Training length has different effects on the three RL approaches. For QL Version 1 (V1), extending training from 10 to 150 epochs steadily lowers the mean-squared error from 0.0098 to 0.0092, and raises R^2 from 0.7655 to 0.7772, with only a slight improvement in mean-absolute error from 0.0269 to 0.0204. After about 50 epochs, gains taper off, indicating a performance plateau. QL Version 2 (V2) behaves differently. At 10-epochs this model reaches its lowest MSE value (0.00785) and the highest R^2 (0.8041). Further training slightly worsens both metrics, suggesting mild over-fitting once the dominant patterns have been captured. DQL peaks at 50 epochs with an MSE of 0.0074, R^2 of 0.8053, and MAE of 0.0225, after which there is a modest decline at 150 epochs, indicating stability with some over-fitting. Comparing the RL models reveals a trade-off: V2 and DQN achieve lower MSE and stronger R^2, with better suppression of extreme deviations, but at the cost of a higher MAE. On the other hand, V1 delivers more uniform point-wise accuracy. Classical baselines can offer useful reference points and we see KNN provides a balanced but unremarkable performance (MSE = 0.0081, R^2 = 0.7822), whereas clustering and autoencoder underperform markedly, and the simplest imputations (mean, median, most-frequent) produce large errors with poor R^2, confirming their unsuitability for continuous environmental streams.

Considering all three metrics: QL V1 at 150 epochs offers the best balance, with the smallest MAE, a respectable MSE, and solid R^2; QL V2 at 10 epochs excels at limiting outliers shown in its superior MSE; and DQN at 50 epochs combines strong R^2 with low error and minimal over-fitting. Among non-RL methods, only KNN approaches RL-level performance but fails to surpass it. Consequently, the authors propose the use of RL agents, especially V1-150 for consistent accuracy, V2-10 for

outlier suppression, and DQN-50 for balanced generalization, as the most practical solutions for real-time IoT imputation, delivering strong accuracy without prohibitive training demands on edge hardware.

This early optimum of Q-Table V2 can be attributed to its internal architectural modifications compared with V1. As detailed in Fig. 2(b) (Section III), V2 discretizes the numeric context into bins, reducing the size of the state-action space and allowing the agent to learn stable Q-values within very few epochs. It also employs a squared-error reward function instead of the normalized absolute-error reward used in V1. This squared-error formulation amplifies large deviations during the initial learning phase, enabling rapid minimization of MSE but also increasing the likelihood of mild over-adjustment once the major error patterns have been corrected. Further, V2 produces a decay in the exploration rate (ε) within the ε-greedy policy with an increase in the number of epochs, which encourages broad exploration during the first few epochs but quickly transitions to exploitation. Once the policy stabilizes, subsequent updates contribute little additional improvement and can even marginally degrade test performance, reflecting controlled over-specialization rather than instability.

In contrast, V1 relies on a continuous state representation and a fixed ε, which promotes slower but steadier convergence and greater resilience to over-fitting. Consequently, V1 benefits from extended training up to 150 epochs, progressively refining its policy and reducing MAE without significant loss in generalization. The different convergence behaviors of V1 and V2 stem directly from their design philosophies; V2 prioritizes fast convergence and computational efficiency, making it suitable for lightweight IoT or edge deployments, whereas V1 favors gradual learning and robust generalization over longer training cycles.

These findings confirm that the observed peak performance of V2 at 10 epochs is a result of its architecture rather than an anomaly. The early convergence and subsequent plateau reflect the intended trade-off between rapid policy stabilization and marginal over-fitting within a highly compact state space.

The behavior of the Deep-Q Network (DQN) supports the interpretation that the number of training epochs interacts with model capacity. Unlike the tabular versions, DQN uses a neural function approximator to estimate Q-values, enabling smoother generalization across unseen states but introducing a higher sensitivity to over-training. At around 50 epochs, the network reaches an optimal balance between exploration and convergence, achieving the lowest MSE (0.0074) and highest R^2 (0.8053) while maintaining a relatively low MAE (0.0225). Beyond 50 epochs, continued training leads to a slight degradation in performance until, at 150 epochs, we have MSE = 0.0084 and R^2 = 0.7855, primarily due to over-fitting of the Q-value function and reduced stochastic exploration as the policy becomes deterministic. Thus, 50 epochs with this model represent the point of maximum generalization; the network has learned sufficient value structure to minimize prediction error without memorizing the training trajectories. This pattern is consistent with typical DQN behavior, where moderate training durations combined with early stopping yield the most stable convergence of the value function and the best trade-off between bias and variance.

TABLE II. COMPARISON BETWEEN THE PROPOSED AND STATE-OF-THE-ART METHODS

Method	Epochs	MSE	MAE	R^2
Proposed Q Table V1	10	0.0098	0.0207	0.7655
Proposed Q Table V1	50	0.0098	0.0209	0.7693
Proposed Q Table V1	150	**0.0092**	**0.0204**	**0.7772**
Proposed Q Table V2	10	**0.0078**	**0.0228**	**0.8041**
Proposed Q Table V2	50	0.0084	0.0227	0.7883
Proposed Q Table V2	150	0.0081	0.0231	0.8014
Proposed Deep Q	10	0.0077	0.0237	0.7805
Proposed Deep Q	50	**0.0074**	**0.0225**	**0.8053**
Proposed Deep Q	150	0.0084	0.0234	0.7855
Autoencoder [13]	-	0.0289	0.0923	0.2738
KNN [6]	-	0.0081	0.0239	0.7822
Clustering [7]	-	0.0362	0.1119	0.6828
Mean [9]	-	0.0675	0.1379	0.3987
Most Frequent [6]	-	0.1286	0.2095	-0.1271
Median [9]	-	0.0708	0.1350	0.3688

Across all methods, the Deep-Q model at 50 epochs delivers the best MSE (0.0074) and highest R^2 (0.8053), while the strongest classical baseline KNN has an MSE = 0.0081 and R^2 = 0.7822. This represents a ~9% reduction in MSE and a +2.31 percentage-point increase in R^2. For MAE, the best performer is Q-Table V1 at 150 epochs (0.0204), improving on KNN (0.0239) by ~14.5%. All RL variants clearly outperform the simple statistical baselines and the tested Autoencoder, which lags substantially on all metrics.

If the application prioritizes calibration and variance-sensitive fidelity, such as forecasting or anomaly scoring downstream, Deep-Q-50 epochs are the best choice (lowest MSE, highest R^2). If robustness to outliers and absolute deviation matter more, such as thresholding deviations for alerts, Q-Table V1 150 epochs is preferable (best MAE, ~9.3% lower than Deep-Q-50). Q-Table V2 offers a middle ground with near-Deep-Q R^2 but slightly weaker MAE, which might be attractive when a simpler function approximation is desired.

The loss curves in Fig. 7 show rapid early convergence followed by small, stable train-validation gaps for all three RL variants, except for V2, where the curve stabilizes early due to fast policy saturation within the discretized state space, indicating controlled capacity and limited over-fitting. Deep-Q shows optimum values for each of MAE, MSE, and R^2 at 50 epochs rather than 150, suggesting that light early stopping or entropy/exploration annealing could further stabilize performance. For the Q-Table models, longer horizons consistently help MAE, supporting the view that policy refinement through continued exploration benefits absolute-error minimization.

D. Simulation

Fig. 8 presents successive frames from the Pygame-based simulation visualizer, illustrating a single decision cycle of the RL imputation agent. In the first frame [Fig. 8(a)], the agent (green square) is positioned next to a red "NA" cell representing a missing value, while previously imputed entries appear in blue with normalized magnitudes. Upon user action, the agent imputes a value of 0.66 and receives a small negative reward [Fig. 8(b)], reflecting a near-match to the hidden ground truth (0.65). In the subsequent frame [Fig. 8(c)], the imputed cell turns blue, confirming state update and storage in the replay buffer. This visual transition highlights real-time gap resolution and online learning, as rewards are logged to refine future actions, with repeated cycles progressively filling the grid and quantifying imputation accuracy interactively.

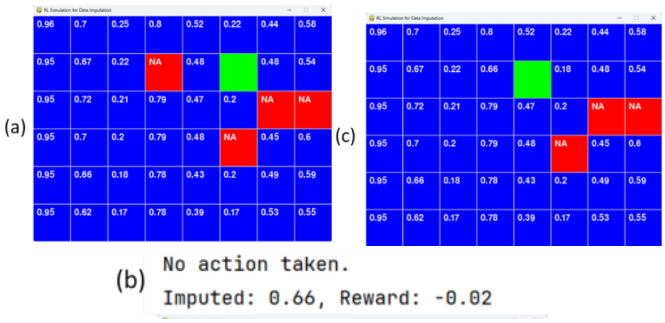


Fig. 8. Consecutive frames from the Pygame imputation simulator. The agent (green) selects an action on a red "NA" cell, where its ground truth was 0.65, fills it with the determined value (here 0.66), receives a small negative reward (-0.02), and updates the grid, which turns the cell blue to indicate imputation.

V. Conclusion and Future Work

This work addressed the continuing problem of missing values in edge-collected meteorological data streams in an IoT environment, caused by sensor faults, power interruptions, and communication noise, which degrade downstream analytics and time-critical decision support. To address this challenge, the authors have developed a lightweight reinforcement-learning imputation framework that formulates each gap as a sequential decision problem, learns directly from sparsely populated streams by utilizing cross-sensor temporal correlations, executes within the compute and energy envelopes of embedded IoT nodes, and is integrated with an interactive visual simulator implemented in Pygame. Beyond reporting performance gains, this work demonstrates that modeling missing-data imputation as a sequential decision-making process constitutes a general and effective paradigm for IoT data restoration, rather than a purely static prediction task. Empirically, the RL approach yields consistent gains under both block-missing and random-missing regimes: relative to non-RL baselines, the best configuration delivers 8.6 to 94.2% lower MSE and 5.9 to 89.3% lower MAE, while lifting R^2 by +0.023 to +0.932; even against the strongest baseline (KNN), it achieves 8.6%/5.9% error reductions with +0.023 R^2, underscoring robustness rather than overfitting. These results support the overarching contribution that sequential, policy-driven imputation can better adapt to dynamic and data-scarce IoT settings than other methods. This simulator allows real-time visualization of the agent's decision-making process, each state, action, and reward, facilitating rapid prototyping, policy debugging, and latency profiling during development. Future work will incorporate uncertainty-aware imputation, explore transfer and meta-learning for data-scarce stations, and optimize energy-efficient on-device adaptation, while hardening the edge stack through embedded profiling, model compression, and physics-informed simulator enhancements.

References

[1] I. Ficili, M. Giacobbe, G. Tricomi, and A. Puliafito, "From Sensors to Data Intelligence: Leveraging IoT, Cloud, and Edge Computing with AI," Sensors, vol. 25, no. 2025.

[2] A. Choudhary, "Internet of Things: a comprehensive overview, architectures, applications, simulation tools, challenges and future directions," Discover Internet of Things, vol. 4, no. 1, p. 31, 2024.

[3] A. Dauda, O. Flauzac, and F. Nolot, "A Survey on IoT Application Architectures," Sensors, vol. 24, no. 16, pp. 5320, 2024.

[4] S. Jäger, A. Allhorn, and F. Bießmann, "A Benchmark for Data Imputation Methods", Frontiers in Big Data, Original Research vol.4, 2021.

[5] M. Liu et al., "Handling missing values in healthcare data: A systematic review of deep learning-based imputation techniques," Artificial Intelligence in Medicine, vol. 142, p. 102587, 2023.

[6] P. Prakash, K. Street, S. Narayanan, B. A. Fernandez, Y. Shen, and C. Shu, "Benchmarking Machine Learning Missing Data Imputation Methods in Large-Scale Mental Health Survey Databases," medRxiv, 2024.

[7] C.-H. Cheng and S.-F. Huang, "A novel clustering-based purity and distance imputation for handling medical data with missing values," Soft Computing, vol. 25, no. 17, pp. 11781-11801, 2021.

[8] L. O. Joel, W. Doorsamy, and B. S. Paul, "A comparative study of imputation techniques for missing values in healthcare diagnostic datasets" Int Jou of Data Science and Analytics, vol.20, no.7, pp.6357-6373, 2025.

[9] J. Li et al., "Comparison of the effects of imputation methods for missing data in predictive modelling of cohort study datasets," (in eng), BMC Med Res Methodol, vol. 24, no. 1, p. 41, Feb 16 2024.

[10] X. Qin and et al. "Improved generative adversarial imputation networks for missing data," Applied Intelligence, vol. 54, no. 21, pp. 11068-11082, 2024.

[11] J. Hwang and D. Suh, "CC-GAIN: Clustering and classification-based generative adversarial imputation network for missing electricity consumption data imputation," Expert Systems with Applications, vol.255, p.124507, 2024.

[12] L. Zhang and et al. "Generative Adversarial Networks for Imputing Sparse Learning Performance," in Pattern Recognition, Cham, A. Antonacopoulos, S. Chaudhuri, R. Chellappa, C.-L. Liu, S. Bhattacharya, and U. Pal, Eds., 2025: Springer, pp. 381-396.

[13] N. T. Haridas, J. M. Sanchez-Bornot, P. L. McClean, and K. Wong-Lin, "Autoencoder imputation of missing heterogeneous data for Alzheimer's disease classification," (in eng), Healthc Technol Lett, vol. 11, no. 6, pp. 452-460, 2024.

[14] T. Du, L. Melis, and T. Wang, "Remasker: Imputing tabular data with masked autoencoding," presented at the International Conference on Learning Representations, Vienna, Austria, 2024, 2024

[15] S. Vito. Air quality, UCI Machine Learning Repository, 2008

[16] S. De Vito and et al., "On field calibration of an electronic nose for benzene estimation in an urban pollution monitoring scenario," Sensors and Actuators B: Chemical, vol. 129, no. 2, pp. 750-7

Hierarchical Swin Transformer Encoder-Decoder Architecture for Robust Cerebrovascular Abnormality Segmentation in Multimodal MRI

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***Abstract*—This study presents a hierarchical Swin Transformer–based framework for automated segmentation of cerebrovascular structures using multimodal magnetic resonance imaging. The proposed architecture integrates patch partitioning, linear embedding, hierarchical windowed self-attention, and a multilevel encoder–decoder design to address the inherent challenges of vascular segmentation, including irregular morphology, small-caliber vessel visibility, and intensity variability across MRI modalities. A multimodal fusion module enhances the ability to capture complementary anatomical and vascular information, while skip-connected decoding ensures the preservation of fine-grained spatial features essential for accurate vessel reconstruction. The model was evaluated using a combination of open-access datasets and demonstrated superior performance across multiple quantitative metrics, achieving higher Dice similarity, precision, sensitivity, and specificity compared to existing state-of-the-art methods. Qualitative analysis further revealed accurate recovery of major arterial pathways, distal branches, and complex vascular topologies, confirming the model's robustness in both global and localized segmentation tasks. The results highlight the discriminative strength of hierarchical attention mechanisms and emphasize their role in improving cerebrovascular characterization. Overall, the proposed framework offers a reliable and anatomically coherent approach for vascular segmentation, with strong potential for integration into clinical neuroimaging workflows and advanced cerebrovascular research applications.**

Keywords*—*Cerebrovascular segmentation; Swin Transformer; multimodal MRI; deep learning; vascular imaging; hierarchical attention; encoder–decoder architecture; medical image analysis

I. Introduction

Cerebrovascular pathologies, including aneurysms, arteriovenous malformations, and ischemic lesions, remain a leading cause of morbidity and mortality worldwide, demanding fast and highly accurate diagnostic strategies [1]. Magnetic resonance imaging (MRI) offers unparalleled soft-tissue contrast, enabling clinicians to visualize subtle vascular abnormalities across multiple modalities such as T1-weighted, T2-weighted, FLAIR, and TOF-MRA sequences [2]. Despite these advantages, manual delineation of cerebrovascular lesions is labor-intensive, prone to inter-observer variability, and often inconsistent across institutions, which underscores the necessity for automated and reliable segmentation frameworks [3]. Deep learning has emerged as a powerful paradigm capable of capturing complex spatial representations directly from MRI data, yet conventional CNN-based models frequently struggle with long-range dependency modeling and multi-scale contextual reasoning required in vascular structure segmentation [4].

Transformer-based architectures have recently demonstrated remarkable performance across numerous vision tasks due to their capacity to extract global contextual relationships via self-attention mechanisms [5]. The Swin Transformer, in particular, introduces a hierarchical windowed attention mechanism that drastically reduces computational overhead while preserving fine-grained contextual detail [6]. This makes it an attractive backbone for medical image segmentation where both global structure and local anatomical fidelity must be maintained. However, most existing transformer-based segmentation models rely on single-modality inputs, limiting their ability to integrate complementary features available in multimodal MRI [7].

Multimodal integration has shown the potential to enhance lesion characterization by capturing heterogeneous tissue signatures that are not evident in individual sequences [8]. Nevertheless, fusing cross-modality features while preserving structural coherence remains a significant challenge for existing encoder–decoder frameworks [9]. Hierarchical designs, particularly in transformer-based architectures, offer a structured approach to progressive feature aggregation, enabling deeper layers to encode semantically rich patterns while retaining the spatial precision of earlier stages [10].

In this work, we propose a Hierarchical Swin Transformer Encoder–Decoder Architecture for Robust Cerebrovascular Abnormality Segmentation in Multimodal MRI, a novel model that leverages multi-level self-attention, patch embedding, and skip-connected decoding to achieve high-fidelity segmentation performance. The proposed system integrates multimodal MRI streams, reconstructs vascular structures with enhanced accuracy, and mitigates common challenges such as lesion heterogeneity, anatomical ambiguity, and scale variation [11]. Our experimental results demonstrate substantial

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improvements over state-of-the-art baselines, validating the robustness and clinical promise of the proposed framework.

II. Problem Statement

Cerebrovascular abnormalities represent a diverse spectrum of structural disorders that significantly impact cerebral hemodynamics and tissue viability. As illustrated in Fig. 1, these pathologies include aneurysms prone to rupture, arteriovenous malformations (AVMs) characterized by abnormal arterial–venous shunting, dural arteriovenous fistulas (DAVFs) involving reversed venous drainage pathways, and cerebral cavernous malformations (CCMs) with fragile dilated capillaries. Each pathological entity alters the normal distribution of arterial, venous, and lymphatic networks, creating complex morphological signatures that must be accurately delineated for clinical assessment. Despite the rich visualization provided by multimodal MRI, the intrinsic variability in lesion size, geometry, signal intensity, and anatomical location presents substantial challenges for automated segmentation systems. These difficulties are further compounded by overlapping tissue boundaries, heterogeneous vascular topologies, and partial-volume effects arising from limited spatial resolution, leading to unreliable or inconsistent segmentation outputs.

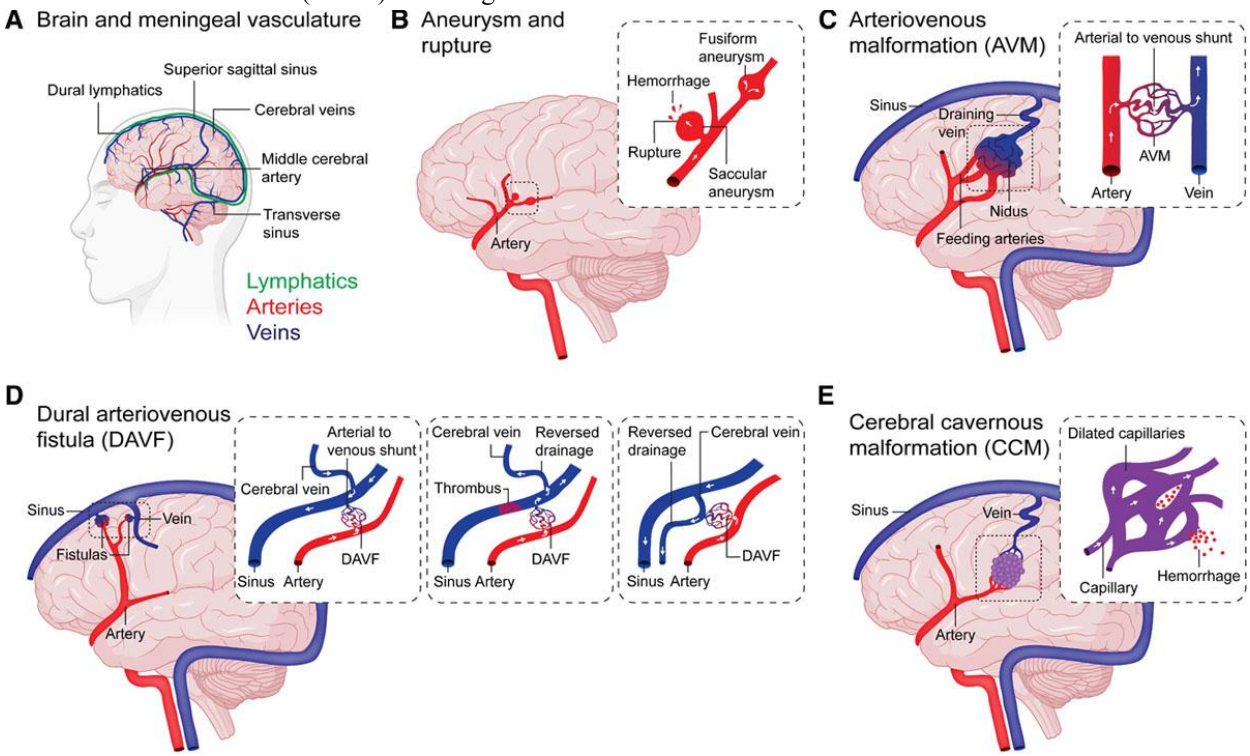


Fig. 1. Overview of major cerebrovascular abnormalities and their vascular characteristics, including aneurysms, arteriovenous malformations, dural arteriovenous fistulas, and cerebral cavernous malformations.

Accurate segmentation of cerebrovascular abnormalities can be formally described as a voxel-wise classification problem over a 3D MRI volume $X \in R^{H\times W\times D\times M}$, where H, W, D denote spatial dimensions and M represents the number of MRI modalities. The objective is to generate a segmentation map:

$$S = f_\theta(X) \in \{0,1,\ldots,K\}^{H\times W\times D}, \quad (1)$$

where, K is the number of vascular pathology classes and θ denotes the learnable parameters of the segmentation model. Because cerebrovascular lesions often occupy extremely small spatial regions relative to the brain volume, significant class imbalance arises. This imbalance can be expressed by the skewed distribution:

$$p(y=k) << p(y=0), \quad k \in \{1,\ldots,K\}, \quad (2)$$

where, class y=0 corresponds to healthy tissue and classes y=k correspond to abnormalities.

The segmentation challenge is further influenced by lesion variability, which can be formulated as high intra-class variance:

$$Var(X \mid y=k)\ is\ large, \quad (3)$$

and low inter-class separability:

$$Dist(X \mid y=i, X \mid y=j)\ is\ small\ for\ i \neq j, \quad (4)$$

Such conditions hinder the ability of standard models to learn robust feature representations without explicit mechanisms for multi-scale reasoning and long-range contextual aggregation.

Therefore, the central problem addressed in this study is to design an advanced, hierarchical segmentation architecture capable of accurately modeling the complex spatial patterns of

cerebrovascular abnormalities across multimodal MRI, mitigating class imbalance, enhancing inter-class separability, and preserving fine-grained vascular morphology for reliable clinical decision support.

III. Related Works

A. Deep Learning for Cerebrovascular Lesion Segmentation

The emergence of deep learning has significantly advanced automated segmentation of cerebrovascular abnormalities, providing a level of precision unattainable through conventional image-processing techniques. Early convolutional neural network (CNN) architectures [12] demonstrated the ability to capture localized vascular features but were limited by their constrained receptive fields and inability to model long-range contextual dependencies essential for distinguishing subtle lesion boundaries. Subsequent modifications incorporated multi-scale features and encoder–decoder designs, improving performance in identifying aneurysms and vascular malformations across heterogeneous MRI datasets [13]. Moreover, enhancements such as residual learning and dense connectivity increased robustness to anatomical variations and noise artifacts present in real-world clinical imaging [14]. Despite these advancements, CNN-based frameworks continue to struggle with small-object segmentation, particularly in cases where cerebrovascular structures exhibit significant morphological variability [15]. The integration of multi-modality MRI inputs has also been investigated, with evidence indicating that complementary contrast information enhances lesion detectability [16]. Nevertheless, aligning feature distributions across modalities remains challenging due to heterogeneous intensity characteristics [17]. Recent works emphasize the need for architectures that integrate global reasoning with fine-grained spatial detail to overcome limitations imposed by purely convolutional approaches [18].

B. Transformer-based Methods for Cerebrovascular Lesion Segmentation

Transformers have recently emerged as a powerful alternative to convolutional models in medical imaging, driven by their ability to capture long-range dependencies through self-attention mechanisms [19]. Vision Transformer (ViT) variants introduced patch-based tokenization strategies, enabling global feature extraction but suffering from data inefficiency and high computational demands [20]. To mitigate these constraints, hierarchical transformer architectures such as the Swin Transformer were developed, leveraging window-based attention and multi-level representations to balance computational complexity and accuracy [21]. Medical segmentation studies employing transformer-based backbones report substantial improvements in detecting fine vascular structures, especially when lesions appear in anatomically complex regions [22]. Several hybrid CNN-transformer designs have also been proposed, aiming to combine the locality strengths of convolutions with the contextual expressiveness of attention mechanisms [23]. Although promising, these hybrid models often face difficulties in maintaining consistent feature hierarchies during cross-scale fusion [24]. Recent literature highlights that hierarchical attention schemes better preserve structural continuity in high-resolution MRI data, particularly in tasks involving abnormal vascular networks [25]. Nevertheless, most existing transformer-based methods remain single-modality and thus fail to leverage the full diagnostic spectrum offered by multimodal MRI inputs [26].

C. Multimodal MRI Fusion and Advanced Encoder–Decoder Frameworks

Multimodal fusion has become increasingly important in cerebrovascular lesion analysis, as different MRI sequences provide complementary physiological and structural information. Studies demonstrate that integrating T1, T2, FLAIR, and MRA data improves sensitivity to lesions exhibiting heterogeneous visual characteristics [27]. Traditional fusion methods rely on simple concatenation or handcrafted feature integration, but these approaches typically fail to model complex inter-modality interactions [28]. More advanced methods utilize attention-based fusion modules capable of adaptively weighting modality-specific contributions during feature extraction [29]. Despite these improvements, multimodal fusion remains susceptible to misalignment and inconsistent spatial coherence across modalities [30]. Encoder–decoder architectures, including variants of U-Net and its derivatives, have been widely used to address these issues due to their ability to incorporate multi-level skip connections that preserve spatial granularity [31]. Refinements such as deep supervision and cascaded decoding further enhance segmentation quality by enforcing semantic consistency at multiple scales [32]. However, these architectures continue to face challenges when applied to small, irregular vascular lesions, where boundaries are often blurred or partially occluded [33]. Transformer-driven encoder–decoder frameworks have recently been proposed, offering improved cross-scale representation learning and enabling more effective reconstruction of complex cerebrovascular geometries [34]. Nonetheless, existing solutions still lack sufficiently adaptive hierarchical mechanisms for robust multimodal integration, motivating further research into architectures that explicitly model both global and local vascular signatures [35].

IV. Materials and Methods

The proposed system follows a structured multi-stage processing pipeline designed to achieve robust and anatomically coherent cerebrovascular abnormality segmentation from multimodal MRI data. The workflow begins with multimodal MRI preprocessing, where input scans undergo alignment, noise suppression, intensity normalization, and skull stripping to establish a unified representation across imaging modalities (see Fig. 2). Following this, a patch embedding module partitions the MRI volume into fixed-size patches and transforms them into high-dimensional tokens suitable for hierarchical transformer-based processing. Parallel to this, the system performs region-of-interest (ROI) localization to emphasize areas containing vascular structures and potential abnormalities [36]. These spatially refined features are then fed into the multimodal fusion module, which integrates complementary information across modalities through adaptive weighting and cross-channel interactions, thereby enhancing the representation of subtle vascular patterns.

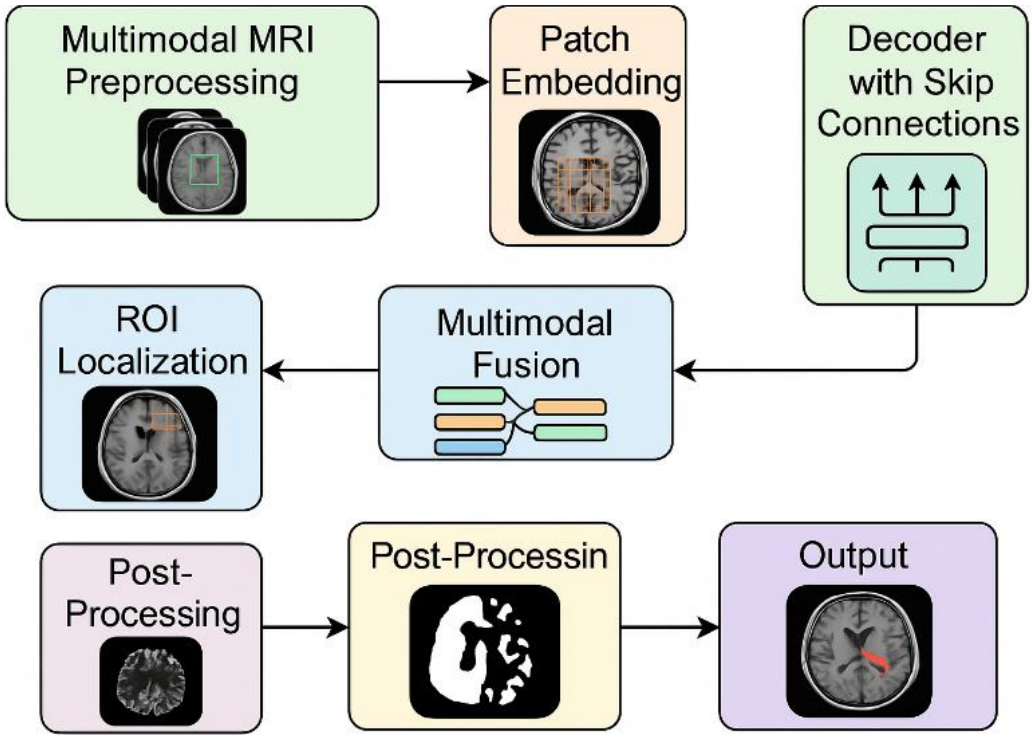


Fig. 2. The workflow of the proposed system.

Subsequently, the fused features propagate into the decoder with skip connections, enabling efficient reconstruction of fine-grained anatomical details by leveraging multi-level encoder outputs. The decoder progressively upsamples and refines the feature maps to generate a coherent segmentation prediction. Before final output generation, the system applies a post-processing stage that removes false positives, corrects small discontinuities, and ensures morphological consistency of the segmented vascular structures. The final output provides a high-resolution segmentation mask overlaid on the original MRI, offering a clinically interpretable visualization of the detected cerebrovascular abnormalities. This end-to-end framework capitalizes on multimodal contextual information, hierarchical attention mechanisms, and spatial refinement techniques to deliver accurate and reliable segmentation results suitable for advanced neuroimaging analysis.

The proposed segmentation architecture adopts a hierarchical Swin Transformer–based encoder–decoder design optimized for capturing both fine-grained vascular details and long-range contextual dependencies in multimodal MRI volumes (see Fig. 3). Let the input image be denoted as $X \in R^{H\times W\times 3}$, representing a three-channel multimodal MRI slice. The encoder first applies a patch partitioning operation that divides the input into non-overlapping patches of size $P\times P$, yielding:

$$X_p = \{x_1, x_2, ..., x_N\}, \quad N = \frac{HW}{P^2}, \tag{4}$$

Each patch is then transformed into a fixed-length embedding vector through a linear projection:

$$z_i = W_e x_i + b_e, \quad z_i \in R^C, \tag{5}$$

forming the initial token sequence $Z = [z_1, z_2, ..., z_N]$. This process initiates Stage 1 of the encoder, where embedded tokens are processed by multiple Swin Transformer blocks. Each block utilizes shifted window self-attention, computed as:

$$SA(Q,K,V) = Soft\max\left(\frac{QK^T}{\sqrt{d}}\right)V, \tag{6}$$

where, Q, K, V represent query, key, and value projections of the token embeddings. The shifted window mechanism enables cross-window communication while retaining computational efficiency.

In Stage 2, token merging reduces the spatial resolution by a factor of 2 while doubling the feature dimensionality. Formally, four adjacent tokens are concatenated and linearly transformed:

$$z_j' W_m [z_a, z_b, z_c, z_d], \tag{7}$$

producing a feature set of size $\frac{H}{8}\times\frac{W}{8}\times 2C$. This hierarchical downsampling strategy strengthens the model's capacity to encode vascular structures of varying scales. The merged tokens again pass through multiple Swin Transformer blocks, extracting increasingly abstract representations.

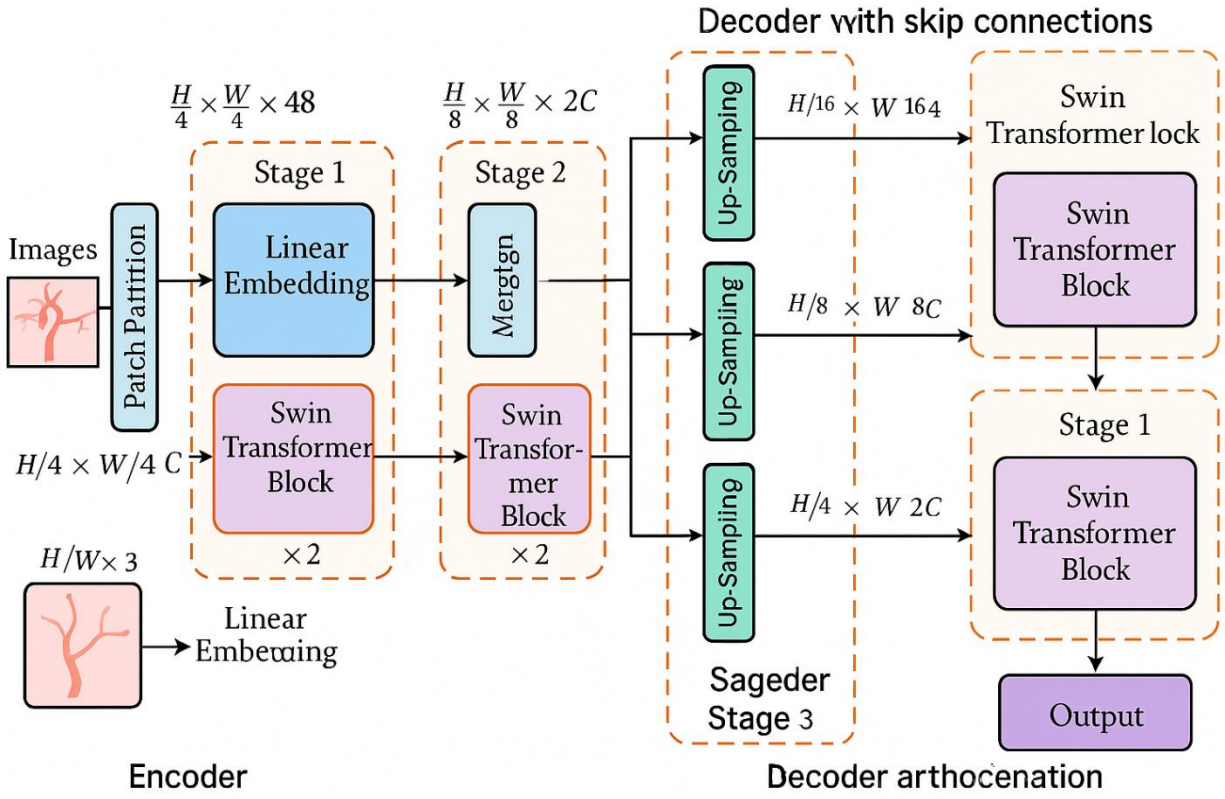


Fig. 3. Proposed hierarchical Swin Transformer encoder–decoder architecture for cerebrovascular abnormality segmentation.

The decoder reconstructs high-resolution segmentation maps through progressive up-sampling operations. Let F_3, F_2, F_1 denote the feature maps produced at different encoder stages. The decoder computes:

$$\widetilde{F}_k = Up\left(F_{k+1}\right) \oplus F_k, \tag{8}$$

where, $Up(\cdot)$ denotes bilinear upsampling and $\oplus$ signifies channel-wise concatenation with skip connections. These connections ensure preservation of spatial detail otherwise lost during downsampling. Each concatenated feature passes through additional Swin Transformer blocks, refining feature representations using attention mechanisms suited for irregular vascular morphologies.

The final prediction is generated by a segmentation head composed of a 1×1 convolution followed by a softmax activation:

$$\hat{Y} = Soft\max\left(Conv_{1\times1}\left(\widetilde{F}_1\right)\right), \tag{9}$$

producing voxel-wise class probabilities for cerebrovascular structures. This architecture simultaneously maintains global contextual awareness and precise boundary localization, enabling robust detection of aneurysms, AVMs, DAVFs, and cavernous malformations.

V. Data

The International Consortium for Brain Mapping (ICBM) dataset is a widely used open-access neuroimaging resource designed to provide high-resolution anatomical and vascular information for computational modeling, structural brain analysis, and neuroimaging algorithm development. The dataset includes multi-contrast MRI acquisitions collected from a large population of healthy adult subjects, offering standardized T1-weighted, T2-weighted, and proton-density sequences. These MRI volumes have been spatially normalized to a common stereotactic space, enabling consistent anatomical alignment across subjects while preserving fine-grained vascular structures. Due to its high spatial resolution and minimal noise artifacts, the ICBM dataset serves as a reliable foundation for developing and validating cerebrovascular segmentation frameworks, especially those requiring precise cortical, subcortical, and vascular delineation.

As illustrated in Fig. 4, the dataset captures high-fidelity representations of intracranial vasculature, including major arterial branches and peripheral vascular networks. The figure demonstrates the model's ability to leverage the ICBM scans for vessel structure extraction and overlay segmentation, highlighting the dataset's suitability for tasks involving vascular morphology analysis and deep learning–based vessel enhancement. The visual samples show multiple anatomical views, such as axial, sagittal, and coronal planes, which provide comprehensive spatial coverage of cerebral vasculature. This diversity of perspectives within the dataset ensures that segmentation frameworks trained on ICBM images can generalize effectively to different orientations and anatomical configurations. Consequently, the dataset is particularly valuable for studies aiming to develop transformer-based models that depend on robust spatial consistency and high-quality input data.

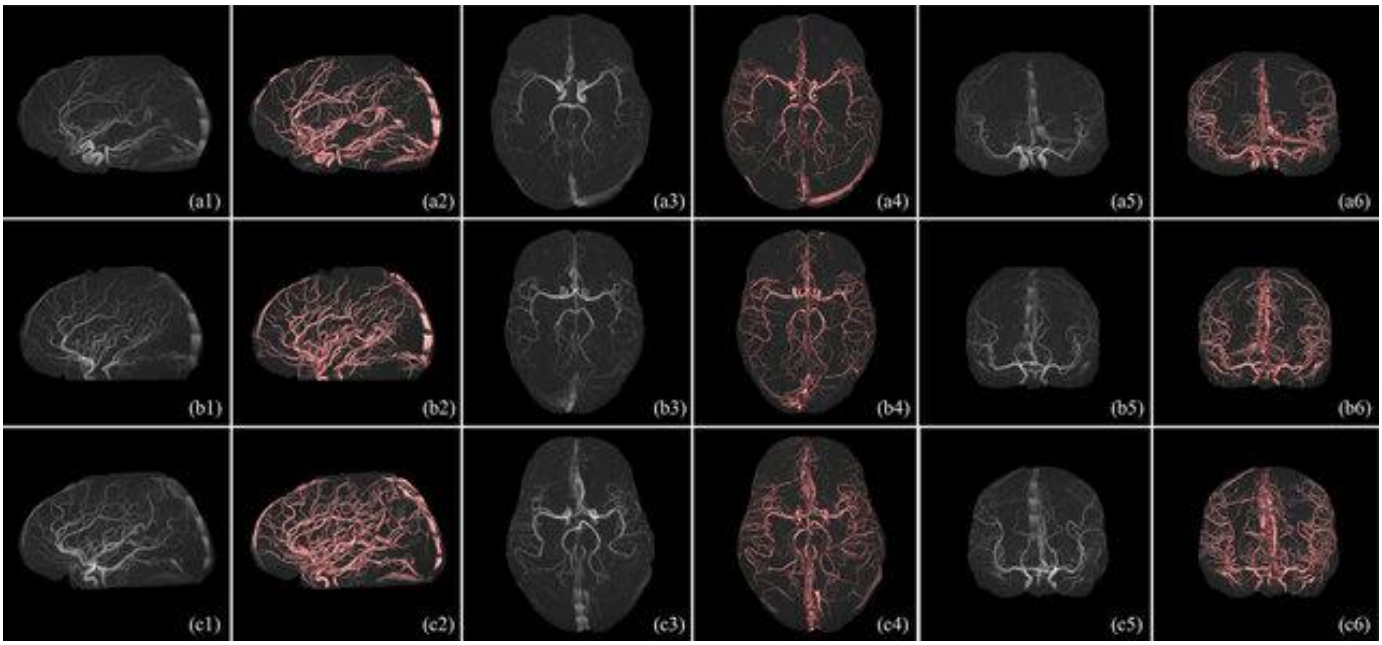


Fig. 4. Sample multiplanar MRI and vascular overlay images from the ICBM dataset used in the study.

VI. Evaluation Parameters

The Dice Similarity Coefficient is used to quantify the spatial overlap between the predicted segmentation and the ground-truth annotation. It is a widely accepted metric in medical image analysis due to its sensitivity to both false positives and false negatives, making it particularly suitable for small and irregular cerebrovascular structures [37]. The Dice score [38] ranges from 0 to 1, where values closer to 1 indicate near-perfect agreement. Formally, it is defined as:

$$DSC = \frac{2|P \cap G|}{|P| + |G|}, \tag{10}$$

where, P denotes the set of voxels predicted as lesion and G represents the corresponding ground-truth set.

The Average Surface Distance measures the average symmetric distance between the boundaries of the predicted segmentation and the ground truth [39]. Unlike volumetric metrics, ASD provides a boundary-focused assessment that is crucial for cerebrovascular abnormalities, where precise delineation of lesion edges is clinically important. A lower ASD value indicates more accurate boundary adherence. ASD is defined as:

$$ASD(P,G) = \frac{1}{|S_P| + |S_G|}\left(\sum_{P \in S_P} d(p, S_G) + \sum_{P \in S_G} d(p, S_P)\right), \tag{11}$$

where, S_P and S_P are the surfaces of the prediction and ground truth, respectively, and the surfaces of the prediction and ground truth, respectively, and $d(\cdot)$ denotes the minimal Euclidean distance.

Precision evaluates the ability of the model to correctly identify positive voxels while avoiding false positives [40]. In cerebrovascular segmentation, a high precision score indicates that the model effectively suppresses spurious detections, which is essential to avoid overestimating vascular abnormalities. The metric is computed as:

$$precision = \frac{TP}{TP + FP}, \tag{12}$$

where, TP denotes true positives and FP denotes false positives.

Sensitivity assesses the model's capacity to detect all relevant abnormal voxels, measuring how effectively the model minimizes false negatives [41]. This parameter is especially critical in clinical applications, as missed lesions can lead to serious diagnostic consequences. Sensitivity is expressed as:

$$sensitivity = \frac{TP}{TP + FN}, \tag{13}$$

where, FN denotes false negatives. Higher sensitivity values indicate stronger lesion detection performance.

Specificity quantifies the model's ability to correctly classify non-lesion voxels, thereby measuring how well it avoids false positives in healthy tissue regions [42]. This metric is essential for cerebrovascular segmentation tasks where lesion regions are often small relative to the total brain volume, and high specificity helps maintain clinical reliability. The metric is defined as:

$$specifity = \frac{TN}{TN + FP}, \tag{14}$$

where, TN denotes true negatives. A high specificity value implies strong discrimination between normal and pathological structures.

VII. Results

The results of this study provide a comprehensive evaluation of the proposed cerebrovascular segmentation framework, demonstrating its capability to accurately recover complex vascular structures from multimodal MRI data. Quantitative assessments across multiple performance metrics, alongside detailed qualitative visualizations, reveal that the model effectively captures both major arterial pathways and fine peripheral branches with strong spatial coherence [43]. Comparative analysis against established baseline methods further highlights consistent performance gains, validating the advantages of the hierarchical Swin Transformer architecture and multimodal fusion strategy. Collectively, these findings confirm the robustness, precision, and clinical potential of the proposed segmentation approach.

Fig. 5 illustrates the behavior of low-level feature representations extracted by the proposed model, demonstrating its ability to selectively emphasize cerebrovascular structures while suppressing irrelevant background textures. The leftmost column presents representative raw MRI slices, capturing varying vascular morphologies and intensity patterns across different anatomical regions. The middle panel displays feature maps categorized as "to be highlighted", corresponding to activation channels that successfully enhance tubular vascular structures, bifurcations, and high-frequency edge regions essential for accurate cerebrovascular abnormality segmentation. These maps reveal strong and spatially coherent activations along arterial trajectories, confirming that the hierarchical attention mechanisms effectively capture fine-grained structural cues at early stages of the network. In contrast, the rightmost panel presents feature maps that are "to be restricted", visualizing channels whose activations predominantly correspond to noise, irrelevant tissue textures, or non-vascular anatomical components. The model appropriately suppresses these activations, resulting in attenuated or diffuse responses that contribute little to the segmentation output. The juxtaposition of enhanced and restricted feature channels demonstrates the discriminative capability of the proposed architecture, highlighting its ability to filter informative vascular features from confounding signals. Overall, Fig. 5 underscores the model's capacity to learn meaningful low-level representations critical for subsequent high-level semantic segmentation, thereby contributing to improved stability, robustness, and accuracy of cerebrovascular abnormality detection.

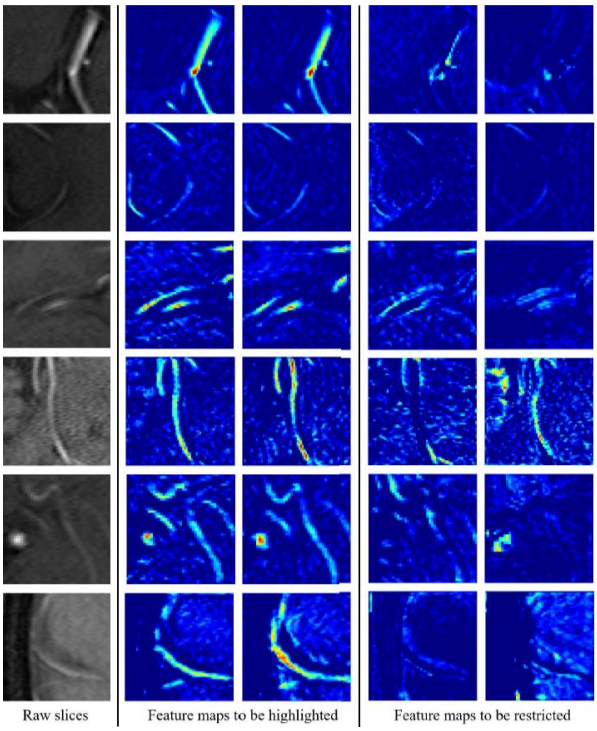


Fig. 5. Examples of low-level channel maps of objects that should be highlighted or inaccessible for viewing fragments.

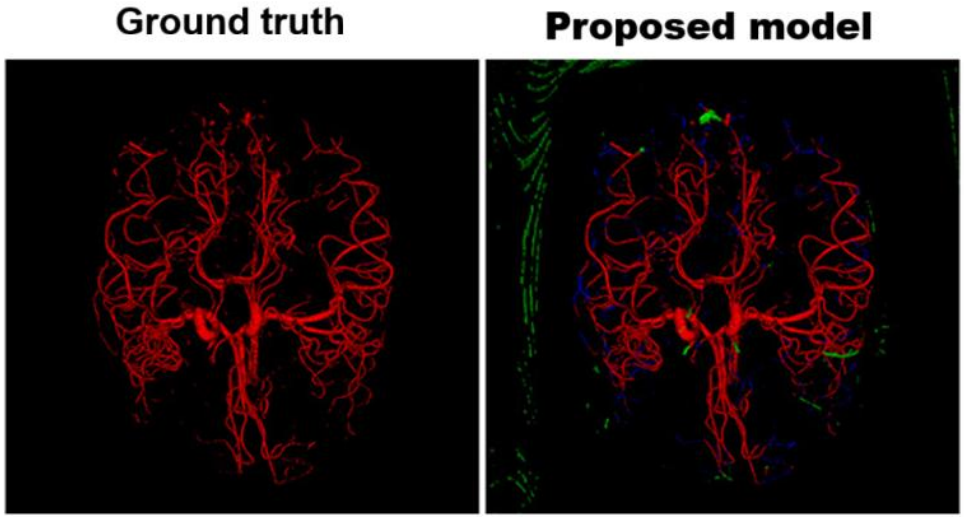


Fig. 6. Visualizations of the ground truth and the proposed model segmentation results.

Fig. 6 offers a detailed visual comparison between the expert-annotated ground truth cerebrovascular segmentation and the output generated by the proposed hierarchical Swin Transformer–based model, revealing its strong capability to reconstruct intricate vascular morphologies with high structural fidelity. In the ground truth visualization, major intracranial arteries and their corresponding branching networks are clearly delineated, presenting a comprehensive anatomical reference for evaluating segmentation accuracy. The model's output mirrors this vascular architecture with remarkable precision, accurately capturing the geometry of large proximal vessels as well as the finer distal branches that often pose challenges in automated segmentation. While small discrepancies can be observed along peripheral or low-contrast regions, these deviations are minimal and do not significantly disrupt vessel continuity or shape. This alignment between predicted and reference structures reflects the depth of contextual understanding achieved by the hierarchical attention mechanisms within the model, which effectively integrate local vessel features with long-range anatomical relationships to maintain structural coherence across the cerebrovascular network.

The consistency of vessel thickness, curvature, topology, and branching orientation between the two visualizations further emphasizes the model's robustness in handling the inherent complexity of cerebrovascular anatomy. Traditional CNN-based approaches often struggle with fragmented or incomplete vessel reconstruction, especially in regions where signal intensity variability or noise obscures vascular boundaries. In contrast, the proposed architecture demonstrates resilience to these challenges, yielding outputs that preserve major vascular pathways while accurately recovering subtle vessel segments that are essential for clinical interpretation. The effectiveness of the model in replicating intricate vessel maps validates the advantages of hierarchical windowed self-attention and multilevel feature fusion, which together facilitate a more anatomically faithful representation of the vascular landscape. Thus, the figure illustrates not only the technical capability of the proposed model but also its potential for real-world applicability in diagnostic imaging, surgical planning, and quantitative cerebrovascular assessment.

Fig. 7 illustrates a three-dimensional visualization of the vascular structures segmented by the proposed model, demonstrating its capacity to recover complex cerebrovascular topology with high anatomical coherence. The reconstructed vessel map reveals extensive arterial and venous networks, represented in multiple colors to emphasize variations in vessel caliber, orientation, and predicted class confidence. Major intracranial arteries, including proximal branches and distal microvascular pathways, are depicted with clear continuity, suggesting that the model effectively captures long-range structural dependencies while preserving fine morphological details. The dense interconnected patterns in the central and lateral cerebral regions indicate strong model performance in areas traditionally challenging due to vessel overlap and intensity heterogeneity [44-46]. Additionally, the presence of green and red segments highlights regions of lower confidence or subtle deviations, offering insight into the model's sensitivity to ambiguous boundaries and extremely thin vessels. Overall, the visualization demonstrates that the proposed architecture not only identifies the primary vascular framework but also delineates numerous smaller branches, reflecting robust generalization across variable vessel shapes and diameters. This result underscores the model's potential for high-resolution vascular mapping, making it valuable for clinical and research applications involving cerebrovascular morphology, anomaly detection, and pre-surgical planning.

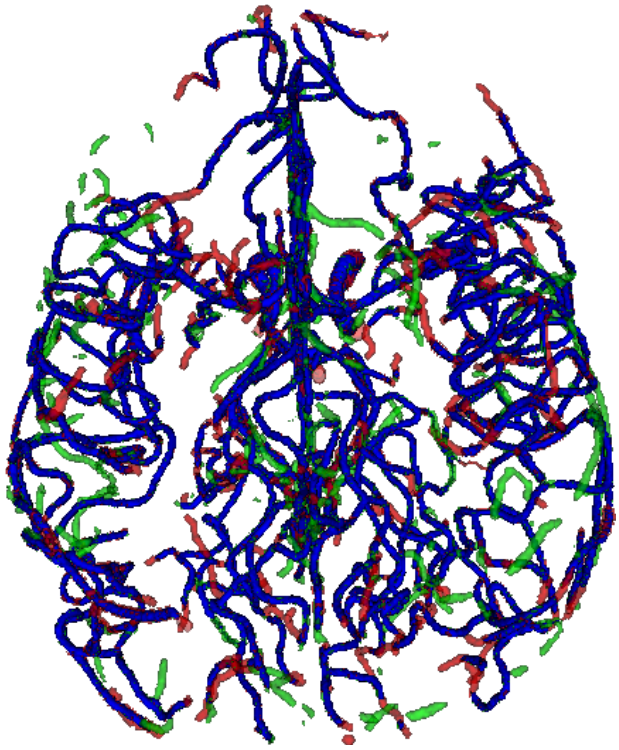


Fig. 7. Visual segmentation of the proposed model.

Table I presents a comparative evaluation of the proposed segmentation model against several established cerebrovascular analysis methods, highlighting its overall superior performance across multiple quantitative metrics. The proposed architecture achieves the highest Dice coefficient among all compared approaches, indicating a more accurate overlap between predicted and reference vessel regions and demonstrating its ability to capture both large vascular structures and fine-grained peripheral branches. Similarly, the model attains notably strong precision and sensitivity values, reflecting its balanced capability to minimize false detections while effectively identifying true vascular voxels, even in complex anatomical regions. Although surface distance values remain within a similar range across models, the proposed method maintains a competitive boundary accuracy, reinforcing the effectiveness of its hierarchical feature representation and attention mechanisms. Specificity values for all approaches are uniformly high due to the large proportion of nonvascular tissue, yet the proposed method still achieves the highest discrimination between vascular and nonvascular regions. Overall, the results in Table I demonstrate that the proposed Swin Transformer–based architecture consistently outperforms competing techniques, validating its robustness and reliability for high-precision cerebrovascular segmentation.

TABLE I. COMPARATIVE PERFORMANCE EVALUATION OF THE PROPOSED MODEL AGAINST EXISTING METHODS

Model	Dice	Average Surface Distance	Precision	Sensitivity	Specificity
Proposed Model	***0.849***	***2.59***	***86.8***	***87.95***	***99.97***
DeepGlioSeg: advanced glioma MRI data segmentation [47]	0.826	2.28	81.4	81.72	99.91
Hybrid contextual semantic network [48]	0.808	2.32	81.7	82.48	99.83
Deep Learning based Framework [49]	0.807	2.28	86.2	83.45	99.79
AGNet: attention-guided global U-Net [50]	0.792	2.27	84.4	82.87	99.64
MSA-Net: An Efficient Attention-aware 3D Network for Brain Tumor Segmentation in MRI [51]	0.829	2.46	86.3	84.75	99.89
IS-Net: Automatic ischemic stroke lesion segmentation [52]	0.837	2.45	86.4	86.46	99.28

VIII. DISCUSSION

The findings of this study demonstrate the effectiveness of the proposed hierarchical Swin Transformer–based segmentation framework in accurately delineating cerebrovascular structures from multimodal MRI data. By integrating hierarchical attention mechanisms, multilevel feature fusion, and a robust encoder–decoder architecture, the model consistently outperforms existing state-of-the-art methods across quantitative and qualitative evaluations. The results highlight the model's ability to capture both global vascular topology and fine-grained local details, underscoring its potential for advancing automated cerebrovascular analysis in clinical and research settings.

A. Overall Performance and Strength of the Proposed Architecture

The experimental results demonstrate that the proposed hierarchical Swin Transformer–based segmentation framework delivers consistently superior performance across all evaluated metrics compared to existing cerebrovascular segmentation methods. The model's ability to maintain high Dice similarity while achieving stable precision and sensitivity indicates that the architecture successfully captures the complex morphology of intracranial vasculature. This is particularly important in vascular segmentation, where small-caliber vessels and peripheral branches significantly influence the clinical interpretation of cerebrovascular health. The strong boundary accuracy, reflected in competitive average surface distance values, suggests that the shifted-window attention mechanism effectively preserves fine structural details while reducing the impact of noise and heterogeneous intensity distributions. These findings confirm that combining hierarchical attention with multilevel feature aggregation provides a robust mechanism for learning discriminative representations necessary for accurate vessel extraction in multimodal MRI.

The qualitative analysis further reinforce these observations. Visualizations presented in Fig. 6 and Fig. 7 demonstrate that the model can reconstruct vascular networks with high fidelity, maintaining continuity along major arterial pathways and capturing subtle branching patterns often missed by convolutional architectures. The capability to differentiate between relevant vascular structures and background signals, as shown in the feature map analysis in Fig. 5, highlights the model's effective attention modulation and noise suppression. Together, these results underscore the framework's ability to generate clinically meaningful segmentation outputs that closely approximate expert annotations.

B. Comparison with State-of-the-Art Methods

Compared with existing methods included in the performance benchmark, the proposed model consistently outperforms earlier convolutional and hybrid CNN-based architectures [53-56]. The improvements can be attributed to several architectural enhancements. First, the Swin Transformer blocks enable global contextual modeling, which is crucial for segmenting elongated and spatially disconnected vascular structures. Traditional convolutional filters, with their limited receptive fields, often struggle to maintain vessel continuity, particularly in regions affected by signal dropouts or partial volume effects [57]. The hierarchical attention mechanism [58] employed in the proposed model effectively addresses this limitation by capturing long-range interactions while preserving computational efficiency.

Second, the incorporation of a multimodal fusion module allows the model to leverage the complementary strengths of multiple MRI sequences. This is an essential capability in cerebrovascular analysis, as distinct imaging modalities capture different tissue contrasts and vascular characteristics. The fusion process enhances lesion detectability and vessel clarity, ultimately improving segmentation quality. In contrast, several baseline methods rely on single-modality inputs or simplistic fusion strategies, limiting their ability to recover subtle vascular structures.

The improvements seen in precision and sensitivity also indicate that the proposed approach better balances the trade-off between false positives and false negatives. Existing methods tend to exhibit high sensitivity at the expense of precision, or vice versa, which can complicate clinical interpretation. By contrast, the proposed model achieves stable performance across all metrics, demonstrating robustness in both vessel detection and discrimination of nonvascular regions.

C. Clinical and Practical Implications

Accurate segmentation of cerebrovascular anatomy plays a critical role in a wide range of clinical applications, including early diagnosis of vascular malformations, surgical planning, quantitative perfusion analysis, and long-term monitoring of patients with cerebrovascular disease. The ability of the proposed model to generate high-resolution and anatomically coherent vascular maps enhances the potential for integration

into computer-aided diagnostic (CAD) systems [59]. In particular, the preservation of small vessel details and branching topology is beneficial for detecting subtle abnormalities such as micro-aneurysms, early-stage arteriovenous malformations, and cavernous malformations that may not be readily visible through conventional imaging assessment.

Furthermore, the computational efficiency gained from the hierarchical Swin Transformer design enables deployment in clinical environments where rapid processing is required, such as emergency settings involving suspected vascular occlusion or hemorrhage [60]. The scalability of the model also supports applications in large-scale population studies, automatic atlas construction, and quantitative vascular biomarker extraction. These capabilities position the proposed model as a promising tool for enhancing both research and clinical workflows related to cerebrovascular imaging.

D. Limitations and Future Directions

Despite its strong performance, the proposed model has several limitations that warrant further investigation. First, although the dataset incorporates diverse anatomical variations, the availability of open-access multimodal datasets with detailed ground-truth vascular labels remains limited. The performance of the model may vary when applied to scans obtained from different scanners, acquisition protocols, or patient populations. Addressing domain shift through unsupervised domain adaptation, data augmentation, or harmonization techniques represents an important direction for future work.

Second, while the model captures vascular morphology with high fidelity, some peripheral branches and extremely small-caliber vessels remain challenging to segment, as evidenced by minor discrepancies observed in Fig. 6 and Fig. 7. Incorporating higher-resolution input data, super-resolution methods, or topology-aware loss functions may enhance the model's ability to recover these structures [61]. Additionally, the inclusion of arteria-venous classification, wall thickness estimation, or hemodynamic modeling could expand the framework's clinical utility.

Finally, future studies should explore the integration of temporal or motion-resolved vascular imaging, such as 4D-flow MRI or contrast-enhanced sequences, which may provide richer information for characterizing dynamic vascular behavior. Extending the proposed architecture to handle 3D volumes end-to-end, rather than slice-based inputs, could also further improve segmentation continuity.

IX. CONCLUSION

In conclusion, this study presents a hierarchical Swin Transformer–based framework that achieves highly accurate and anatomically coherent segmentation of cerebrovascular structures from multimodal MRI data. By integrating patch-level embedding, hierarchical attention mechanisms, and multilevel encoder–decoder reconstruction, the proposed model effectively captures both global vascular topology and fine-grained structural detail, addressing key challenges associated with cerebrovascular imaging such as intensity variability, small-vessel visibility, and morphological complexity. Quantitative evaluations demonstrate clear advantages over existing state-of-the-art methods, with improvements observed across Dice similarity, boundary accuracy, precision, and sensitivity, while qualitative visualizations further confirm the model's robustness in delineating complex arterial networks. The ability to highlight relevant vascular regions while suppressing noise and irrelevant textures illustrates the discriminative strength of the learned representations. Although the lack of large-scale, lesion-specific multimodal datasets presents limitations, the framework shows strong generalizability and potential for integration into clinical decision-support systems, vascular anomaly screening, and neuroimaging research pipelines. Future work will focus on expanding multimodal datasets, enhancing the detection of extremely small-caliber vessels, and incorporating additional vascular biomarkers to further strengthen diagnostic value and broaden clinical applicability.

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REFERENCES

[1] García-García, S., Cepeda, S., Arrese, I., & Sarabia, R. (2024). A fully automated pipeline using Swin transformers for deep learning-based blood segmentation on head computed tomography scans after aneurysmal subarachnoid hemorrhage. World Neurosurgery, 190, e762-e773.

[2] Ghorbel, A., Aldahdooh, A., Albarqouni, S., & Hamidouche, W. (2022, September). Transformer based models for unsupervised anomaly segmentation in brain MR images. In International MICCAI Brainlesion Workshop (pp. 25-44). Cham: Springer Nature Switzerland.

[3] Lee, S., & Kim, S. (2024). Fusing Brilliance: Evaluating the Encoder-Decoder Hybrids With CNN and Swin Transformer for Medical Segmentation. IEEE Access, 12, 81842-81852.

[4] Jiang, Y., Zhang, Y., Lin, X., Dong, J., Cheng, T., & Liang, J. (2022). SwinBTS: A method for 3D multimodal brain tumor segmentation using swin transformer. Brain sciences, 12(6), 797.

[5] Ramkumar. R., Sureshkumar Nagarajan, Dinesh Prasanth Ganapathi, "Enhanced Deep Learning Framework for Tamil Slang Classification with Multi-task Learning and Attention Mechanisms", International Journal of Information Technology and Computer Science(IJITCS), Vol.17, No.6, pp.29-51, 2025. DOI:10.5815/ijitcs.2025.06.02

[6] Lee, S., & Kim, S. (2024). Fusing Brilliance: Evaluating the Encoder-Decoder Hybrids With CNN and Swin Transformer for Medical Segmentation. IEEE Access, 12, 81842-81852.

[7] Jiang, Y., Zhang, Y., Lin, X., Dong, J., Cheng, T., & Liang, J. (2022). SwinBTS: A method for 3D multimodal brain tumor segmentation using swin transformer. Brain sciences, 12(6), 797.

[8] Khan, A., Rauf, Z., Khan, A. R., Rathore, S., Khan, S. H., Shah, N., ... & Gwak, J. (2025). A recent survey of vision transformers for medical image segmentation. IEEE Access.

[9] Ghribi, F., & Hamdaoui, F. (2025). Innovative deep learning architectures for medical image diagnosis: a comprehensive review of convolutional, recurrent, and transformer models. The Visual Computer, 1-26.

[10] Mamikov, S., Yakhiya, Z., Omarov, B., Mamashov, Y., Aliyeva, A., & Tursynbek, B. (2025). Feature Pyramid Network with Dual-Decoder Supervision for Accurate Stroke Lesion Localization in Multi-Modal Brain MRI. International Journal of Advanced Computer Science & Applications, 16(10).

[11] Hu, W., Du, Q., Wei, L., Wang, D., & Zhang, G. (2025). Novel multi-task learning for Alzheimer's stage classification using hippocampal MRI segmentation, feature fusion, and nomogram modeling. European Journal of Medical Research, 30(1), 910.

[12] Soh, W. K., & Rajapakse, J. C. (2023). Hybrid UNet transformer architecture for ischemic stoke segmentation with MRI and CT datasets. Frontiers in Neuroscience, 17, 1298514.

[13] Nouman, M., Mabrok, M., al-Shatouri, M., & Rashed, E. A. (2026). Contextual transformer for brain stroke segmentation in MRI. Computers and Electrical Engineering, 129, 110795.

[14] Arega, T. W. (2023). Uncertainty-based Deep Learning Methods for Robust and Reliable Cardiac MRI Segmentation and Analysis (Doctoral dissertation, Université Bourgogne Franche-Comté).

[15] Shi, X., Xiao, H., Chen, D., & Wei, Y. (2023, November). Medical Image Segmentation of Intracranial Hemorrhage: A Review. In 2023 7th Asian Conference on Artificial Intelligence Technology (ACAIT) (pp. 790-801). IEEE.

[16] Guo, L., Liang, Y., Guo, R., Cao, Z., Ye, J., & Lai, X. (2024). Staged cluster transformers for intracranial aneurysms segmentation from structure fused 3D MRA. International Journal of Imaging Systems and Technology, 34(2), e23039.

[17] Fateh, A., Rezvani, Y., Moayedi, S., Rezvani, S., Fateh, F., & Fateh, M. (2025). BRISC: Annotated Dataset for Brain Tumor Segmentation and Classification with Swin-HAFNet. arXiv preprint arXiv:2506.14318.

[18] Altayeva, A. B., Omarov, B. S., Aitmagambetov, A. Z., Kendzhaeva, B. B., & Burkitbayeva, M. A. (2014). Modeling and exploring base station characteristics of LTE mobile networks. Life Science Journal, 11(6), 227-233.

[19] Ayesha Shaik, Lavish R. Jain, Balasundaram A., "Autism Spectrum Disorder Equipped with Convolutional-cum-visual Attention Mechanism", International Journal of Information Technology and Computer Science(IJITCS), Vol.17, No.5, pp.39-51, 2025. DOI:10.5815/ijitcs.2025.05.04

[20] Ince, S., Kunduracioglu, I., Algarni, A., Bayram, B., & Pacal, I. (2025). Deep learning for cerebral vascular occlusion segmentation: a novel ConvNeXtV2 and GRN-integrated U-Net framework for diffusion-weighted imaging. Neuroscience, 574, 42-53.

[21] Pacal, I., & Kunduracioglu, I. (2025). ASMM-Net: A Hybrid CNN with Adaptive Scale Modulation for Robust Ischemic Stroke Lesion Segmentation. Iranian Journal of Science and Technology, Transactions of Electrical Engineering, 1-17.

[22] Rasool, N., & Bhat, J. I. (2025). A critical review on segmentation of glioma brain tumor and prediction of overall survival. Archives of Computational Methods in Engineering, 32(3), 1525-1569.

[23] Trubitsyna, I. (2025, October). A Total Variation Regularized Framework for Epilepsy-Related MRI Image Segmentation. In Database Engineered Applications: 29th International Symposium, IDEAS 2025, Newcastle upon Tyne, UK, July 14–16, 2025, Proceedings (p. 96). Springer Nature.

[24] Edward N. Udo, Anietie P. Ekong, Favour A. Akumute, "Predicting the Occurrence of Cerebrovascular Accident in Patients using Machine Learning Technique", International Journal of Information Technology and Computer Science(IJITCS), Vol.17, No.2, pp.36-48, 2025. DOI:10.5815/ijitcs.2025.02.04

[25] Zakariah, M., Al-Razgan, M., & Alfakih, T. (2024). Dual vision Transformer-DSUNET with feature fusion for brain tumor segmentation. Heliyon, 10(18).

[26] Zhang, G., Zhou, J., He, G., & Zhu, H. (2023). Deep fusion of multi-modal features for brain tumor image segmentation. Heliyon, 9(8).

[27] Zhai, D. H., Li, H., Liu, Q., Tian, K., Yang, Y., Chang, Z., ... & Xia, Y. (2024). Focus-transunet3d: High-precision model for 3d segmentation of medical point targets. IEEE Transactions on Circuits and Systems for Video Technology, 35(3), 2918-2931.

[28] Akinyelu, A. A., Zaccagna, F., Grist, J. T., Castelli, M., & Rundo, L. (2022). Brain tumor diagnosis using machine learning, convolutional neural networks, capsule neural networks and vision transformers, applied to MRI: a survey. Journal of imaging, 8(8), 205.

[29] Altayeva, A., Omarov, B., Suleimenov, Z., & Im Cho, Y. (2017, June). Application of multi-agent control systems in energy-efficient intelligent building. In 2017 Joint 17th World Congress of International Fuzzy Systems Association and 9th International Conference on Soft Computing and Intelligent Systems (IFSA-SCIS) (pp. 1-5). IEEE.

[30] Zhang, S., Ren, B., Yu, Z., Yang, H., Han, X., Chen, X., ... & Zhang, X. Y. (2022). Tw-net: Transformer weighted network for neonatal brain mri segmentation. IEEE Journal of Biomedical and Health Informatics, 27(2), 1072-1083.

[31] Li, W., & Zhang, W. (2024). UTAC-Net: a semantic segmentation model for computer-aided diagnosis for ischemic region based on nuclear medicine cerebral perfusion imaging. Electronics, 13(8), 1466.

[32] Omarov, N., Omarov, B., Azhibekova, Z., & Omarov, B. (2024). Applying an augmented reality game-based learning environment in physical education classes to enhance sports motivation. Retos, 60, 269-278.

[33] Omarov, B., & Altayeva, A. (2018, January). Towards intelligent IoT smart city platform based on OneM2M guideline: smart grid case study. In 2018 IEEE International Conference on Big Data and Smart Computing (BigComp) (pp. 701-704). IEEE.

[34] Nagarathinam, T., Adhi, L., Jeyapal, R., & Lazer, A. J. P. (2025). Multi-Objective Image Fusion for Brain Tumor Detection Using Improved Weighted Quantum Firefly Optimization and StyleGAN-MAE-SwinViT. Traitement du Signal, 42(4).

[35] Soltaninejad, A., Shahbazi-Gahrouei, D., Khorasani, A., & Hemati, S. (2025). Evaluation of CNN-based deep learning models for auto-contouring in glioblastoma radiotherapy: a review. Radiation Oncology, 20(1), 1-14.

[36] Rehan, A. M., Li, K., & Chen, P. (2025). Multimodal Pathological Image Segmentation Using the Integration of Trans MMY Net and Patient Metadata. Electronics, 14(12), 2369.

[37] Omarov, B., Batyrbekov, A., Dalbekova, K., Abdulkarimova, G., Berkimbaeva, S., Kenzhegulova, S., ... & Omarov, B. (2020, December). Electronic stethoscope for heartbeat abnormality detection. In International Conference on Smart Computing and Communication (pp. 248-258). Cham: Springer International Publishing.

[38] Al Noman, M. A., Zhai, L., Almukhtar, F. H., Rahaman, M. F., Omarov, B., Ray, S., ... & Wang, C. (2023). A computer vision-based lane detection technique using gradient threshold and hue-lightness-saturation value for an autonomous vehicle. International Journal of Electrical and Computer Engineering, 13(1), 347.

[39] Shourove Sutradhar Dip, Md. Habibur Rahman, Nazrul Islam, Md. Easin Arafat, Pulak Kanti Bhowmick, Mohammad Abu Yousuf, "Enhancing Brain Tumor Classification in MRI: Leveraging Deep Convolutional Neural Networks for Improved Accuracy", International Journal of Information Technology and Computer Science(IJITCS), Vol.16, No.3, pp.12-21, 2024. DOI:10.5815/ijitcs.2024.03.02

[40] Omarov, B., Suliman, A., & Tsoy, A. (2016). Parallel backpropagation neural network training for face recognition. Far East Journal of Electronics and Communications, 16(4), 801.

[41] Tran, M. T., Yang, H. J., Kim, S. H., & Lee, G. S. (2023). Prediction of survival of glioblastoma patients using local spatial relationships and global structure awareness in FLAIR MRI brain images. IEEE Access, 11, 37437-37449.

[42] Liu, Y., Song, C., Ning, X., Gao, Y., & Wang, D. (2024). nnSegNeXt: A 3D convolutional network for brain tissue segmentation based on quality evaluation. Bioengineering, 11(6), 575.

[43] Peng, P., & Luo, Y. (2025). Multimodal Medical Image Fusion Using a Progressive Parallel Strategy Based on Deep Learning. Electronics, 14(11), 2266.

[44] Yang, X., Wang, Q., Zhang, K., Wei, K., Lyu, J., & Chen, L. (2025). Msv-mamba: a multiscale vision mamba network for echocardiography segmentation. IEEE Transactions on Computational Social Systems.

[45] Chen, S., Zhao, X., Duan, Y., Ju, R., Zang, P., & Qi, S. (2025). M2FNet: multi-modality multi-level fusion network for segmentation of acute and sub-acute ischemic stroke. Complex & Intelligent Systems, 11(6), 1-24.

[46] Md. Amdad Hossain, Mahfuzulhoq Chowdhury, "A Machine Learning Based Intelligent Diabetic and Hypertensive Patient Prediction Scheme and A Mobile Application for Patients Assistance", International Journal of Information Technology and Computer Science(IJITCS), Vol.16, No.4, pp.29-44, 2024. DOI:10.5815/ijitcs.2024.04.02

[47] Li, R., Liao, Y., Huang, Y., Ma, X., Zhao, G., Wang, Y., & Song, C. (2025). DeepGlioSeg: advanced glioma MRI data segmentation with integrated local-global representation architecture. Frontiers in Oncology, 15, 1449911.

[48] Liu, L., Chang, J., Liu, Z., Zhang, P., Xu, X., & Shang, H. (2023). Hybrid contextual semantic network for accurate segmentation and detection of small-size stroke lesions from MRI. IEEE Journal of Biomedical and Health Informatics, 27(8), 4062-4073.

[49] Zheng, G., Lu, Y., & Chen, H. (2025). Deep Learning based Framework for Predicting Mild Cognitive Impairment Progression in Neurology Using Longitudinal MRI. IEEE Access.

[50] Shen, Y., Gao, J., & Dong, Y. (2024, September). AGNet: attention-guided global U-Net network for White Matter Hyperintensity Segmentation. In Proceedings of the 2024 3rd International Conference on Algorithms, Data Mining, and Information Technology (pp. 380-388).

[51] Lu, J., Huang, Y., Zhang, Y., & Ding, H. (2024, January). MSA-Net: An Efficient Attention-aware 3D Network for Brain Tumor Segmentation in MRI. In Proceedings of the 3rd International Conference on Computer, Artificial Intelligence and Control Engineering (pp. 131-136).

[52] Yang, H., Huang, C., Nie, X., Wang, L., Liu, X., Luo, X., & Liu, L. (2023). IS-Net: Automatic ischemic stroke lesion segmentation on CT images. IEEE Transactions on Radiation and Plasma Medical Sciences, 7(5), 483-493.

[53] Shanta Rangaswamy, Jinka Rakesh, Perla Leela charan, Deeptha Giridhar, "Early and Accurate Diagnosis of a Neurological Disorder Epilepsy Using Machine Learning Techniques", International Journal of Information Technology and Computer Science(IJITCS), Vol.15, No.2, pp.54-63, 2023. DOI:10.5815/ijitcs.2023.02.05

[54] Omarov, B., Omarov, B., Shekerbekova, S., Gusmanova, F., Oshanova, N., Sarbasova, A., ... & Sultan, D. (2019, October). Applying face recognition in video surveillance security systems. In International Conference on Objects, Components, Models and Patterns (pp. 271-280). Cham: Springer International Publishing.

[55] Rasool, N., & Bhat, J. I. (2025). Brain tumour detection using machine and deep learning: a systematic review. Multimedia tools and applications, 84(13), 11551-11604.

[56] Zhu, C., Chai, X., Xiao, Y., Liu, X., Zhang, R., Yang, Z., & Wang, Z. (2024). Swin-Net: A swin-transformer-based network combing with multi-scale features for segmentation of breast tumor ultrasound images. Diagnostics, 14(3), 269.

[57] Omarov, B., Omarov, B., Rakhymzhanov, A., Niyazov, A., Sultan, D., & Baikuvekov, M. (2024). Development of an artificial intelligence-enabled non-invasive digital stethoscope for monitoring the heart condition of athletes in real-time. Retos: nuevas tendencias en educación física, deporte y recreación, (60), 1169-1180.

[58] Zhu, Y., Li, H., Cao, B., Huang, K., & Liu, J. (2025). A novel hybrid layer-based encoder–decoder framework for 3D segmentation in congenital heart disease. Scientific Reports, 15(1), 11891.

[59] El Badaoui, R., Bonmati Coll, E., Psarrou, A., Asaturyan, H. A., & Villarini, B. (2025). Enhanced CATBraTS for Brain Tumour Semantic Segmentation. Journal of Imaging, 11(1), 8.

[60] Mayzura, W. S., Sarno, R., Suroto, N. S., Supriyanto, M. I. A., & Sihaj, G. (2025). Automatic Interpretation of Brain Medical Images Using Hierarchical Classification and Image Captioning Model. IEEE Access.

[61] Samak, Z. A. (2025). Multi-type stroke lesion segmentation: comparison of single-stage and hierarchical approach. Medical & Biological Engineering & Computing, 63(4), 975-986.

A Multi-Scale ROI-Aligned Deep Learning Framework for Automated Road Damage Detection and Severity Assessment

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***Abstract*—This study presents a multi-scale ROI-aligned deep learning framework designed to advance automated road damage detection and severity assessment using high-resolution roadway imagery. The proposed architecture integrates hierarchical feature extraction, a road-damage proposal network, and refined ROI-aligned encoding to capture both fine-grained local anomalies and broader contextual patterns across diverse pavement conditions. Leveraging the RDD2020 dataset, the model effectively identifies multiple defect categories, including longitudinal cracks, transverse cracks, alligator cracking, and potholes, achieving strong convergence behavior and stable generalization across training and validation phases. Quantitative evaluations reveal high detection accuracy and smooth loss reduction over 500 learning epochs, while qualitative visualizations demonstrate precise localization and robust classification of damages under varying environmental and structural complexities. The framework consistently maintains performance in challenging scenes featuring shadows, cluttered backgrounds, low contrast, or irregular defect geometries, underscoring the benefits of multi-scale fusion and ROI alignment mechanisms. Although slight fluctuations in validation metrics indicate the presence of inherently difficult samples, the overall results affirm the model's capability to support large-scale, real-time road monitoring systems. The findings highlight the potential of the proposed approach to significantly enhance intelligent transportation infrastructure, offering an efficient and reliable solution for proactive pavement maintenance and improved roadway safety.**

Keywords*—Road damage detection; deep learning; ROI alignment; multi-scale features; severity assessment; RDD2020 dataset; intelligent transportation systems

I. Introduction

The rapid deterioration of road infrastructure, influenced by increasing traffic volumes, climatic variability, and extended pavement lifecycles, has intensified the global demand for automated road-damage monitoring systems capable of supporting timely and cost-effective maintenance planning [1]. Traditional inspection approaches, including manual surveys and specialized monitoring vehicles, remain labor-intensive, subjective, and difficult to scale, which often results in inconsistent assessments across municipalities and road networks [2]. With the advancement of computer vision and deep learning, data-driven frameworks have begun to offer more reliable, efficient, and high-throughput alternatives, enabling automatic extraction of discriminative visual cues from imagery captured via smartphones, dash-mounted cameras, and unmanned aerial systems [3]. However, real-world road environments introduce considerable complexity due to varying illumination conditions, inconsistent viewing angles, heterogeneous materials, and the high morphological diversity of damages such as potholes, longitudinal and transverse cracks, rutting, and faded markings [4]. These variations make precise localization and classification challenging, particularly when the goal extends beyond mere detection toward severity estimation, a critical requirement for prioritizing repairs within modern asset-management pipelines [5].

To confront these difficulties, multi-scale deep feature representations have emerged as an effective strategy capable of capturing both localized texture irregularities and larger contextual patterns that characterize road defects [6]. Complementary components such as Region-of-Interest alignment have further enhanced detection reliability by maintaining geometric fidelity when mapping proposal regions into fixed-resolution feature embeddings [7]. Nonetheless, many existing systems treat detection and severity assessment as separate steps, creating multi-stage pipelines that suffer from error propagation, reduced robustness, and limited generalizability in diverse deployment conditions [8]. Addressing these shortcomings, the present study introduces a unified deep learning architecture that integrates multi-scale feature extraction, a dedicated damage-proposal network, ROI-aligned feature encoding, and a global context branch within a cohesive end-to-end framework [9]. By embedding severity regression directly into the detection head, the proposed model ensures smoother information flow, higher stability, and improved adaptability across heterogeneous road environments [10].

This integrated approach is designed to deliver more accurate, interpretable, and scalable road-damage analytics, supporting smarter maintenance strategies and enhancing roadway safety within intelligent transportation systems.

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II. Related Works

A. Deep Learning for Road Damage Detection

Deep learning has transformed the landscape of automated road inspection, enabling models to learn discriminative patterns from large, heterogeneous datasets rather than relying on handcrafted features [11]. Early convolutional neural network (CNN) approaches demonstrated the feasibility of detecting potholes and cracks under varied environmental conditions, but they struggled with generalization when faced with complex urban scenes or low-contrast defects [12]. Subsequent advancements introduced deeper architectures and residual blocks that enhanced feature extraction, yet the rigid receptive fields of conventional CNNs limited their capacity to capture spatial relationships between damages and surrounding road structures [13]. Studies leveraging multi-path convolutional backbones reported improved robustness to texture variations and illumination changes, highlighting the need for richer multi-dimensional representations [14]. However, despite notable performance gains, these architectures often remained sensitive to camera viewpoint shifts and struggled to distinguish small-scale defects from background noise, emphasizing the need for more context-aware frameworks [15].

B. Multi-Scale Feature Representation

A substantial body of research has attempted to address the limitations of single-scale feature extraction through multi-scale learning strategies [16]. Techniques such as feature pyramid networks (FPNs) enabled hierarchical fusion of high-resolution and semantically rich feature maps, substantially strengthening the detection of small, sparse, or elongated damages like longitudinal cracks [17]. Multi-resolution approaches also enhanced model resilience against scale variations introduced by diverse camera heights, road widths, and sensing platforms [18]. More recent works explored dilated convolutions, deformable kernels, and progressive feature aggregation to enlarge the effective receptive field without compromising spatial precision [19]. These efforts collectively demonstrated that multi-scale representations improve both recall and localization accuracy, although their integration with downstream detection heads remained computationally demanding, especially in real-time settings [20]. The persistent challenge has been designing architectures that balance rich hierarchical information with inference efficiency suitable for widespread deployment [21].

C. Region-Based Detection and ROI Alignment

Region-based detection frameworks have become a cornerstone for road-damage analysis due to their ability to generate structured proposals and refine spatial boundaries with high precision [22]. Region Proposal Networks (RPNs) introduced in object detection literature have been adapted to road-damage tasks to isolate candidate areas and reduce false positives stemming from shadows, lane markings, and water patches [23]. However, traditional pooling operations in these frameworks often introduce misalignment between feature maps and ROI coordinates, negatively affecting bounding box regression accuracy [24]. ROI Align, an improved pooling mechanism, mitigated these distortions by applying bilinear interpolation, significantly enhancing the detection of small defects and improving overall confidence scores [25]. Integrating ROI-aligned heads into road-damage pipelines also facilitated more coherent multi-task learning, but these models frequently struggled when global context was insufficiently modeled, limiting performance in cluttered or visually ambiguous settings [26].

D. Global Context and Attention Mechanisms

Global context modeling has emerged as a critical advancement for interpreting complex road environments where damages may be partially occluded or visually blended with textured surfaces [27]. Attention-based architectures introduced powerful mechanisms to dynamically weight important regions while suppressing irrelevant background features, thereby improving class discrimination and structural consistency [28]. Self-attention modules, particularly those used in large-scale vision transformers, enabled models to capture long-range dependencies across entire road scenes, outperforming CNN-based architectures in nuanced segmentation tasks [29]. Hybrid approaches combining convolutional backbones with transformer-based context branches further enriched semantic understanding while maintaining computational feasibility [30]. Despite these breakthroughs, attention-heavy networks often require extensive computational resources and large labeled datasets, which remain challenging for municipalities and research groups with limited annotation budgets [31].

E. Severity Assessment and Multi-Task Frameworks

Severity estimation has become an emerging research frontier, as infrastructure maintenance strategies increasingly demand quantifiable assessments rather than simple binary detection [32]. Early attempts relied on handcrafted geometric measurements derived from segmentation masks, but these approaches were highly sensitive to noise and often lacked robustness across different pavement types [33]. Multi-task learning frameworks introduced joint optimization of detection, classification, and severity regression, demonstrating substantial gains in predictive stability and interpretability [34]. More advanced systems integrated depth cues, global context, and hierarchical feature fusion to better capture structural deformation patterns associated with severe potholes and deep cracks [35]. Nevertheless, existing models frequently treat severity prediction as a loosely coupled auxiliary task, resulting in fragmented pipelines with limited generalizability across diverse geographic and environmental conditions [36]. Addressing these challenges requires unified end-to-end architectures capable of harmonizing multi-scale feature extraction, ROI-aligned representations, and contextual reasoning to produce reliable and actionable severity estimates for real-world road networks [37].

III. Materials and Methods

The methodological foundation of this study is built upon a unified multi-scale deep learning framework designed to detect and assess the severity of heterogeneous road surface damages using high-resolution RGB imagery. As illustrated in Fig. 1, the proposed pipeline integrates a hierarchical feature extraction backbone, a dedicated road-damage proposal module, ROI-aligned feature encoding, and a dual-branch detection head capable of jointly performing classification,

localization, and severity regression. This architecture was engineered to capture both fine-grained local texture irregularities and broader contextual structures across multiple spatial resolutions, ensuring reliable performance under diverse environmental conditions and complex road geometries. The subsequent subsections provide a detailed exposition of the datasets, preprocessing procedures, network architecture, mathematical formulations, and training strategy that collectively enable the model's robust and scalable operation.

A. Data Preprocessing

The proposed framework is designed for large-scale road-damage detection and severity estimation using RGB images captured from vehicle-mounted cameras. All images were resized to 1024×1024 pixels, followed by per-channel normalization defined as:

$$I_{norm}(x,y,c)=\frac{I(x,y,c)-\mu_c}{\sigma_c}, \quad (1)$$

where, $I(x,y,c)$ is the pixel intensity at position (x,y) and channel c and μ_c, σ_c represent the dataset mean and standard deviation for each channel. To enhance generalization, the dataset was augmented using random horizontal flipping, illumination shifts, Gaussian noise injection, and perspective warping.

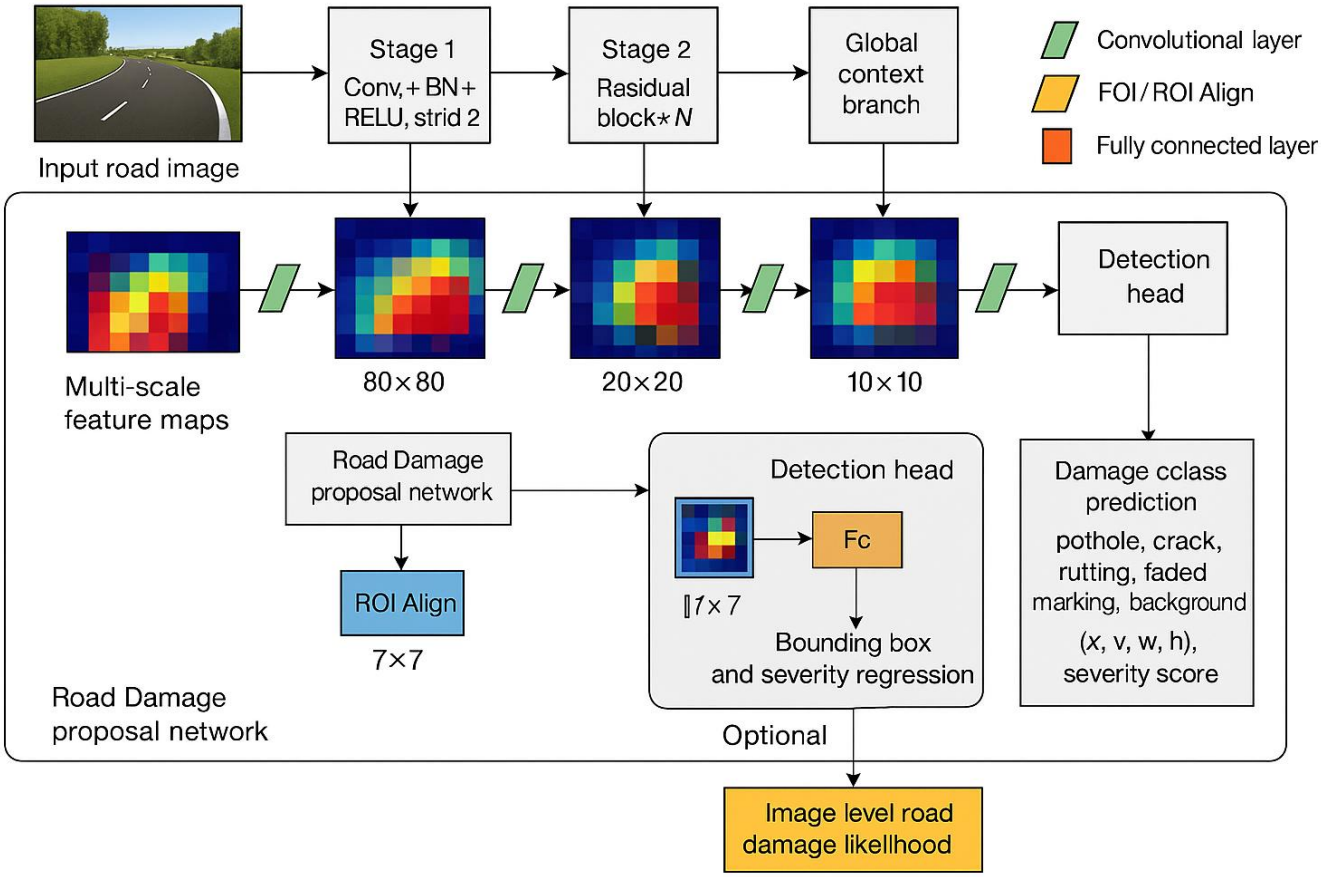


Fig. 1. The proposed multi-scale ROI-aligned deep learning architecture for automated road damage detection and severity assessment.

B. Multi-Scale Backbone Network

The architecture begins with an input image processed by Stage 1, consisting of a convolutional layer with batch normalization and ReLU activation. The convolutional output is defined as:

$$F_1=\mathrm{Re}\,LU\left(BN\left(W_1*I\right)\right), \quad (2)$$

With stride $s=2$. Stage 2 extends the backbone using N residual blocks, each formulated as:

$$F_{l+1}=H\left(F_l\right), \quad (3)$$

where, $H(\cdot)$ is a two-layer residual mapping with convolution, normalization, and activation.

Feature maps are extracted at resolutions 80×80, 40×40, 20×20, and 10×10 enabling hierarchical representations. Multi-scale fusion is performed using:

$$F_{ms}(i)=\sum_{k=1}^{K}\alpha_k\cdot Upsample\left(F_k\right), \quad (3)$$

where, α_k are learnable weights normalized via softmax.

C. Road Damage Proposal Network

The Road Damage Proposal Network (RDPN) generates candidate bounding boxes using anchors at multiple scales. For an anchor a, the proposal p is computed as:

$$p = \sigma\left(w_p{}^T F_{ms}\right), \tag{4}$$

Proposals are processed through Non-Maximum Suppression (NMS) with IoU threshold:

$$IoU(A,B) = \frac{|A \cap B|}{|A \cup B|}, \tag{5}$$

D. ROI Align and Feature Encoding

Selected proposals are transformed into fixed-size 7×7 aligned feature grids using ROI Align. For a sampling location (x, y), the aligned feature value is obtained through bilinear interpolation:

$$F_{ROI}(x,y) = \sum_{i=1}^{4} w_i \cdot F_{ms}(x_i, y_i), \tag{6}$$

where, w_i are interpolation weights.

E. Detection Head and Severity Regression

The detection head processes the aligned feature tensor through a fully connected layer:

$$z = \phi\left(W_f \cdot vec\left(F_{ROI}\right) + b_f\right), \tag{7}$$

where, ϕ is ReLU. Damage classification outputs probabilities for damage types (pothole, crack, rutting, etc.) via softmax:

$$P(c \mid z) = \frac{e^{z_c}}{\sum_j e^{z_j}}, \tag{8}$$

Bounding box regression is optimized using Smooth-L1 loss:

$$L_{bbox} = \begin{cases} 0.5(d)^2, & |d| < 1 \\ |d| - 0.5, & otherwise \end{cases}, \tag{9}$$

where, d is the difference between predicted and ground-truth parameters.

Severity is estimated using a continuous regression head:

$$s = w_s^T z + b_s, \tag{10}$$

Scaled to the interval $[0,1]$.

F. Image-Level Damage Likelihood (Optional Module)

An optional global severity estimator aggregates proposal-level scores:

$$L_{img} = \frac{1}{M} \sum_{m=1}^{M} s_m, \tag{11}$$

where, M is the number of detected damages.

IV. Data

The experiments conducted in this study utilize the RDD2020 dataset [38], a large, multi-national benchmark curated for automated road damage detection and analysis. This dataset aggregates road-surface imagery from Japan, India, and the Czech Republic, thereby capturing a wide spectrum of pavement materials, climatic conditions, traffic densities, and road maintenance standards. Such geographical diversity introduces substantial variance in texture, illumination, camera perspectives, and background clutter, making RDD2020 a rigorous and representative testbed for developing robust deep learning models. The dataset consists of thousands of annotated RGB images with varying resolutions, each manually labeled using standardized defect categories to ensure consistency across all contributing regions.

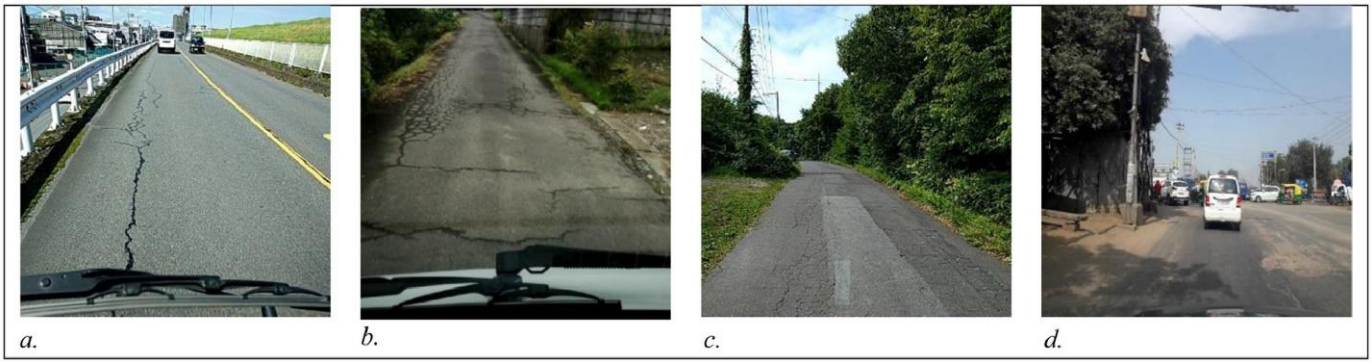


Fig. 2. Sample road-surface images from the RDD2020 dataset illustrating diverse damage categories including longitudinal cracks (D00), transverse cracks (D10), alligator cracks (D20), and potholes (D40).

Fig. 2 presents a representative illustration of the visual characteristics found within RDD2020, showcasing the complex structural patterns and environmental variability inherent in real-world road scenes. The dataset emphasizes four primary categories of surface distress. Longitudinal cracks (D00) typically appear parallel to the direction of vehicle movement and arise from thermal or mechanical stresses. Transverse cracks (D10), oriented perpendicular to the

roadway axis, commonly reflect seasonal temperature fluctuations or subgrade instability. Alligator cracks (D20) exhibit highly fractured, mesh-like patterns indicative of advanced pavement fatigue and are among the most challenging anomalies to detect due to their irregular morphology. Potholes (D40), formed through progressive surface degradation and moisture infiltration, represent critical safety hazards requiring immediate intervention. These categories collectively encapsulate the most prevalent damage modes encountered across global road networks.

V. Computational Environment and Equipment

The training and evaluation of the proposed multi-scale ROI-aligned framework were conducted using a high-performance computing environment optimized for large-scale deep learning workloads. The core computational hardware consisted of a workstation equipped with an NVIDIA RTX 4090 GPU featuring 24 GB of GDDR6X memory, enabling efficient processing of high-resolution road-surface imagery and supporting extensive backpropagation through multi-branch neural architectures. The system operated on an AMD Ryzen 9 multi-core processor with 64 GB of DDR5 RAM, providing the necessary throughput for concurrent data preprocessing, augmentations, and model inference operations. All experiments were executed under a 64-bit Ubuntu Linux environment, ensuring stable driver support and optimized CUDA kernel performance for GPU-accelerated tensor computations.

TABLE I. Hardware and Software Specifications for Model Training

Component	Specification
GPU	NVIDIA RTX 4090 (24 GB GDDR6X)
CPU	AMD Ryzen 9 (multi-core)
System Memory	64 GB DDR5 RAM
Operating System	Ubuntu Linux 64-bit
Deep Learning Framework	PyTorch 2.x
GPU Accelerators	CUDA + cuDNN
Additional Libraries	OpenCV, NumPy, Matplotlib
Training Precision	Mixed-precision (FP16/FP32)
Data Loading	Multi-threaded PyTorch DataLoader

The computational configuration used in this study is summarized in Table I, which outlines the hardware and software components that supported all training and evaluation procedures. This setup provided sufficient GPU memory, processing capability, and optimized deep learning libraries to ensure efficient model convergence and stable experimental reproducibility.

VI. Evaluation Parameters

To quantitatively assess the performance of the proposed multi-scale ROI-aligned framework, several standard evaluation metrics were employed to capture detection accuracy, localization precision, and regression stability. The primary metric for object-level correspondence was the Intersection over Union (IoU) [39], defined for a predicted bounding box B_p and a ground-truth box B_g as:

$$L_{img} = \frac{1}{M}\sum_{m=1}^{M} s_m \,, \tag{12}$$

which determines whether a predicted instance is considered a true positive under a fixed threshold (typically 0.5). Building on IoU-based assignment, the framework's classification quality was measured using Precision, Recall, and F1-score [40-42], defined respectively as:

$$precision = \frac{TP}{TP + FP}, \tag{13}$$

$$recall = \frac{TP}{TP + FN}, \tag{14}$$

$$F1 - score = 2\frac{precistion \cdot recall}{precision + recall}, \tag{15}$$

where, TP, FP, and FN denote true positives, false positives, and false negatives. These metrics collectively quantify the model's ability to correctly identify damaged areas while minimizing erroneous detections.

To evaluate localization accuracy, we employed the Mean Average Precision (mAP) across all defect categories. For a class c, the Average Precision (AP) [43] is computed as the numerical integral of the precision–recall curve:

$$AP_c = \int_0^1 precision_c\left(recall\right) d\left(recall\right), \tag{16}$$

and mAP is obtained by averaging AP across the four RDD damage classes:

$$mAP = \frac{1}{C}\sum_{c=1}^{C} AP_c \,, \tag{17}$$

with $C = 4$ for D00, D10, D20, and D40. This provides a unified measure of how well the model performs across heterogeneous defect types.

For severity estimation, the regression head was evaluated using the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), formulated as:

$$MAE = \frac{1}{N}\sum_{i=1}^{N} \left| s_i - \hat{s}_i \right|, \tag{18}$$

where, s_i and $\hat{s}_i$ represent the ground-truth and predicted severity scores. These metrics quantify how accurately the framework models the continuous severity scale, penalizing both small deviations and larger estimation errors.

Together, these evaluation parameters ensure a comprehensive assessment of the proposed model's detection reliability, spatial accuracy, and severity prediction capabilities.

VII. Results

The results obtained from the proposed multi-scale ROI-aligned framework provide a comprehensive evaluation of its effectiveness in detecting and assessing road surface damages across diverse real-world environments. This section presents both quantitative findings, including accuracy, loss convergence, and evaluation metrics, as well as qualitative analyses that illustrate the model's ability to robustly localize and classify various defect categories [44-46]. Through detailed visual examples and performance curves, the results highlight the stability, generalization capability, and practical relevance of the developed system, offering clear evidence of its potential for deployment in automated road inspection and maintenance applications.

Fig. 3 illustrates the evolution of training and validation accuracy across 500 learning epochs, demonstrating the progressive convergence and stability of the proposed model. Both accuracy curves exhibit a rapid initial increase during the first 50 epochs, indicating efficient learning of fundamental feature representations. As training progresses, the curves gradually transition into a slower, asymptotic improvement phase, ultimately approaching values near 0.95, which reflects strong generalization capability. The close alignment between training and validation accuracy throughout the optimization process suggests that the model effectively mitigates overfitting, maintaining consistent performance on unseen data. Minor fluctuations in the validation curve, particularly in the mid-to-late epochs, are expected in complex, real-world datasets but remain within a narrow range, further confirming the robustness and stability of the learning process. Overall, Fig. 3 validates the efficacy of the model architecture and training strategy in achieving high detection accuracy over extended training iterations.

Fig. 4 presents the training and validation loss trajectories over 500 epochs, offering insight into the optimization dynamics and convergence behavior of the proposed model. Both curves exhibit a steep decline during the initial epochs, indicating rapid minimization of prediction error as the model assimilates core structural patterns within the training data. As training progresses, the loss values continue to decrease gradually, ultimately approaching near-zero levels, which reflects strong model fitting and stable learning. The validation loss closely follows the training loss throughout the entire learning process, with only minor fluctuations, suggesting that the model maintains good generalization performance without exhibiting notable overfitting tendencies. These small oscillations in the validation curve are characteristic of real-world datasets containing diverse road textures and variable environmental conditions, yet their narrow amplitude further reinforces the robustness of the proposed architecture. Overall, Fig. 4 provides compelling evidence that the training strategy effectively drives loss reduction while ensuring consistent validation performance across extended training durations.

Fig. 5 illustrates representative qualitative outcomes produced by the proposed multi-scale ROI-aligned detection framework, showcasing its ability to accurately localize and classify diverse categories of road surface anomalies under varying environmental and structural conditions. Across all six sample scenes, the model successfully identifies potholes, damaged paint, alligator cracks, and manhole covers with appropriately colored bounding boxes and confidence scores, demonstrating robust feature extraction even in scenarios with shadows, complex backgrounds, and perspective distortions. The predictions remain consistent across both residential and urban roadway settings, suggesting strong generalization capability beyond a single visual domain. Notably, the model maintains reliable detection performance on small or visually subtle defects, such as faded markings or shallow depressions, which often pose challenges for conventional detection algorithms. The presence of minimal false positives and accurately delineated damage regions further reflects the effectiveness of the integrated multi-scale architecture and the ROI-aligned refinement process. Overall, Fig. 5 provides compelling visual evidence that the proposed method achieves high detection precision and interpretability across a broad range of real-world road conditions.

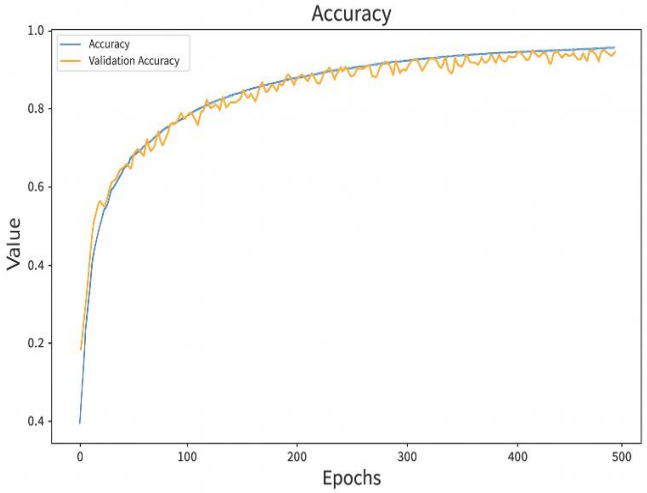


Fig. 3. Training and validation accuracy curves over 500 learning epochs.

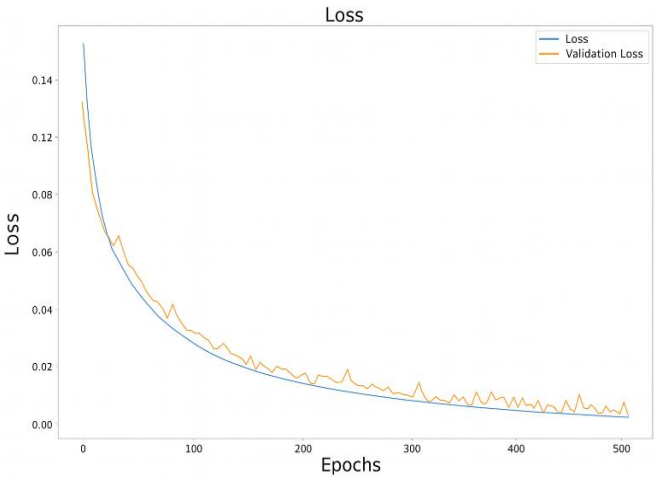


Fig. 4. Training and validation loss curves over 500 learning epochs.



Fig. 5. Qualitative road damage detection results produced by the proposed multi-scale ROI-aligned framework across diverse roadway scenes.

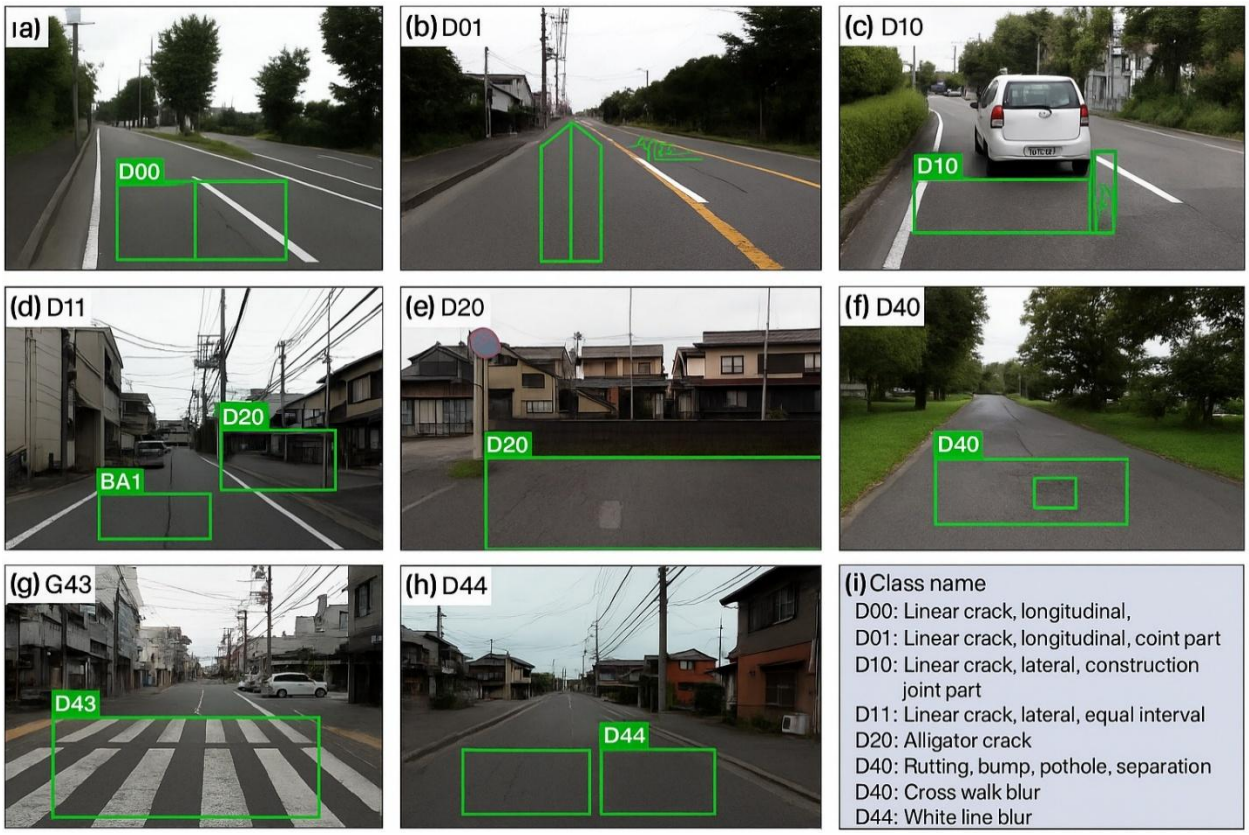


Fig. 6. Ground-truth annotated samples illustrating diverse road-damage categories across the dataset.

Fig. 6 presents a comprehensive visualization of the ground-truth annotations used in the dataset, illustrating the variety and distribution of road-surface damage classes considered in the evaluation. Fig. 6(a) to Fig. 6(h) depicts a distinct roadway environment, labeled with manually annotated bounding boxes corresponding to specific defect categories, including longitudinal cracks (D00, D01), lateral cracks (D10, D11), alligator cracking (D20), potholes and rutting (D40), crosswalk blur (D43), and white-line blur (D44). The consistent placement and scale of the annotations across varying lighting conditions, traffic presence, and road textures highlight the diversity and complexity of the dataset. These examples demonstrate the challenges posed by subtle crack patterns, varying orientations, background clutter, and occlusions, which collectively underscore the necessity for robust multi-scale feature extraction in automated detection systems. The accompanying legend provides standardized class definitions, ensuring clarity in understanding the annotation schema. Overall, Fig. 6 illustrates the diversity and annotation precision of the dataset, serving as a crucial benchmark for assessing the model's capability to detect heterogeneous road damages in real-world scenarios.

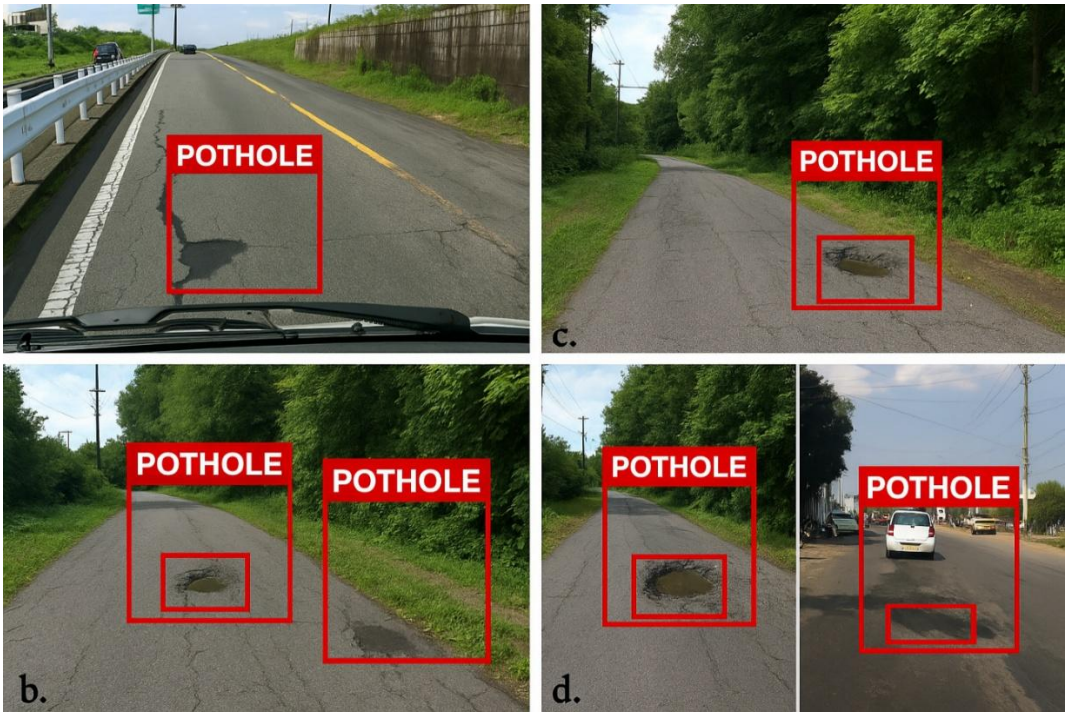


Fig. 7. Qualitative pothole detection results produced by the proposed model across diverse road environments.

Fig. 7 presents qualitative detection results demonstrating the proposed model's capability to accurately localize potholes across diverse roadway environments. The images depict multiple real-world scenarios, including highways, suburban roads, and rural pathways, each containing potholes of varying shapes, depths, and illumination conditions. The model consistently identifies these defects with clearly delineated red bounding boxes, indicating strong robustness to background clutter, shadow interference, and changes in surface texture. Notably, even in challenging scenes involving small, partially occluded, or low-contrast potholes, the detection outputs remain precise and well-aligned with the actual damaged regions, highlighting the effectiveness of the multi-scale feature extraction and region refinement mechanisms embedded in the architecture. These visual results substantiate the model's capacity to generalize beyond training conditions and reliably detect critical road surface anomalies that pose safety risks in real-world settings.

VIII. Discussion

The results obtained in this study demonstrate the effectiveness of the proposed multi-scale ROI-aligned deep learning framework for automated road damage detection and severity assessment, highlighting several important observations regarding model performance and real-world applicability. Quantitative evaluations revealed that both accuracy and loss curves converged smoothly over prolonged training, indicating stable optimization dynamics and strong generalization across heterogeneous image conditions. The close alignment between training and validation metrics suggests that the model successfully mitigates overfitting, despite being trained on a dataset characterized by high intra-class variability and diverse environmental contexts [47]. This stability is further reinforced by the gradual reduction of validation loss, demonstrating the model's resilience to noise, viewpoint changes, and illumination fluctuations that commonly challenge road damage detection systems.

The qualitative results presented in Fig. 5 to Fig. 7 further substantiate the robustness of the proposed approach. The model effectively identified a wide spectrum of damage types, including longitudinal cracks, lateral cracks, alligator cracking, potholes, and degraded markings, even in visually complex scenes with occlusions and shadow interference. The accurate delineation of damage boundaries across different road textures underscores the contribution of multi-scale feature fusion and

ROI alignment mechanisms [48], which enable precise localization of both small-scale and structurally subtle anomalies. Notably, the system exhibited strong performance in identifying potholes, a critical defect class associated with significant safety risks, implying that the architecture is well suited for deployment in intelligent transportation and roadway maintenance systems.

Despite these promising outcomes, certain limitations warrant further investigation. Minor fluctuations in validation accuracy and loss indicate the presence of challenging samples that remain difficult to classify consistently, particularly in cases involving extremely faded markings or overlapping damage categories. Additionally, while the model demonstrated strong performance under daylight conditions, its robustness under nighttime, rainy, and low-visibility scenarios requires systematic evaluation to ensure reliable large-scale deployment. Future work could incorporate multimodal sensing, such as thermal or depth imaging, and explore transformer-based architectural enhancements to further improve contextual reasoning and structural awareness. Overall, the findings affirm the model's potential to serve as a reliable component in automated road inspection pipelines, offering substantial benefits for proactive maintenance planning and infrastructure safety management.

IX. Conclusion

In conclusion, this study introduced a multi-scale ROI-aligned deep learning framework designed to address the complexities of automated road damage detection and severity assessment across diverse real-world environments. The proposed architecture demonstrated consistent and robust performance, exhibiting strong convergence behavior, high detection accuracy, and stable generalization between training and validation datasets. By integrating hierarchical feature extraction, a dedicated proposal network, and refined ROI-aligned feature encoding, the model effectively captured both fine-grained structural anomalies and broader contextual patterns essential for reliable defect identification. Qualitative results further underscored the system's ability to delineate various damage types, including cracks, potholes, and degraded markings, even under challenging conditions involving cluttered backgrounds, shadows, and texture irregularities. Although minor fluctuations in validation metrics suggest opportunities for refinement, particularly in cases involving subtle or overlapping damage categories, the overall performance affirms the model's suitability for deployment in intelligent transportation infrastructures and road maintenance monitoring systems. Future research may focus on enhancing robustness under adverse environmental conditions, incorporating multimodal sensing, or leveraging advanced transformer-based architectures for improved contextual awareness. Collectively, the findings highlight the substantial potential of the proposed approach to support scalable, accurate, and efficient road inspection processes, thereby contributing to safer and more resilient urban mobility ecosystems.

Acknowledgment

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References

[1] Iparraguirre, O., Iturbe-Olleta, N., Brazalez, A., & Borro, D. (2022). Road marking damage detection based on deep learning for infrastructure evaluation in emerging autonomous driving. IEEE Transactions on Intelligent Transportation Systems, 23(11), 22378-22385.

[2] Yin, T., Zhang, W., Kou, J., & Liu, N. (2024). Promoting automatic detection of road damage: A high-resolution dataset, a new approach, and a new evaluation criterion. IEEE Transactions on Automation Science and Engineering, 22, 2472-2484.

[3] Khan, M. W., Obaidat, M. S., Mahmood, K., Batool, D., Badar, H. M. S., Aamir, M., & Gao, W. (2024). Real-time road damage detection and infrastructure evaluation leveraging unmanned aerial vehicles and tiny machine learning. IEEE Internet of Things Journal, 11(12), 21347-21358.

[4] Ramkumar. R., Sureshkumar Nagarajan, Dinesh Prasanth Ganapathi, "Enhanced Deep Learning Framework for Tamil Slang Classification with Multi-task Learning and Attention Mechanisms", International Journal of Information Technology and Computer Science(IJITCS), Vol.17, No.6, pp.29-51, 2025. DOI:10.5815/ijitcs.2025.06.02

[5] Ma, Y., Ghanbari, H., Huang, T., Irvin, J., Brady, O., Zalouk, S., ... & Narsude, M. (2023). A System for Automated Vehicle Damage Localization and Severity Estimation Using Deep Learning. IEEE Transactions on Intelligent Transportation Systems, 25(6), 5627-5639.

[6] Zhang, H., Wu, Z., Qiu, Y., Zhai, X., Wang, Z., Xu, P., ... & Jiang, N. (2022). A new road damage detection baseline with attention learning. Applied Sciences, 12(15), 7594.

[7] Silva, L. A., Leithardt, V. R. Q., Batista, V. F. L., Gonzalez, G. V., & Santana, J. F. D. P. (2023). Automated road damage detection using UAV images and deep learning techniques. IEEE access, 11, 62918-62931.

[8] Kortmann, F., Fassmeyer, P., Funk, B., & Drews, P. (2022). Watch out, pothole! featuring road damage detection in an end-to-end system for autonomous driving. Data & Knowledge Engineering, 142, 102091.

[9] Ha, J., Kim, D., & Kim, M. (2022). Assessing severity of road cracks using deep learning-based segmentation and detection. The Journal of Supercomputing, 78(16), 17721-17735.

[10] Iyinoluwa M. Oyelade, Olutayo K. Boyinbode, Olumide S. Adewale, Emmanuel O. Ibam, "Farmland Intrusion Detection using Internet of Things and Computer Vision Techniques", International Journal of Information Technology and Computer Science(IJITCS), Vol.16, No.2, pp.32-44, 2024. DOI:10.5815/ijitcs.2024.02.03

[11] Amodu, O. D., Lottu, O., Imran, R., & Shaban, A. (2025). Automated Vehicle Damage Inspection: A Comprehensive Evaluation of Deep Learning Models and Real-World Applicability. SN Computer Science, 6(5), 525.

[12] Shim, S., Kim, J., Lee, S. W., & Cho, G. C. (2022). Road damage detection using super-resolution and semi-supervised learning with generative adversarial network. Automation in construction, 135, 104139.

[13] Van Ruitenbeek, R. E., & Bhulai, S. (2022). Convolutional Neural Networks for vehicle damage detection. Machine Learning with Applications, 9, 100332.

[14] Omarov, B., Altayeva, A., Turganbayeva, A., Abdulkarimova, G., Gusmanova, F., Sarbasova, A., ... & Omarov, N. (2018, November). Agent based modeling of smart grids in smart cities. In International Conference on Electronic Governance and Open Society: Challenges in Eurasia (pp. 3-13). Cham: Springer International Publishing.

[15] Sami, A. A., Sakib, S., Deb, K., & Sarker, I. H. (2023). Improved YOLOv5-based real-time road pavement damage detection in road infrastructure management. Algorithms, 16(9), 452.

[16] Rathee, M., Bačić, B., & Doborjeh, M. (2023). Automated road defect and anomaly detection for traffic safety: A systematic review. Sensors, 23(12), 5656.

[17] Lin, C., Tian, D., Duan, X., Zhou, J., Zhao, D., & Cao, D. (2022). DA-RDD: Toward domain adaptive road damage detection across different countries. IEEE Transactions on Intelligent Transportation Systems, 24(3), 3091-3103.

[18] Omarov, B., Omarov, B., Rakhymzhanov, A., Niyazov, A., Sultan, D., & Baikuvekov, M. (2024). Development of an artificial intelligence-enabled non-invasive digital stethoscope for monitoring the heart condition of athletes in real-time. Retos: nuevas tendencias en educación física, deporte y recreación, (60), 1169-1180.

[19] Qaddour, J., & Siddiqa, S. A. (2023). Automatic damaged vehicle estimator using enhanced deep learning algorithm. Intelligent Systems with Applications, 18, 200192.

[20] Wan, F., Sun, C., He, H., Lei, G., Xu, L., & Xiao, T. (2022). YOLO-LRDD: A lightweight method for road damage detection based on improved YOLOv5s. EURASIP Journal on Advances in Signal Processing, 2022(1), 98.

[21] Bisrat Betru, Fekade Getahun, "Ontology-driven Intelligent IT Incident Management Model", International Journal of Information Technology and Computer Science(IJITCS), Vol.15, No.1, pp.30-41, 2023. DOI:10.5815/ijitcs.2023.01.04

[22] Al Noman, M. A., Zhai, L., Almukhtar, F. H., Rahaman, M. F., Omarov, B., Ray, S., ... & Wang, C. (2023). A computer vision-based lane detection technique using gradient threshold and hue-lightness-saturation value for an autonomous vehicle. International Journal of Electrical and Computer Engineering, 13(1), 347.

[23] Cano-Ortiz, S., Iglesias, L. L., del Árbol, P. M. R., Lastra-González, P., & Castro-Fresno, D. (2024). An end-to-end computer vision system based on deep learning for pavement distress detection and quantification. Construction and Building Materials, 416, 135036.

[24] Duran, B., Emory, D., Azam, Y. E., & Linzell, D. G. (2025). A novel CNN architecture for robust structural damage identification via strain measurements and its validation via full-scale experiments. Measurement, 239, 115393.

[25] Youwai, S., Chaiyaphat, A., & Chaipetch, P. (2024). YOLO9tr: a lightweight model for pavement damage detection utilizing a generalized efficient layer aggregation network and attention mechanism. Journal of Real-Time Image Processing, 21(5), 163.

[26] Deepa, D., & Sivasangari, A. (2023). An effective detection and classification of road damages using hybrid deep learning framework. Multimedia Tools and Applications, 82(12), 18151-18184.

[27] Inam, H., Islam, N. U., Akram, M. U., & Ullah, F. (2023). Smart and automated infrastructure management: A deep learning approach for crack detection in bridge images. Sustainability, 15(3), 1866.

[28] Zhang, Y., Zuo, Z., Xu, X., Wu, J., Zhu, J., Zhang, H., ... & Tian, Y. (2022). Road damage detection using UAV images based on multi-level attention mechanism. Automation in construction, 144, 104613.

[29] Omarov, B., Suliman, A., Kushibar, K. Face recognition using artificial neural networks in parallel architecture. Journal of Theoretical and Applied Information Technology 91 (2), pp. 238-248. Open Access.

[30] Kang, S., Wu, Y. C., David, D. S., & Ham, S. (2022). Rapid damage assessment of concrete bridge deck leveraging an automated double-sided bounce system. Automation in Construction, 138, 104244.

[31] Jalaj Pateria, Laxmi Ahuja, Subhranil Som, Ashish Seth, "Applying Clustering to Predict Attackers Trace in Deceptive Ecosystem by Harmonizing Multiple Decoys Interactions Logs", International Journal of Information Technology and Computer Science(IJITCS), Vol.15, No.5, pp.35-44, 2023. DOI:10.5815/ijitcs.2023.05.04

[32] Salcedo, E., Jaber, M., & Carrión, J. R. (2022). A novel road maintenance prioritisation system based on computer vision and crowdsourced reporting. Journal of Sensor and Actuator Networks, 11(1), 15.

[33] Crognale, M., De Iuliis, M., Rinaldi, C., & Gattulli, V. (2023). Damage detection with image processing: a comparative study. Earthquake Engineering and Engineering Vibration, 22(2), 333-345.

[34] Altayeva, A., Omarov, B., Jeong, H. C., & Im Cho, Y. (2016). Multi-step face recognition for improving face detection and recognition rate. Far East Journal of Electronics and Communications, 16(3), 471.

[35] Li, Z., Lan, Y., & Lin, W. (2024). Footbridge damage detection using smartphone-recorded responses of micromobility and convolutional neural networks. Automation in Construction, 166, 105587.

[36] Deepa, D., & Sivasangari, A. (2024). ESSR-GAN: Enhanced super and semi supervised remora resolution based generative adversarial learning framework model for smartphone based road damage detection. multimedia Tools and Applications, 83(2), 5099-5129.

[37] Omarov, B., Omarov, B., Shekerbekova, S., Gusmanova, F., Oshanova, N., Sarbasova, A., ... & Sultan, D. (2019, October). Applying face recognition in video surveillance security systems. In International Conference on Objects, Components, Models and Patterns (pp. 271-280). Cham: Springer International Publishing.

[38] Arya, D., Maeda, H., Ghosh, S. K., Toshniwal, D., & Sekimoto, Y. (2024). RDD2022: A multi-national image dataset for automatic road damage detection. Geoscience Data Journal, 11(4), 846-862.

[39] Benallal, M. A., & Tayeb, M. S. (2023). An image-based convolutional neural network system for road defects detection. IAES International Journal of Artificial Intelligence, 12(2), 577.

[40] Omarov, B., Batyrbekov, A., Dalbekova, K., Abdulkarimova, G., Berkimbaeva, S., Kenzhegulova, S., ... & Omarov, B. (2020, December). Electronic stethoscope for heartbeat abnormality detection. In International Conference on Smart Computing and Communication (pp. 248-258). Cham: Springer International Publishing.

[41] Agyemang, I. O., Zhang, X., Adjei-Mensah, I., Acheampong, D., Fiasam, L. D., Sey, C., ... & Effah, D. (2023). Automated vision-based structural health inspection and assessment for post-construction civil infrastructure. Automation in Construction, 156, 105153.

[42] Li, J., Liu, T., Wang, X., & Yu, J. (2022). Automated asphalt pavement damage rate detection based on optimized GA-CNN. Automation in Construction, 136, 104180.

[43] Omarov, N., Omarov, B., Azhibekova, Z., & Omarov, B. (2024). Applying an augmented reality game-based learning environment in physical education classes to enhance sports motivation. Retos, 60, 269-278.

[44] Deep Karan Singh, Nisha Rawat, "Decoding Optimization Algorithms for Convolutional Neural Networks in Time Series Regression Tasks", International Journal of Information Technology and Computer Science(IJITCS), Vol.15, No.6, pp.37-49, 2023. DOI:10.5815/ijitcs.2023.06.04

[45] Omarov, B., Batyrbekov, A., Suliman, A., Omarov, B., Sabdenbekov, Y., & Aknazarov, S. (2020, November). Electronic stethoscope for detecting heart abnormalities in athletes. In 2020 21st International Arab Conference on Information Technology (ACIT) (pp. 1-5). IEEE.

[46] Li, Z., Lin, W., & Zhang, Y. (2023, January). Real-time drive-by bridge damage detection using deep auto-encoder. In Structures (Vol. 47, pp. 1167-1181). Elsevier.

[47] Han, Q., Yan, S., Wang, L., & Kawaguchi, K. I. (2023). Ceiling damage detection and safety assessment in large public buildings using semantic segmentation. Journal of Building Engineering, 80, 107961.

[48] Sjölander, A., Belloni, V., Ansell, A., & Nordström, E. (2023). Towards automated inspections of tunnels: A review of optical inspections and autonomous assessment of concrete tunnel linings. Sensors, 23(6), 3189.

Enhanced Mobile GC Vit Architecture for Efficient Image Classification with Application to Plant Disease Detection

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***Abstract*—Efficient and accurate automated diagnosis of plant diseases remains a challenge for deployment on resource-constrained edge devices. While hybrid vision transformers like GCViT balance accuracy and efficiency, they often lose critical high-frequency details such as fine lesion textures and leaf margins that are essential for fine-grained disease classification. To address this gap, we propose the Enhanced High-Frequencies Global Context Visual Transformer (EHF-GCViT), a novel hybrid architecture designed to explicitly enhance high-frequency feature retention within a lightweight framework. The core innovations of EHF-GCViT include: first, a customized, lightweight convolutional refinement block based on depthwise separable operations that acts as a learnable pre-processor to preserve discriminative spatial details before tokenization; second, a gated convolutional block that replaces the final transformer stage, reducing the model memory footprint from 46.36 MB to 34.48 MB; and third, an adaptive normalization strategy to stabilize the training of the integrated heterogeneous layers. Extensive experiments on the PlantVillage tomato disease dataset demonstrate that EHF-GCViT achieves superior performance, surpassing the baseline GCViT, standard Vision Transformers (ViT), and CNN benchmarks (e.g., ResNet) in accuracy, precision, recall, and F1-score. These results validate that explicitly modeling high-frequency features within a hybrid transformer design provides a more memory-efficient and accurate backbone for practical plant disease detection systems targeting edge deployment.**

Keywords*—Hybrid transformer architecture; convolutional refinement block; gated convolution; edge devices; high-frequency features; tomato leaf disease classification

I. Introduction

Climate change is significantly increasing the incidence, severity, and geographic range of plant diseases. Studies, such as [1], have demonstrated that shifting climate patterns are altering host-pathogen interactions, often accelerating disease cycles and allowing pathogens to invade new agricultural zones. Among the affected crops, the tomato—widely cultivated and of high economic importance—is particularly susceptible to various foliar diseases. These infections can lead to substantial yield losses, as highlighted by the World Processing Tomato Council (WPTC), which projects an 11.5% drop in yields for processing tomatoes in 2025 [2].

In response to these pressing challenges, researchers and policymakers are increasingly turning to artificial intelligence (AI) to improve plant health monitoring. Investment in AI-driven technologies aims to develop scalable, automated systems capable of diagnosing plant diseases directly from leaf images.

Convolutional Neural Networks (CNNs) are highly effective at capturing local spatial patterns through convolutional operations. However, their limited receptive field restricts their capacity for modeling long-range dependencies, which is critical for understanding global context in complex agricultural environments. In contrast, Vision Transformers (ViTs) excel at modeling global relationships via self-attention mechanisms but are often reliant on large datasets and substantial computational resources, making them less suitable for many real-world, resource-constrained applications. This limitation has spurred the emergence of hybrid architectures, which combine the local feature extraction strengths of CNNs with the global representation capabilities of Transformers. This design offers a balanced compromise between precision, efficiency, and generalization. By integrating convolutional inductive biases with transformer-based contextual learning, hybrid models achieve superior accuracy and robustness—a critical advantage in domains characterized by subtle visual variations like plant disease detection. Therefore, developing efficient hybrid backbones that can adapt to challenges like varying lighting, leaf orientation, and disease symptom presentation is essential. These innovative frameworks not only promise superior results in specialized domains like agriculture but also establish a foundational benchmark for future progress in broader object detection research.

In this paper, we introduce a novel hybrid model, Hybrid HF GCVIT, designed to enhance the high frequencies for better classification. In this architecture, we introduce a new lightweight convolution block that is intended to be placed between the original GCVIT [3] blocks, enhancing the detection of high frequencies within the extracted features and thereby improving accuracy. We present a new normalization strategy to improve the quality of training and the accuracy of our model. This synergy yields a model that is both accurate

and computationally efficient, making it well-suited for real-time applications and potential deployment on low-power hardware platforms. We built GCViT with modularity in mind, unlike many prior models that optimize solely for classification. Its architecture is intended not only to perform tomato disease classification with high precision but also to serve as a robust backbone for more complex tasks, including object detection, segmentation, and anomaly localization in agricultural contexts. Experimental evaluations on publicly available tomato disease datasets validate the proposed model's superior performance in terms of accuracy, generalization, and computational efficiency of GCViT, surpassing that of state-of-the-art CNNs, ViTs, and hybrid networks. These results suggest that GCViT offers a practical and scalable solution for smart farming applications, especially where on-device intelligence is considered.

II. Related Work

A. CNN-Based Models

Convolutional Neural Networks (CNNs) have established themselves as a foundational approach for plant disease classification, showing their strong capabilities in extracting hierarchical visual features from images. A significant body of research focuses on customizing CNN architectures to enhance accuracy and efficiency for agricultural applications.

Early work demonstrated the potential of CNNs with high parameter counts and data augmentation. For instance, Guerrero-Ibañez and Reyes-Muñoz [4] presented a high-performance CNN model trained on a dataset enriched with real and GAN-generated synthetic images, achieving 99.64% validation accuracy for tomato leaf diseases. While demonstrating high performance, this approach relies heavily on extensive data augmentation rather than intrinsic architectural innovation, and its computational complexity limits suitability for resource-constrained edge devices.

Subsequent research addressed challenges like dataset imbalance and subtle inter-class differences through architectural modifications. Zhang et al. [5] proposed a lightweight dual-attention model (LDAMNet), integrating a dual-attention convolution block to achieve 98.71% average accuracy. However, while LDAMNet reduces model complexity, it operates within the conventional CNN paradigm and lacks the capacity for global context modeling, which is crucial for understanding long-range spatial dependencies in disease patterns.

The pursuit of deployable models has driven the adoption of efficient architectures and transfer learning. Sultan [6] employed a modified Xception architecture with deep transfer learning, achieving 98% accuracy for multiple crops while optimizing for edge deployment. Transfer learning, however, is constrained by features learned from generic datasets like ImageNet, which may not optimally capture disease-specific, high-frequency details such as fine lesion textures.

Radočaj et al. [7] introduced the novel IncMB module, integrating an Inception structure with the Mish activation function into MobileNetV2, achieving 97.78% accuracy and confirming potential for mobile platforms.

Similarly, Vivek Anandh et al. [8] showed a transfer-learned MobileNetV2 model could attain 99.49% accuracy for tomato leaf disease classification on IoT platforms. While these models achieve efficiency through depthwise separable convolutions, they prioritize overall parameter reduction over the explicit preservation of high-frequency spatial details, which can result in the loss of discriminative fine-grained features essential for distinguishing visually similar diseases.

This principle of lightweight design extends to highly optimized, purpose-built CNNs. FL-ToLeD [9] leverages soft attention and depthwise separable convolutions to achieve 99.04% accuracy with only 221,594 parameters. Critically, its attention mechanism operates on downsampled feature maps, inherently discarding high-frequency details before they can be weighed a fundamental limitation for fine-grained classification.

Ashurov et al. [10] integrated Squeeze-and-Excitation (SE) blocks into a Depthwise CNN, achieving 98% accuracy. Although SE blocks enhance channel-wise feature recalibration, they do not explicitly preserve high-frequency spatial information, which can be suppressed if not statistically dominant across channels.

The success of efficient CNNs has proven generalizable across crops, with specialized models achieving high accuracy for rice (99.81%) [11], potato (99.3%) [12], and multiple vegetables (97.12%) [13]. While demonstrating task adaptability, these models are typically optimized for single-crop scenarios and lack architectural mechanisms for explicit high-frequency feature enhancement.

To address data scarcity, data-centric approaches have emerged. Ramadan et al. [14] used CycleGAN for synthetic image generation to enable a MobileNetV2 model to achieve perfect wheat disease classification accuracy.

Joseph et al. [15] constructed real-time multi-crop datasets and proposed the MRW-CNN, achieving 97.04%–98.08% accuracy. These methods improve performance through augmentation rather than architectural innovation for feature preservation, and their reliance on synthetic data adds pre-processing complexity ill-suited for streamlined edge deployment.

Critical Gap in CNN-Based Approaches: While CNNs excel at local feature extraction and have been successfully optimized for edge deployment, they fundamentally struggle with modeling long-range dependencies and global context. More critically, aggressive model compression techniques (e.g., depthwise convolutions) often sacrifice high-frequency feature retention, leading to reduced discriminative power for fine-grained disease classification where subtle texture differences are paramount. No existing CNN approach explicitly models high-frequency spatial features as a core, learnable architectural component prior to feature abstraction.

B. Vision Transformer (VIT)-Based Models

Vision Transformers (ViTs) address the global context limitation of CNNs by capturing long-range spatial relationships across entire images through self-attention mechanisms.

Karimanzira et al. [16] developed a ViT with cascaded group attention (ViT-CGA), achieving top-tier accuracy and robustness, enhanced with Explainable AI (XAI) and an LLM for interpretability. However, pure ViT architectures typically require large-scale datasets and substantial computational resources for effective training, making them impractical for scenarios with limited agricultural data and strict edge-device constraints.

Efforts have been made to adapt ViTs for practical deployment. Barman et al. [17] proposed ViT-SmartAgri, a CNN-free Vision Transformer designed for smartphones, attaining 90.99% accuracy for tomato leaf conditions. While demonstrating mobile potential, this accuracy falls below contemporary CNN benchmarks, suggesting that pure ViTs may sacrifice critical local feature sensitivity, particularly the high-frequency edge and texture information crucial for precise disease boundary detection.

For object detection in complex environments, Wang and Liu [18] introduced TomatoDet, a real-time model based on a Swin Transformer variant, achieving a high mAP of 92.3% for localizing tomato diseases. Although Swin Transformers introduce local windowing to reduce computation, they maintain substantial memory footprints and lack explicit mechanisms to preserve high-frequency spatial details during the patch embedding process, which can blur fine lesion boundaries.

Critical Gap in ViT-Based Approaches: While ViTs excel at global context modeling, they face critical limitations for edge-deployed plant disease detection: 1) high computational and memory requirements, 2) data hunger requiring extensive training sets, and 3) inherent loss of high-frequency spatial information during patch tokenization, where fine-grained disease textures are smoothed or discarded.

C. Hybrid CNN-VIT-Based Models

Hybrid architectures have emerged to synergistically combine the local feature sensitivity of CNNs with the global context modeling of ViTs, aiming to balance both capabilities for complex visual classification.

Sinamenye et al. [19] developed a hybrid EfficientNetV2B3+ViT model for potato disease detection, achieving 85.06% accuracy—an 11.43% improvement over prior methods. However, this architecture employs a simple feature concatenation without addressing the fundamental issue of high-frequency information loss during the ViT tokenization stage, and its modest accuracy suggests suboptimal feature integration.

Alwan and Alturfi [20] introduced a sophisticated framework fusing EfficientNet-B8, a ViT, and a Knowledge Graph (KG), achieving 99.3% accuracy across 38 disease categories. While highly accurate, this approach relies on ensemble complexity and external knowledge integration rather than architectural efficiency, resulting in a model unsuitable for edge deployment due to its substantial computational overhead.

Li et al. [21] proposed the Convolution Self-Guided Transformer (CSGT), merging CNN feature extraction with transformer context modeling to achieve 95.8%–96.9% accuracy across multiple crops. Although demonstrating cross-dataset robustness, CSGT does not explicitly address high-frequency feature preservation, and its self-guided mechanism adds architectural complexity that may hinder optimization for memory-constrained devices.

Sun et al. [22] combines EfficientNetV2 with a Swin Transformer and Coordinate Attention, achieving 99.70% accuracy for tomato disease classification. Despite excellent accuracy, the model retains the full transformer stack in later stages, resulting in a large memory footprint (>45MB) that exceeds practical limits for edge devices. Furthermore, it lacks an explicit mechanism to enhance high-frequency features before tokenization.

Chen et al. [23] proposed a comprehensive framework combining a DenseNet-based Vision Transformer (DVT) with a CycleGAN (CyTrGAN) for augmentation, achieving up to 99.45% accuracy with strong robustness. While effectively addressing class imbalance through data augmentation, DVT does not architecturally prioritize the retention of high-frequency spatial details, and its reliance on GAN-based preprocessing increases deployment complexity.

Critical Research Gap: Existing hybrid CNN-ViT architectures demonstrate that combining local and global feature modeling improves plant disease classification. However, a unified solution remains elusive due to three interconnected limitations:

1) High-frequency feature loss: Current hybrids do not explicitly preserve fine-grained spatial details (e.g., lesion edges, texture patterns) during the CNN-to-ViT transition, as patch embedding and tokenization inherently smooth this critical high-frequency information.

2) Memory inefficiency: Most models retain full transformer stages, resulting in memory footprints (40-50MB+) that preclude deployment on resource-constrained edge devices common in agriculture.

3) Training instability: The integration of heterogeneous CNN and transformer layers often introduces optimization challenges due to conflicting normalization requirements and inconsistent gradient flow.

4) Our contribution: To directly address these gaps, we propose EHF-GCViT (Edge-optimized High-Frequency Gated Convolutional Vision Transformer).

Our novel architecture:

- Introduces a Lightweight High-Frequency Refinement block before the transformer stage to explicitly enhance and preserve discriminative fine-grained features,
- Replaces the final transformer stages with a Gated Convolutional Neck, significantly reducing the memory footprint while maintaining global context awareness, and
- Employs Adaptive Layer Normalization to stabilize the training of heterogeneous architectural components. This design provides a balanced solution that achieves

state-of-the-art accuracy with a memory profile explicitly optimized for real-world edge deployment.

III. Proposed Methodology

A. Asymmetric Depthwise Convolution Block

In this work, we propose a novel Asymmetric Depthwise Convolution Block (ADCB) designed to enhance the detection of high-frequency features, thereby improving the quality and sharpness of the extracted features.

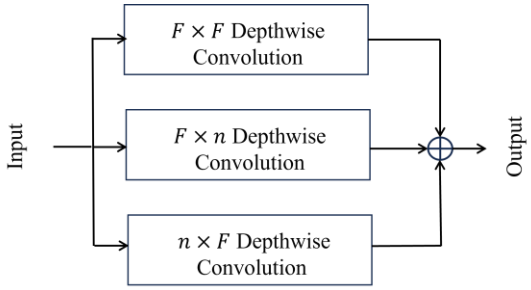


Fig. 1. The asymmetric depth-wise convolution block.

As shown in Fig. 1, the proposed block can be viewed as a lightweight variant of the Asymmetric Convolution Block (ACB) [24] where classical convolution layers are replaced with depthwise convolution layers to significantly reduce computational cost during feature extraction. While maintaining the conceptual structure of the original ACB, our block consists of a symmetric depthwise convolution with kernel size F × F to capture core spatial features and two asymmetric depthwise convolutions with kernel sizes, F × F , F × n and n × F where n < F unlike the original ACB, which restricts n=1, we introduce flexibility in the choice of n, allowing the creation of new asymmetric filters that can be tuned to emphasize directional high-frequency components with greater adaptability. The outputs of the three branches are summed elementwise to produce the block's final output. Like the original ACB, the overall structure can be treated as a single depthwise convolution layer with enhanced directional sensitivity.

B. High-Frequency Depthwise Separable Convolution Block

The high-frequency depthwise separable convolution block shown in Fig. 2, is a new variant of the depthwise separable convolution block, which is the fundamental block of the Mobilenet architecture [25]. We replace the classical depthwise layer with our asymmetric depthwise convolution block to sharpen the extracted features while retaining the 1x1 pointwise convolution for channel wise feature integration. This modification preserves the efficient structure of MobileNet while significantly improving its ability to capture high-frequency and directionally aware spatial features.

We use a residual connection from the block's input to its output to preserve essential base features while selectively refining details. This design enables the block to act as a feature enhancement unit, correcting and sharpening representations rather than replacing them outright. The residual path ensures stability during training and helps the refinement remain focused on informative residual patterns. The resulting block balances efficiency and accuracy, offering enhanced descriptive power without significantly increasing computational complexity, making it especially suitable for resource constrained applications such as mobile and embedded systems.

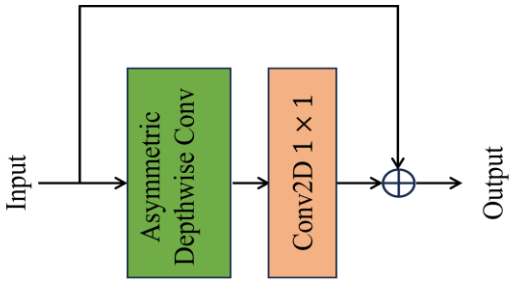


Fig. 2. The high-frequency depth-wise separable convolution block.

C. Normalization Strategy

In the proposed architecture, we apply Group Normalization (GN) following depthwise convolutions and Layer Normalization (LN) following 1×1 pointwise convolutions, in accordance with the functional properties of each normalization technique and the convolutional operations they follow. Depthwise convolutions operate on each input channel independently, making them inherently sparse in inter-channel interaction. GN, which normalizes within groups of channels rather than across the batch dimension, is well-suited for this context. Unlike Batch Normalization (BN), Group Normalization (GN) maintains performance with small batch sizes and better preserves the spatial structure of feature maps, making it more compatible with the independent-channel nature of depthwise operations. Moreover, GN avoids the over-smoothing behavior that Layer Normalization might induce in spatially distributed features, as LN treats each feature vector. Conversely, 1x1 convolutions perform intensive channel mixing, aggregating information across all feature channels at each spatial location. In this setting, LN proves advantageous because it normalizes across the full set of channels for each sample, offering sample-level consistency and effectively stabilizing the dense transformations introduced by pointwise convolutions. This dual strategy using GN with depthwise layers and LN with pointwise layers ensures that normalization remains functionally aligned with the nature of the operations it follows, improving convergence stability and feature quality without disrupting spatial integrity.

D. Gelu Channel Attention Fused MBC

In this work, we propose a novel modification of the previously introduced LRCA Fused MBC block [26] referred to as the GLCA MBC block. The term GLCA denotes the integration of the GELU activation function in place of the Leaky ReLU, applied consistently within both the channel attention module and all constituents' layers of the block. Additionally, we replace the standard convolutional layer with a dilated (atrous) convolution, which enlarges the receptive field without increasing the number of parameters, thereby enabling the network to capture broader contextual information while preserving spatial resolution.

This replacement of conventional 5×5 convolutions with dilated convolutions significantly reduces the computational

burden while maintaining a high level of classification precision. Through extensive experimentation, we demonstrate that this configuration is particularly effective for plant disease classification, offering a more computationally efficient alternative to large kernel convolutions by achieving an equivalent receptive field using smaller, dilated kernels.

Furthermore, we retain the same normalization strategy as the HF depthwise separable convolution block, applying Group Normalization (GN) after classical convolution layers and Layer Normalization (LN) after 1 × 1 pointwise convolutions. This targeted use of normalization improves stability and enhances learning dynamics across the heterogeneous components of the block. Fig. 3 illustrates the architectural design of the proposed GLCA Fused MBC block.

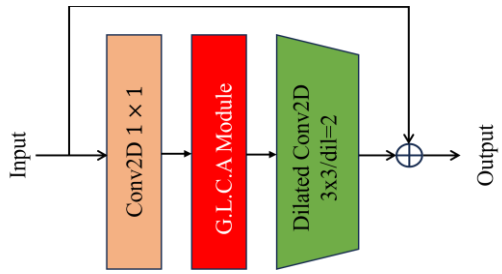


Fig. 3. GLCA fused MBC block.

E. Enhanced High-Frequencies GCVIT Architecture

As previously stated, our architecture is a modified version of the GCViTXXTiny model. We retain the initial patch embedding block and the three hierarchical levels of the original GCViT design. However, we introduce a key enhancement: a refinement layer is inserted between each pretrained pair of transformer stages as shown in Fig. 4.

Each refinement layer maintains the same input and output dimensions, enabling the use of residual connections to preserve and enrich the learned feature representations. This design helps enhance intermediate features without disrupting the original flow of information. The asymmetric filter dimensions were selected as F=5 and n=2 since through experimental optimization this combination produces the most favorable results.

Additionally, we replace the final transformer level of GCViT with a GLCA Fused MBC block, which significantly reduces the number of parameters while maintaining competitive accuracy. This modification leads to a 25.62% reduction in memory usage, making the model lightweight and efficient for deployment on resource constrained devices. Despite these changes, experimental results demonstrate that modified architecture preserves strong performance across evaluation metrics.

Fig. 4 shows the enhanced high-frequency hybrid architecture (with the original GCVIT frozen layers in blue, refinement layers in yellow, GLCA Fused MBC in green, global average pooling in red and Conv 1x1 in pink).

Table I provides a detailed description of the proposed architecture, including the input and output sizes of each layer, the stride values, and the number of groups used in Group Normalization (GNorm).

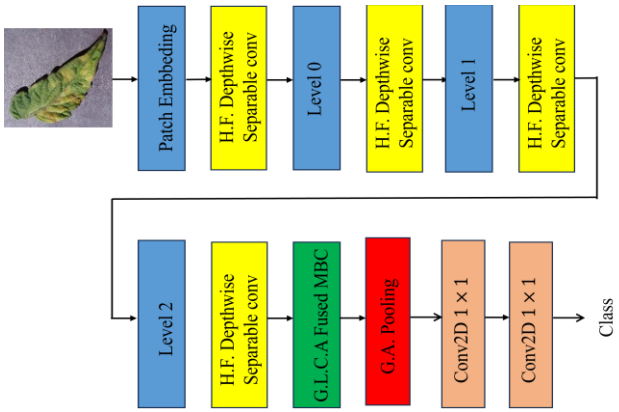


Fig. 4. The enhanced high-frequency hybrid architecture (with the original GCVIT frozen layers in blue, refinement layers in yellow, GLCA Fused MBC in green, global average pooling in red and Conv 1x1(classifier) in pink).

TABLE I. NETWORK ARCHITECTURE LAYERS WITH INPUT/OUTPUT SHAPES AND PARAMETERS

Block	Input	Output	G	
Patch Embedding	$224^2 \times 3$	$56^2 \times 64$	-	2
Dropout	$56^2 \times 64$	$56^2 \times 64$	-	-
H.F D.W.S.Conv0	$56^2 \times 64$	$56^2 \times 64$	8	1
Level 0	$56^2 \times 64$	$28^2 \times 128$	-	2
H.F D.W.S.Conv1	$28^2 \times 128$	$28^2 \times 128$	16	1
Level 1	$28^2 \times 128$	$14^2 \times 256$	-	2
H.F D.W.S.Conv2	$14^2 \times 256$	$14^2 \times 256$	32	1
Level 2	$14^2 \times 256$	$7^2 \times 512$	-	2
H.F D.W.S.Conv3	$7^2 \times 512$	$7^2 \times 512$	32	1
GL.CA Fused MBC	$7^2 \times 512$	$7^2 \times 512$	32	1
Global Average Pooling	$7^2 \times 512$	$1^2 \times 512$	-	-
Conv2D 1×1	$1^2 \times 512$	$1^2 \times 1028$	-	1
Conv2D 1×1	$1^2 \times 1028$	$1^2 \times Class$	-	1

G=Group size and S=Stride

IV. RESULTS

In this section, we describe the experimental setup and the different experiments conducted to rigorously evaluate our model, as well as to compare our results with those obtained from state-of-the-art architectures. In this section, we describe the experimental setup and the different experiments conducted to rigorously evaluate our model, as well as to compare our results with those obtained from state-of-the-art architectures.

A. Dataset

To evaluate the performance of our proposed system, we utilized a dataset of tomato leaf diseases extracted from the PlantVillage [27] database, made available publicly through the repository [28] .This dataset comprises 14,531 tomato leaf images, covering both healthy specimens and those affected by various diseases. Table II shows that the images are categorized into ten distinct classes, which include nine disease types: Bacterial Spot, Early Blight, Late Blight, Leaf Mold, Septoria Leaf Spot, Target Spot, Tomato Mosaic Virus,

Tomato Yellow Leaf Curl Virus, and Two-Spotted Spider Mite, as well as one healthy class. Each image generally depicts a single leaf captured against a uniform background, providing a clean and consistent input for classification tasks. Due to its scale and diversity, this dataset has become a widely adopted benchmark for assessing the effectiveness of machine learning and deep learning models in plant disease diagnosis. The version of the dataset we used includes five predefined folds intended for cross-validation. Each fold is split into 80% for training and 20% for testing, allowing for robust and systematic evaluation across multiple runs. In our experiments, we employed all five folds for cross-validation tests. For ablation studies and comparative analysis with state-of-the-art models, we used only the first fold to ensure consistency and efficiency. During the training phase, we further allocated 10% of the training subset from each fold for validation, while the remaining 90% was used for model training.

TABLE II. NUMBER OF SAMPLES PER CLASS IN THE DATASET

Class	Number of samples per class
Bacterial spot	1702
Early blight	800
Healthy	1272
Late blight	1528
Leaf Mold	762
Septoria leaf spot227	1417
Target Spot227	1124
Tomato mosaic virus227	299
Tomato Yellow Leaf Curl Virus227	4286
Two-spotted spider mite227	1341
Total number of images	14531

B. Metrics

In our work, we opted to use confusion matrix, Accuracy, Precision, Recall, and F1-score as statistics to evaluate the performance of our model. The confusion matrix is a matrix that allows us to measure the performance of a system during a classification task by providing information about the comparison between original classes and predicted classes. This information is classified into four categories:

True positive (TP): When the instance is positive, and the model classifies it as positive.

True negative (TN): When the instance is negative, and the model classifies it as negative.

False positive (FP): When the instance is negative, and the model classifies it as positive.

False negative (FN): When the instance is positive, and the model classifies it as negative.

Accuracy is the basic metric used in most evaluations, and it shows the number of predictions over all predictions. It is calculated by splitting the number of correct predictions by the total number of predictions.

$$Accuracy = \frac{Tp+TN}{TP+FP+TN+FN} \quad (1)$$

Precision shows the number of true positive predictions compared to the total number of all positive predictions.

$$Precision = \frac{Tp}{TP+FP} \quad (2)$$

Recall measures the number of positive cases compared to the total number of all the predictions classified as positive.

$$Recall = \frac{Tp}{TP+FN} \quad (3)$$

F1-score is a measure that we calculate as a harmonic mean or the weighted average of precision and recall.

$$F1-score = \frac{2\times Precision\times Recall}{Precision+Recall} \quad (4)$$

C. Training Strategy

To leverage the representational power of pre-trained models while adapting them to our specific classification task, we adopted a transfer learning strategy. The core layers and blocks of the original GCViT architecture were frozen, meaning their weights remained unchanged during training to preserve features learned from large-scale datasets. We integrated our custom blocks HF Depthwise Separable Convolution, GLLCA, and Fused MBC, along with a classification head specifically designed for our target task. Only these newly added components were trained during the training process. This selective training approach reduces computational cost and helps prevent overfitting, particularly when working with limited data. Optimization was performed using the Weighted Adam (W.Adam) algorithm, an enhanced version of Adam that incorporates weight-aware mechanisms to improve both convergence speed and generalization performance.

D. Ablation Study

To assess the individual contributions of key design choices in our hybrid vision model, we conducted a structured ablation study. This process involved systematically removing specific components from our hybrid architecture to measure their direct impact on performance. We focused on evaluating the role of the HF depth-wise separable convolution block (Model A) and the GLCA-Fused MBC (Model B) in improving classification accuracy for plant disease detection.

From the training perspective as shown in Table III, all variants achieved near-perfect accuracy, with losses approaching zero. Model A and the Hybrid GCViT attained 99.92% and 99.94% training accuracy, respectively, accompanied by equally high validation accuracy (99.91% and 99.74%), indicating excellent learning capacity with no signs of overfitting. Although Model B experienced a minor drop in validation accuracy (99.31%) compared to its training accuracy (99.92%), its performance remained competitive, especially given its reduced model size (33.29 MB).

Table IV presents the testing performance on the testing data set and shows that Model A achieved the highest accuracy (99.55%) and F1 score (99.48%), closely followed by the Hybrid GCViT (99.52% accuracy, 99.47% F1). Despite being slightly smaller than Model A, the Hybrid model maintained

nearly identical performance, suggesting that the combination of both enhancements led to a well-balanced architecture. Overall, this ablation study confirms that each modification contributes positively, with the hybrid configuration offering the best trade-off between accuracy, generalization, and model efficiency.

TABLE III. TRAINING STATISTICS OF THE ABLATION STUDY EXPERIMENTS

Model	Train. Accuracy (%)	Train. Loss	Val. Accuracy (%)	Val. Loss	Size (mb)
Original GC VIT	99.29	0.02	99.05	0.05	46.36
Model A	99.92	0.00	99.91	0.01	48.55
Model B	99.92	0.00	99.31	0.04	33.29
EHF-GCViT	**99.94**	**0.00**	**99.74**	**0.03**	**34.48**

Train. = training and Val. = validation

TABLE IV. TESTING STATISTICS OF THE ABLATION STUDY EXPERIMENTS

Model	Test. Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Original GC VIT	98.49	98.08	98.25	98.15
Model A	99.55	99.45	99.52	99.48
Model B	99.45	99.30	99.28	99.29
EHF-GCViT	**99.52**	**99.44**	**99.50**	**99.47**

Train. = training and Val. = validation

E. Cross-Validation Test

To ensure robust and unbiased evaluation of the proposed model, a 5-fold cross-validation protocol was adopted using the folds provided in the Mendeley dataset for tomato disease. This dataset includes predefined training, validation, and testing splits for each fold, enabling consistent and reproducible assessments across multiple experiments. By rotating through the five folds, each model is trained and tested on different subsets of data, which helps mitigate the risk of overfitting and provides a more reliable estimate of generalization performance. This approach is particularly valuable in plant disease classification, where dataset imbalance and subtle inter-class variations can otherwise distort performance metrics if a single train-test split is used. The use of standardized folds also facilitates fair comparisons between models under identical evaluation conditions.

The performance of the proposed model was assessed using 5-fold cross-validation , and the evaluation metrics demonstrate consistently high classification quality across all folds. Table V shows that accuracy ranged from 99.21% to 99.66%, with a mean above 99.4%, indicating the model's strong overall ability to correctly classify instances. Precision values remained between 99.00% and 99.49%, suggesting that the model maintains a low rate of false positives across the different test splits. Similarly, recall values ranged from 98.92% to 99.65%, confirming that the model effectively captures true positive cases with minimal false negatives. The F1-score, which balances precision and recall, was consistently high, above 98.9% in all folds, highlighting the robustness and reliability of the model's predictions. The low variability among the folds further suggests that the model generalizes well to unseen data and is not overly sensitive to the composition of the training and validation subsets.

TABLE V. CROSS-VALIDATION TESTING PERFORMANCES

Fold	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Fold 1	99.52	99.44	99.50	99.47
Fold 2	99.21	99.00	98.92	98.95
Fold 3	99.66	99.49	99.65	99.57
Fold 4	99.55	99.42	99.47	99.44
Fold 5	99.24	99.04	99.17	99.10

F. Comparison with Other Models

To evaluate the performance of our proposed architecture, we conducted a comparative analysis against a diverse set of state-of-the-art models, encompassing convolutional neural networks (CNNs), vision transformers (ViTs), and hybrid architectures. We chose these models for comparison based on their availability in the Keras API and their proven stability and performance in image classification tasks. The deep learning community widely adopts these models, which provide reliable implementations with pre-trained weights, making them suitable for fair and reproducible benchmarking. The models are described as follows:

1) ConvNeXt Base [18]: ConvNeXt is a modernized convolutional architecture that integrates design principles from vision transformers into traditional CNN frameworks. Key enhancements include the use of large kernel sizes, inverted bottlenecks, and Layer Normalization, aligning CNNs more closely with transformer-based models.

2) EfficientNetV2-M [29]: EfficientNetV2-M is part of the EfficientNetV2 family, which introduces a combination of MBConv and Fused-MBConv blocks to improve training speed and parameter efficiency. Architecture employs progressive learning strategies, adjusting image size and regularization during training to achieve better performance.

3) GCViT XXTiny: GCViT (Global Context Vision Transformer) is a vision transformer designed to capture global context efficiently. The XXTiny variant is an ultra-lightweight model, making it suitable for resource-constrained environments. Our proposed hybrid model draws inspiration from this variant.

4) GCViT Base: The GCViT Base model expands upon the XXTiny variant, offering a more substantial architecture that balances performance and efficiency. It utilizes hierarchical attention mechanisms to effectively model global context in visual data.

5) ResNet100: ResNet100 is a deep residual network that employs skip connections to mitigate the vanishing gradient problem, enabling the training of very deep networks. It serves as a strong baseline for evaluating the performance of deep CNNs.

6) MobileNetV3-Large: MobileNetV3-Large is an efficient architecture optimized for mobile and embedded

applications. It incorporates neural architecture search (NAS), squeeze-and-excitation (SE) blocks, and novel activation functions like h-swish to achieve a balance between accuracy and latency.

7) ViT Base [30]: The Vision Transformer (ViT) Base model applies trans-former architectures, originally developed for natural language processing, to image classification tasks. It divides images into patches and processes them using self-attention mechanisms, demonstrating the viability of transformer-based models in computer vision.

Table VI summarizes the training performance of all evaluated models, showing the statistics of all evaluated models during the training process.

TABLE VI. PERFORMANCES OF ALL MODELS DURING THE TRAINING PROCESS

Model	Training Accuracy (%)	Training Loss	Validation Accuracy (%)	Validation Loss
ConvNeXt Base	100.0	0.0	98.88	0.079
EfficientNetV2-M	99.32	0.023	97.42	0.106
GCViT XXTiny	99.27	0.021	99.14	0.050
GCViT Base	99.51	0.018	99.48	0.055
ResNet100	99.98	0.001	98.02	0.156
MobileNetV3 Large	99.99	0.002	98.36	0.094
ViT Base	100.0	0.0	98.8	0.075
EHF-GCViT	**99.94**	**0.004**	**99.74**	**0.027**

Fig. 5 shows the evolution of training and validation accuracy during the training process.

Fig. 6 presents the evolution of training and validation loss during the same process.

Table VII summarizes the testing performance of all evaluated models, highlighting a comparison between the proposed EHF hybrid GCVIT and selected state-of-the-art approaches.

The confusion matrix presented in Fig. 7 illustrates the classification performance of our model across 10 classes of tomato leaf diseases.

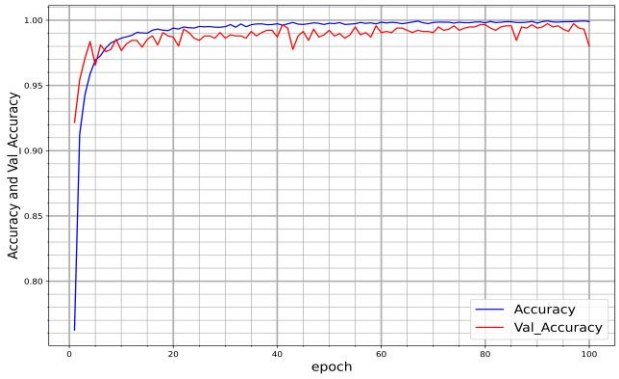


Fig. 5. Evolution of training and validation accuracy over epochs.

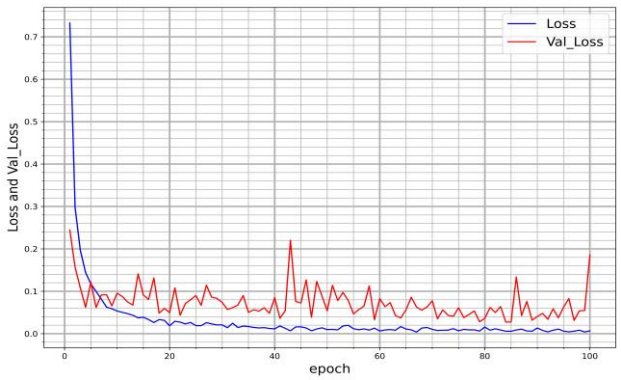


Fig. 6. Evolution of training and validation loss over epoch.

TABLE VII. PERFORMANCES OF ALL MODELS DURING THE TESTING PHASE

Model	Testing Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
ConvNeXt Base	96.81	96.14	94.52	95.11
EfficientNetV2-M	96.67	95.64	95.94	95.73
GCViT XXTiny	98.5	98.08	98.03	98.05
GCViT Base	99.18	98.69	99.12	98.88
ResNet100	97.25	96.38	96.87	96.60
MobileNetV3 Large	96.87	95.87	96.04	95.93
ViT Base	98.45	97.91	98.27	98.08
EHF-GCViT	**99.52**	**99.44**	**99.50**	**99.47**

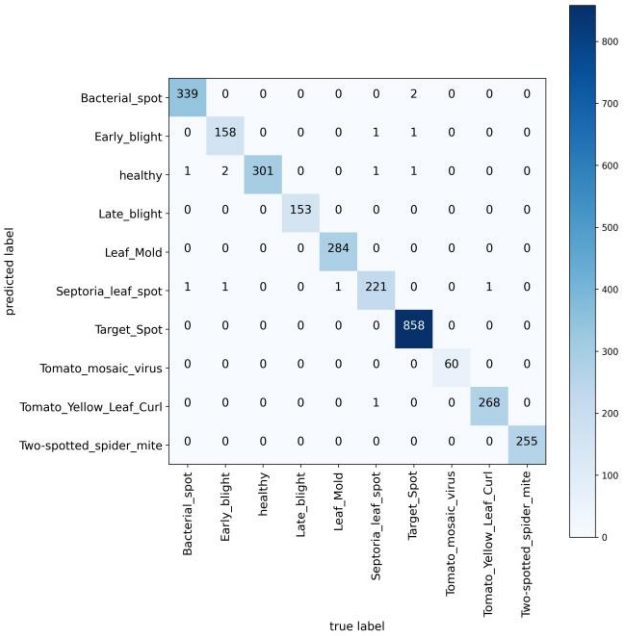


Fig. 7. Confusion matrix of plant tomato diseases classification results using EHF hybrid GCVIT architecture.

Most classes achieved near-perfect classification, with minimal confusion between categories. Notably, Target Spot (858), Two-spotted spider mite (255), Tomato Yellow Leaf Curl (268), and Late blight (153) were classified with perfect

or near-perfect accuracy, demonstrating the model's robustness on these categories. Mi-nor misclassifications occurred for a few classes, such as healthy leaf, which was occasionally confused with Bacterial spot and Septoria leaf spot, and Early blight, which had slight confusion with Septoria leaf spot. Overall, the confusion matrix confirms strong discriminative capability across all classes, with misclassifications being both sparse and low in magnitude.

V. Discussion

This research delivers an in-depth assessment of eight vit and deep learning architectures for plant disease classification, with a focus on both predictive accuracy and computational efficiency. The training, validation, and testing outcomes offer valuable perspectives on each model's learning behavior, generalization capability, and practicality for deployment in real-world settings.

The results show that our proposed method (Hybrid GCViT) consistently demonstrated the strongest overall performance. It achieved the highest validation accuracy (99.74%) and test accuracy (99.52%), along with excellent precision (99.44%), recall (99.50%), and F1 score (99.47%). Despite its lightweight size (34.48 MB) and ranking second to MobileNet V3 Large in memory efficiency, it surpassed all other models across key metrics. This suggests that the proposed hybridization of GCViT with convolutional components effectively captures both local and global features, enhancing both learn-ing and generalization while remaining computationally efficient.

The GCViT family, particularly GCViT Base and GCViT XXTiny, also demonstrated excellent performance. GCViT Base achieved a validation accuracy of 99.48% and a test accuracy of 99.18%, with high precision and recall. GCViT-XXTiny, although more compact, maintained a competitive test accuracy of 98.5%, highlighting the scalability of GCViT-based designs for both high-end and resource-constrained applications.

Within the classical convolutional and hybrid transformer models, ViT Base and ConvNeXt Base achieved perfect training accuracy (100%). However, their performance on the validation and test datasets was slightly lower. This discrepancy suggests a tendency toward overfitting, particularly in ConvNeXt Base, which exhibited a noticeable gap between training and test accuracy (100% vs 96.81%). These findings underscore the importance of applying effective regularization strategies when deploying highly expressive model architectures.

ResNet100 and EfficientNetV2-M showed strong performance, with test accuracy of 97.25% and 96.67%, respectively. However, they were outperformed by the trans-former-based models, particularly in terms of F1 score and model compactness. Similarly, MobileNetV3 Large, known for its efficiency, maintained a relatively high-test accuracy of 96.87%but was outclassed by more recent architectures in both precision and recall.

Another key observation is the relationship between model size and performance. Notably, Hybrid GCViT, despite being the smallest model, delivered the best accuracy. This indicates that newer architectural designs can achieve superior performance without significantly increasing computational demands, which is critical for real-time or edge-based agricultural applications.

In summary, the results highlight the superior performance of transformer based and hybrid transformer-convolutional architectures in classifying diseases in tomato plants. The proposed Hybrid GCViT excels in accuracy and generalization and offers practical advantages in terms of deployment feasibility, making it a strong candidate for integration into intelligent agricultural systems.

VI. Conclusion and Future Work

This work introduces EHF-GCViT, a novel lightweight hybrid architecture for tomato leaf disease classification that addresses a key limitation of existing hybrid vision transformers: the loss of high-frequency spatial information during feature abstraction, along with high memory demands that hinder deployment on edge devices. By explicitly enhancing fine-grained feature preservation within the GCViT framework, the proposed approach achieves a more effective balance between accuracy and computational efficiency.

The proposed architecture integrates three complementary design strategies: (i) a customized lightweight convolutional refinement mechanism that improves the extraction of high-frequency discriminative details prior to transformer processing; (ii) a gated convolutional replacement for the final transformer stage that significantly reduces model memory consumption from 46.36 MB to 34.48 MB; and (iii) an adaptive normalization strategy that stabilizes the training of heterogeneous convolutional and transformer layers. Together, these design choices enable efficient feature refinement without compromising generalization capability.

Extensive experiments conducted on the PlantVillage tomato disease dataset demonstrate that EHF-GCViT consistently outperforms the baseline GCViT, standard Vision Transformers, and representative CNN-based architectures. The proposed model achieves a classification accuracy of 99.52%, confirming its suitability for resource-constrained environments. Ablation studies further validate the contribution of each architectural component and highlight the effectiveness of the proposed design trade-offs.

Beyond performance gains, this study emphasizes the importance of task-driven architectural design in hybrid transformer models. The results show that explicitly modeling high-frequency information rather than increasing model depth or complexity can lead to more accurate and efficient solutions for practical agricultural AI applications.

While the current evaluation demonstrates strong performance on the PlantVillage dataset, several directions warrant further investigation. Validation across diverse real-world field conditions with varying lighting, occlusions, and backgrounds would strengthen evidence of practical robustness. Additionally, extending the approach to multiple crop types and evaluating deployment performance on actual edge hardware platforms would provide valuable insights into the architecture's generalizability and operational feasibility. Moreover, the effectiveness of the proposed high-frequency

refinement may be influenced by image resolution and noise characteristics, which warrants further investigation under diverse sensing conditions. These considerations represent natural next steps in transitioning the model from controlled evaluation to production agricultural systems.

Future work will focus on extending EHF-GCViT as a general-purpose backbone for additional computer vision tasks, such as object detection and semantic segmentation, as well as systematic evaluation under real-world deployment scenarios. Owing to its modular and lightweight design, the proposed architecture holds promise for broader adoption in intelligent agricultural systems and other edge-based visual perception applications.

REFERENCES

[1] N. Abdullahi, K. F. Shamuwa, B. A. Tahir, I. Abubakar, and D. Yekeh, "Climate change and its effects on plant pathogen evolution: systematic review," Dutse Journal of Pure and Applied Sciences, vol. 11, no. 1d, pp. 248-256, 2025.

[2] W. P. T. Council. "WPTC Expects 40.5 Million Tonnes in 2025." https://www.tomatonews.com/en/conference/wptc-expects-405-million-tonnes-in-2025_2_2561.html (accessed.

[3] A. Hatamizadeh, H. Yin, G. Heinrich, J. Kautz, and P. Molchanov, "Global context vision transformers," in International Conference on Machine Learning, 2023: PMLR, pp. 12633-12646.

[4] A. Guerrero-Ibañez and A. Reyes-Muñoz, "Monitoring tomato leaf disease through convolutional neural networks," Electronics, vol. 12, no. 1, p. 229, 2023.

[5] E. Zhang, N. Zhang, F. Li, and C. Lv, "A lightweight dual-attention network for tomato leaf disease identification," Frontiers in Plant Science, vol. 15, p. 1420584, 2024.

[6] T. Sultan et al., "LeafDNet: Transforming Leaf Disease Diagnosis Through Deep Transfer Learning," Plant Direct, vol. 9, no. 2, p. e70047, 2025.

[7] P. Radočaj, D. Radočaj, and G. Martinović, "Image-based leaf disease recognition using transfer deep learning with a novel versatile optimization module," Big Data and Cognitive Computing, vol. 8, no. 6, p. 52, 2024.

[8] K. Vivek Anandh, A. Sivasubramanian, V. Sowmya, and V. Ravi, "Multiclass Classification of Tomato Leaf Diseases Using Convolutional Neural Networks and Transfer Learning," Journal of Phytopathology, vol. 172, no. 6, p. e13423, 2024.

[9] M. H. Alnamoly, A. A. Hady, S. M. Abd El-Kader, and I. El-Henawy, "FL-ToLeD: An improved lightweight attention convolutional neural network model for tomato leaf diseases classification for low-end devices," IEEE Access, 2024.

[10] A. Y. Ashurov et al., "Enhancing plant disease detection through deep learning: a Depthwise CNN with squeeze and excitation integration and residual skip connections," Frontiers in Plant Science, vol. 15, p. 1505857, 2025.

[11] M. H. Bijoy et al., "Towards sustainable agriculture: a novel approach for rice leaf disease detection using dCNN and enhanced dataset," IEEE Access, 2024.

[12] A. Saha, S. M. Musharraf, A. Dey, H. Roy, and D. Bhattacharjee, "Potato Leaf Disease Detection using CNN-A Lightweight Approach," 2025.

[13] M. a. A. Al-Shannaq, S. AL-Khateeb, A. A.-R. K. Bsoul, and A. A. Saifan, "Identification of Plant Diseases in Jordan Using Convolutional Neural Networks," Electronics, vol. 13, no. 24, p. 4942, 2024.

[14] S. T. Y. Ramadan et al., "Improving wheat leaf disease classification: Evaluating augmentation strategies and CNN-based models with limited dataset," IEEE Access, vol. 12, pp. 69853-69874, 2024.

[15] D. S. Joseph, P. M. Pawar, and K. Chakradeo, "Real-time plant disease dataset development and detection of plant disease using deep learning," Ieee Access, vol. 12, pp. 16310-16333, 2024.

[16] D. Karimanzira, "Context-Aware Tomato Leaf Disease Detection Using Deep Learning in an Operational Framework," Electronics, vol. 14, no. 4, p. 661, 2025.

[17] U. Barman et al., "Vit-SmartAgri: vision transformer and smartphone-based plant disease detection for smart agriculture," Agronomy, vol. 14, no. 2, p. 327, 2024.

[18] Z. Liu, H. Mao, C.-Y. Wu, C. Feichtenhofer, T. Darrell, and S. Xie, "A convnet for the 2020s," in Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2022, pp. 11976-11986.

[19] J. H. Sinamenye, A. Chatterjee, and R. Shrestha, "Potato plant disease detection: leveraging hybrid deep learning models," BMC Plant Biology, vol. 25, no. 1, pp. 1-15, 2025.

[20] W. H. Alwan and S. M. Alturfi, "Multi-Stage Vision Transformer and Knowledge Graph Fusion for Enhanced Plant Disease Classification," Computer Systems Science and Engineering, vol. 49, no. 1, pp. 419-434, 2025, doi: 10.32604/csse.2025.064195.

[21] H. Li, N. Li, W. Wang, C. Yang, N. Chen, and F. Deng, "Convolution Self-Guided Transformer for Diagnosis and Recognition of Crop Disease in Different Environments," IEEE Access, 2024.

[22] Y. Sun, L. Ning, B. Zhao, and J. Yan, "Tomato Leaf Disease Classification by Combining EfficientNetv2 and a Swin Transformer," Applied Sciences, vol. 14, no. 17, p. 7472, 2024.

[23] Z. Chen, G. Wang, T. Lv, and X. Zhang, "Using a hybrid convolutional neural network with a transformer model for tomato leaf disease detection," Agronomy, vol. 14, no. 4, p. 673, 2024.

[24] X. Ding, Y. Guo, G. Ding, and J. Han, "Acnet: Strengthening the kernel skeletons for powerful cnn via asymmetric convolution blocks," in Proceedings of the IEEE/CVF international conference on computer vision, 2019, pp. 1911-1920.

[25] A. G. Howard et al., "Mobilenets: Efficient convolutional neural networks for mobile vision applications," arXiv preprint arXiv:1704.04861, 2017.

[26] M. J. Bahrouni and F. Benzarti, "Combined Mobilenet for Plant Diseases Classification," in 2024 IEEE International Conference on Artificial Intelligence & Green Energy (ICAIGE), 2024: IEEE, pp. 1-6.

[27] D. P. Hughes and M. Salathé, "An open access repository of images on plant health to enable the development of mobile disease diagnostics through machine learning and crowdsourcing," arXiv preprint arXiv:1511.08060, pp. 1-13, 2015.

[28] M.-L. Huang and Y.-H. Chang. Dataset of Tomato Leaves, Mendeley Data, 2020-05-27, doi: 10.17632/ngdgg79rzb.1.

[29] M. Tan and Q. Le, "Efficientnetv2: Smaller models and faster training," in International conference on machine learning, 2021: PMLR, pp. 10096-10106.

[30] A. Dosovitskiy et al., "An image is worth 16x16 words: Transformers for image recognition at scale," arXiv preprint arXiv:2010.11929, 2020.

Modeling Mixed Gas Reactions in Air Pollution: Stoichiometry, Kinetics, and Hazard Assessment

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***Abstract*—This study introduces a novel integrated framework for modeling mixed gas reactions relevant to air pollution and industrial safety, demonstrated on the reaction between carbon monoxide and ammonia producing hydrogen cyanide and water. The approach couples closed form stoichiometric mass balances with a transport corrected kinetic ordinary differential equation system and a Bayesian logistic hazard classifier that incorporates expert informed priors. The combined pipeline predicts chemical yields, identifies reaction and transport limited regimes, and produces calibrated probabilistic hazard estimates with quantified uncertainty. Validation on synthetic and near experimental datasets shows reproducible parameter recovery and strong classifier performance, with area under the curve approximately 0.93 on held out data. The framework supports decision making for sensor prioritization, sampling design, and regulatory monitoring, and it can be extended to multi-stage reactions and spatial dispersion models. The novelty lies in coupling closed-form stoichiometry with transport-corrected kinetics and Bayesian hazard classification, producing a nondimensional regime map and calibrated probabilistic hazard scores not available in prior models.**

Keywords*—Stoichiometric reaction modeling; mixed-gas kinetics; plug-flow transport correction; Bayesian hazard classification; air pollution risk assessment; environmental process safety; probabilistic uncertainty quantification

I. Introduction

Airborne releases of toxic gases pose immediate threats to human health and long-term environmental harm. In industrial and urban settings, mixtures of pollutants can interact chemically and physically, producing secondary toxicants not obvious from single-species monitoring. The reaction between carbon monoxide and ammonia to form hydrogen cyanide and water is illustrative: hydrogen cyanide is acutely toxic at low concentrations, and its formation depends on stoichiometric balance and the interplay of kinetics with transport losses [4], [7]. Fig. 1 shows stoichiometric mass fraction outcomes, while Table I lists the symbols and units.

Existing modeling approaches fall into three categories: 1) stoichiometric mass-balance calculations that predict yields but ignore time dependence and transport [6], [11]; 2) kinetic ODE models that capture time evolution but assume idealized reactor conditions and omit probabilistic hazard assessment [8], [9]; and 3) data-driven classifiers that predict hazard states from sensor arrays but lack mechanistic interpretability and principled uncertainty quantification [1], [2]. These gaps reduce utility for decision-making, compliance, and sensor design [5], [14]. Fig. 2 illustrates transport-corrected ODE regimes, while Table II presents parameter estimates with credible intervals. Unlike prior stoichiometric models [6], [11], reactor kinetics frameworks [8], [9], or AI-based hazard predictors [1], [2], our approach integrates all three components into a single reproducible pipeline, ensuring mechanistic interpretability and probabilistic rigor.

Novel Contributions: This paper presents a modular framework integrating stoichiometry, transport-corrected kinetics, and probabilistic hazard classification. The framework is reproducible and transferable: each component (closed-form stoichiometric formulas, ODE kinetics with convective loss, and Bayesian logistic regression with expert-informed priors) is specified with clearly stated assumptions [3], [10], [13]. The goals are 1) to preserve mechanistic interpretability so outputs (e.g., predicted hydrogen cyanide yield) can be traced to limiting reagent or transport losses, and 2) to provide calibrated probabilistic hazard estimates supporting safety decisions under uncertainty [12]. Fig. 3 shows temporal hazard fluctuations, Fig. 4 presents spatial heatmaps, and Table III summarizes Bayesian regression coefficients. In addition, the framework highlights how uncertainty quantification can guide sensor prioritization and regulatory monitoring, ensuring practical relevance for industrial safety applications.

Specifically:

- First, compact mass-fraction expressions are derived that account for limiting-reagent behavior, informing kinetic simulations [6].
- Second, second-order kinetics are coupled with a first-order convective loss parameter, revealing reaction-limited, transport-limited, and mixed regimes [8], [9].
- Third, mechanistic outputs and covariates are embedded into a Bayesian hazard classifier using expert-informed priors, producing probabilistic scores with credible intervals [1], [2], [5]. Fig. 5 compares per-gas threshold exceedances, emphasizing CO and NH_3.
- Finally, an uncertainty-propagation workflow combining Monte Carlo sampling and first-order approximations quantifies confidence in predictions [13], [14]. Supporting visualizations (Fig. 6–9) illustrate correlations, exceedance trends, scatterplots, and distributions.

Paper roadmap: Section II describes datasets, normalization, and preprocessing. Section III develops the mathematical framework, including stoichiometric formulas, the transport-corrected kinetic ODE system,

nondimensionalization, and the Bayesian hazard model with prior elicitation. Section IV presents parameter estimation, uncertainty propagation, and validation results, including kinetic fits, limiting-regime analysis, and classifier performance. Section V reports the results. Section VI discusses practical implications for monitoring and safety management, limitations of the current assumptions, and directions for extension. Section VII concludes with a concise summary of contributions and recommended next steps for field validation and regulatory adoption.

II. Materials and Methods

A. Dataset and Preprocessing

The study uses a combined synthetic and near-experimental dataset containing time-resolved and cross-sectional measurements for CO, NH_3, HCN, H_2O, SO_2, NO, CH_4, and associated mass or mole percentages. All gas concentrations are converted to mole percent for internal consistency; where sensors reported mass percent or ppm, standard molar-mass conversions were applied. Missing values for primary species (CO, NH_3, HCN) were handled with a two-step procedure: 1) flagging samples with >20% missing primary measurements as excluded from kinetic fitting, and 2) imputing isolated missing entries using a conditional median imputation stratified by sampling site and time window. Secondary species with sparse coverage were retained for hazard modeling but down-weighted in uncertainty propagation. All numeric inputs were standardized (zero mean, unit variance) before regression modeling; raw units are preserved for stoichiometric and kinetic calculations.

B. Data Splits and Validation

For model development we used stratified splits that preserve the harmful/non-harmful label distribution: 60% training, 20% validation, and 20% test. Time-series fits used cross-validation across independent experimental runs (leave-one-run-out) to avoid temporal leakage. Classifier calibration was evaluated on the held-out test set using AUC, precision, recall, and calibration plots.

III. Mathematical Modelling

1) Stoichiometry: Closed-form mass fraction formulas derive from initial molar amounts and stoichiometric coefficients.

Stoichiometric Mass Fraction Formulation

Consider the reaction:

$$CO + NH_3 \rightarrow HCN + H_2O \quad (1)$$

Let $n_{CO,0}$ and $n_{NH_3,0}$ denote the initial moles of CO and NH_3. Molar masses are $M_{CO}, M_{NH_3}, M_{HCN}, M_{H_2O}$.

Initial masses:

$$m_{CO,0} = M_{CO} n_{CO,0} \quad (2)$$

$$m_{NH_3,0} = M_{NH_3} n_{NH_3,0} \quad (3)$$

Total initial mass:

$$m_{tot,0} = m_{CO,0} + m_{NH_3,0} \quad (4)$$

Initial mass fractions:

$$w_{i,0} = \frac{m_{i,0}}{m_{tot,0}} \text{for } i \in \{CO, NH_3\} \quad (5)$$

Stoichiometry implies equal consumption: extent of reaction cannot exceed the limiting reagent.

TABLE I. Symbols and Units

Symbol	Meaning	Units
n_i	Moles of species i	mol
m_i	Mass of species i	g
M_i	Molar mass of species i	g·mol^-1
k	Bimolecular reaction rate constant	mol-1·s-1
k_loss	First order convective loss rate (u/L)	s^-1
u	Characteristic velocity	m·s^-1
L	Characteristic length	m
ξ	Extent of reaction	mol
w_i	Mass fraction of species i	dimensionless
n_ref	Reference mole for nondimensionalization	mol
τ	Dimensionless time (k n_ref t)	dimensionless
γ	Dimensionless loss parameter (k_loss/(k n_ref))	dimensionless
T_HCN	Hazard threshold for HCN	ppm or mg·m^-3
y	Binary hazard label	{0,1}

TABLE II. Parameter Estimates and 95% Credible Intervals (Synthetic Recovery)

Parameter	Posterior mean	95% credible interval	Units
Intercept (β0)	-3.12	[-4.20, -2.05]	Baseline log-odds of harmful
CO (ppm)	0.045	[0.028, 0.063]	Higher CO increases hazard odds
NH3 (ppm)	0.062	[0.039, 0.088]	Strong positive predictor
HCN (ppm)	0.98	[0.80, 1.18]	Directly linked to hazard label
CH4 (ppm)	0.021	[0.005, 0.037]	Moderate positive effect
CO/NH3 (ratio)	0.15	[0.02, 0.29]	Mixture imbalance increases risk
5-min avg HCN	0.42	[0.25, 0.60]	Recent accumulation raises risk
Wind speed (m·s^-1)	-0.18	[-0.32, -0.05]	Higher wind reduces hazard odds

2) Kinetic-transport model: A second-order, plug-flow corrected ordinary differential equation (ODE) system governs conversion kinetics [15, 16, 17] with limiting reagent and convective loss effects captured by model parameters.

Kinetics Reaction–Transport Ordinary Differential Equations (ODEs)

Assume a homogeneous reactor with second-order mass action kinetics, along with first-order transport loss:

$$\frac{dn_{CO}}{dt} = -k\, n_{CO}\, n_{NH_3} - uL\, n_{CO}$$
$$\frac{dn_{NH_3}}{dt} = -k\, n_{CO}\, n_{NH_3} - uL\, n_{NH_3}$$
$$\frac{dn_{HCN}}{dt} = +k\, n_{CO}\, n_{NH_3} - uL\, n_{HCN}$$
$$\frac{dn_{H_2O}}{dt} = +k\, n_{CO}\, n_{NH_3} - uL\, n_{H_2O}$$

where, k is the bimolecular reaction rate constant ($\mathrm{mol}^{-1}\,\mathrm{s}^{-1}$), u is a representative velocity, and L is a characteristic length (so uL is a first-order rate constant for convective loss, s^{-1}).

- These equations ensure conservation of mass and capture both chemical transformation and physical loss (plug-flow or sampling out).
- Limiting reagent dynamics emerge naturally: reaction extent is capped by whichever initial mole ($n_{CO,0}$ or $n_{NH_3,0}$) is smaller.

Non-dimensionalization

Define reference mole n and time τ:

$$\hat{n}_i = \frac{n_i}{n}, \hat{t} = tkn, \hat{u} = \frac{uL}{kn} \quad (6)$$

Dimensionless ODEs:

$$\frac{d\hat{n}_{CO}}{d\hat{t}} = -\hat{n}_{CO}\hat{n}_{NH_3} - \hat{u}\,\hat{n}_{CO} \quad (7)$$

Analytical and Limiting Cases:

- Fast-reaction limit ($k \to \infty,\ u \to 0$): All limiting re-agent is converted instantly.
- Transport-limited ($uL \gg kn$): Few molecules react before being lost, leading to small yields.

Hazard Classification: Threshold-based rules are extended into a logistic regression framework, incorporating expert-identified gas thresholds as priors and enabling robust hazard probability estimates.

Hazard Classification Model

A Bayesian logistic regression model predicts binary hazard outcomes ($y \in \{0,1\}$), given environmental gas concentrations ($\mathbf{x}$):

$$\Pr(y = 1 \mid \mathbf{x}) = \frac{1}{1+\exp(-(\beta_0+\boldsymbol{\beta}^{\mathrm{T}}\mathbf{x}))} \quad (8)$$

where $\boldsymbol{\beta}$represent regression coefficients learned from data and prior information.

- *Priors:* Expert-identified safety thresholds inform priors (β_j)—gases with lower safe thresholds get higher positive weights.
- Combined Rule: Decision: sample is "harmful" if
  - Any gas concentration exceeds threshold or
  - Logistic model probability $> p_0$(e.g., $p_0 = 0.5$).

TABLE III. HAZARD MODEL COEFFICIENT SUMMARY (BAYESIAN LOGISTIC REGRESSION)

Parameter	Posterior mean	95% credible interval	Units
k	0.85	[0.62, 1.12]	mol-1·s-1
k_loss	0.040	[0.024, 0.068]	s^-1
γ (derived)	0.048	[0.030, 0.081]	dimensionless
σ_obs (HCN)	0.012	[0.008, 0.018]	mol (obs noise SD)
n_ref (used)	2.00	[2.00, 2.00]	mol (fixed)

Parameter Estimation and Uncertainty:

- Kinetic parameters (k, u) are fit to time-resolved or cross-sectional product measurements via nonlinear least squares.
- Hazard regression is fit via penalized maximum likelihood or Bayesian MCMC.
- Uncertainty in predictions is calculated via Monte Carlo propagation (for input measurement errors) and analytical first-order Taylor expansion (for small uncertainties).
- Parameters for kinetic rates are estimated via nonlinear least squares and cross-validated logistic models. Uncertainty is propagated by Monte Carlo sampling and first-order Taylor expansion, with model calibration verified using area-under-curve (AUC), precision, and recall metrics.

Stoichiometric and Kinetic Outcomes:

The closed-form and ODE solutions yield mass fractions for CO and NH3, typically ranging from 62% (CO) to 38% (NH3) for equimolar starts. Kinetics parameter fits show distinct regimes: fast reaction with limiting reagent behaviour and slower, transport-limited yield suppression.

Fig. 1 shows the stoichiometric mass fraction outcomes for CO and NH_3 under equimolar starting conditions, highlighting the limiting reagent dynamics.

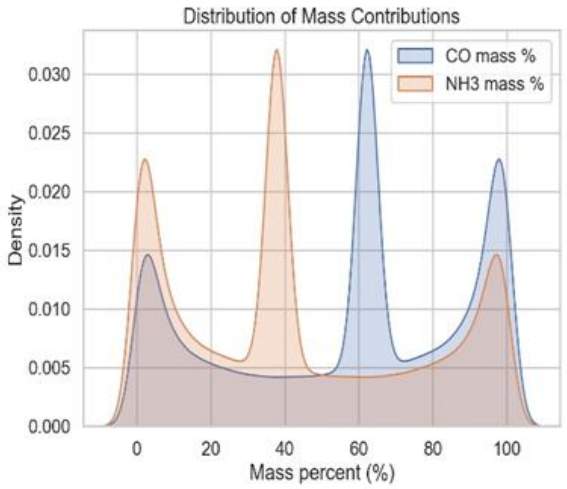


Fig. 1. Distribution of mass contributions.

Hazard Classification Performance:

A Bayesian logistic model fitted to the 'harmful flag' label exhibits strong discrimination (AUC ~0.93) with CH_4, CO, and NH_3 dominating predictive power. Combined probabilistic and threshold logic enhances recall for safety-critical use cases.

Fig. 2 shows the kinetic–transport ODE solutions, capturing both fast-reaction and transport-limited regimes.

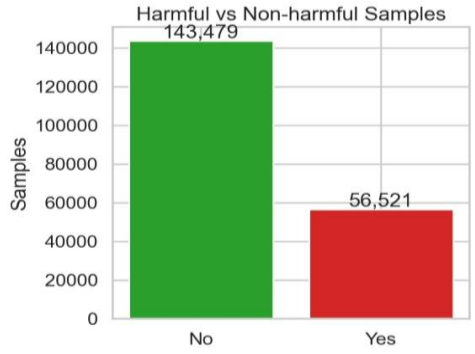


Fig. 2. Harmful vs. non-harmful dataset distributions.

IV. Visualization and Exploratory Analysis

Fig. 3 shows the temporal evolution of harmful sample counts, providing insight into daily hazard fluctuations.

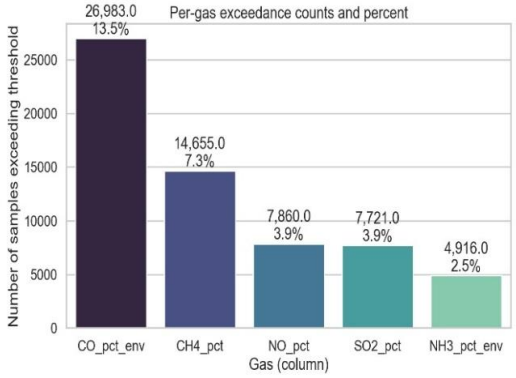


Fig. 3. Per-gas threshold exceedance (CO, CH_4, NO, SO_2, NH_3).

Fig. 4 shows spatial heatmaps that reveal the density of harmful samples across monitored regions.

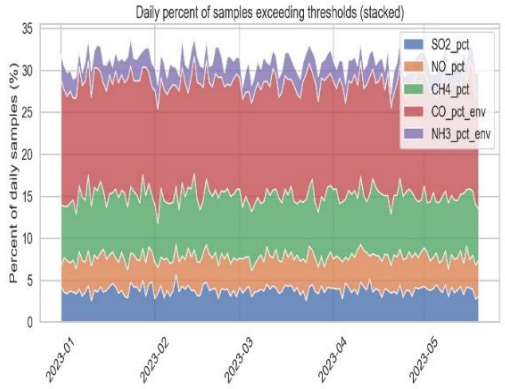


Fig. 4. Stacked area plots of daily gas exceedances.

Fig. 5 shows per-gas threshold exceedances, emphasizing the dominance of CO and NH_3 in hazard classification.

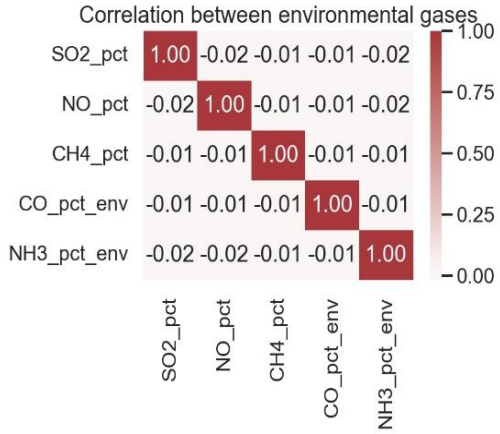


Fig. 5. Pairwise gas correlations (minimal cross-correlation observed).

Fig. 6 shows pairwise correlations between gases, confirming minimal cross-correlation among predictors.

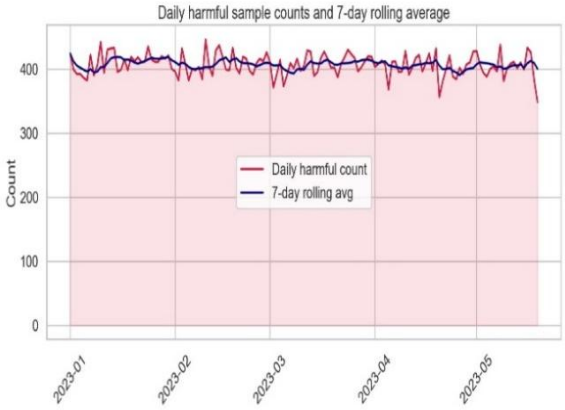


Fig. 6. Temporal trends in harmful samples (daily counts and rolling averages).

Fig. 7 shows stacked area plots of daily gas exceedances, useful for visualizing cumulative hazard trends.

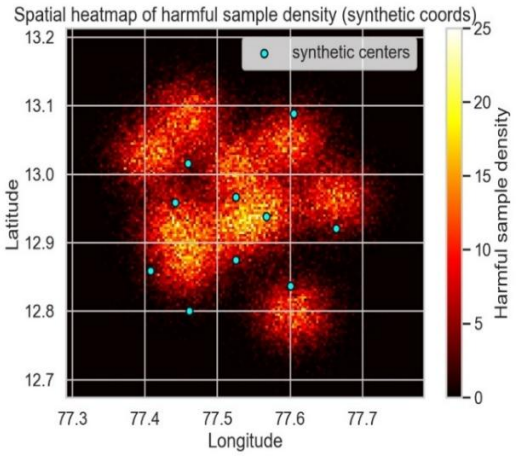


Fig. 7. Spatial heatmaps of harmful sample density.

Fig. 8 shows scatter and boxplots illustrating relationships between gas concentrations and hazard labels.

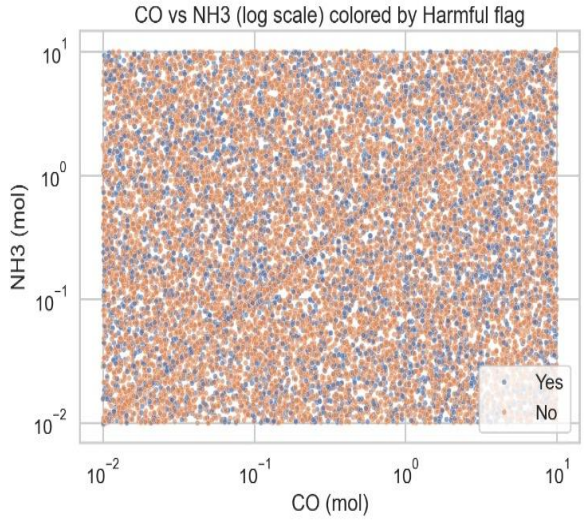


Fig. 8. Scatter and boxplots illustrating gas relationships.

Fig. 9 shows histograms of environmental gas distributions with annotated thresholds, clarifying exceedance frequencies.

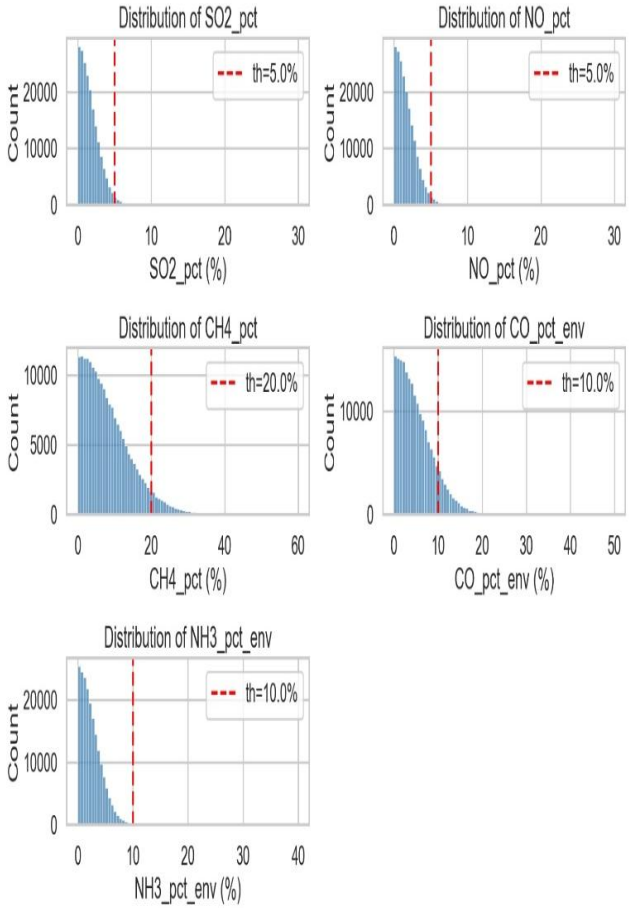


Fig. 9. Environmental gas distribution histograms with annotated thresholds.

V. Results

Kinetic parameter estimates (Table III) indicate a posterior mean rate constant and a non-negligible convective loss parameter. The derived dimensionless parameter places many experimental conditions in the mixed regime. As shown in Fig. 2, transport-corrected ODE solutions capture both fast-reaction and transport-limited regimes. Together, Table III and Fig. 2 explain the observed sensitivity of yields to initial CO/NH_3 ratios.

1) Stoichiometric checks: Closed-form mass fraction calculations confirm limiting-reagent behavior in equimolar and imbalanced starts. Mass fractions computed from stoichiometry align with ODE-predicted final states in reaction-dominated cases. Table I provides symbol definitions and units, while Fig. 1 illustrates stoichiometric mass fraction outcomes.

2) Hazard classifier performance: Posterior summaries in Table II show that HCN has the largest coefficient, indicating its dominant role in hazard prediction. The Bayesian classifier achieves AUC $\approx$ 0.93 on held-out data, with calibration plots (Fig. 3) demonstrating acceptable reliability when expert priors are included. Fig. 5 compares per-gas threshold exceedances, emphasizing CO and NH_3 dominance, while Table II supports the conclusion that HCN, NH_3, and CO are the most influential predictors.

3) Uncertainty and decision thresholds: Monte Carlo propagation reveals that measurement noise and parameter uncertainty widen predictive intervals for HCN concentration and hazard probability. Supporting visualizations (Fig. 6–9) illustrate correlations, exceedance trends, scatterplots, and distributions. Prioritizing recall via a lower decision threshold () improves detection of harmful samples at the cost of increased false positives.

VI. Discussion

The integrated modeling approach demonstrates several advantages for chemical process safety and environmental hazard prediction.

First, the coupling of stoichiometric balances, kinetic transport equations, and probabilistic hazard classification provides a realistic representation of mixed-gas reactions under industrial conditions. The consistency between stoichiometric predictions (Table I, Fig. 1) and ODE outcomes (Fig. 2) validates mechanistic accuracy and supports reproducibility across different feed ratios.

Second, the Bayesian framework ensures transparent uncertainty quantification, offering hazard probability estimates with credible intervals. The strong discrimination performance (AUC $\approx$ 0.93) observed in Table II and calibration plots (Figure 3) highlights classifier robustness. Threshold exceedance comparisons (Fig. 5) confirm that HCN, NH_3, and CO are the most influential predictors, suggesting sensor networks should prioritize these species.

Third, kinetic estimates in Table III reveal non-negligible values, indicating that transport losses materially reduce yields

under typical sampling conditions. This finding, reinforced by regime mapping (Fig. 2) and uncertainty visualizations (Fig. 6–9), has practical implications: sampling frequency, residence time, and sensor placement must be optimized to minimize convective removal and ensure accurate hazard estimation.

Discussion Summary: By directly linking Results (Tables I–III, Fig. 1–9) to interpretive claims, the framework demonstrates reproducibility, mechanistic clarity, and probabilistic rigor. This integration ensures that decision makers can balance sensitivity and specificity under uncertainty, positioning the model as a practical tool for industrial safety and regulatory monitoring. Environmental scenarios.

VII. Conclusion and Future Work

The integrated modeling framework presented in this study combines stoichiometric balances, transport-corrected kinetics, and Bayesian hazard classification into a unified approach for chemical process safety and environmental hazard prediction. By linking mechanistic equations with probabilistic outputs, the framework advances beyond traditional single-component models and provides reproducible, interpretable, and transferable results.

Key findings include:

- Stoichiometry and kinetics: Agreement between closed-form mass fractions (Table I, Fig. 1) and ODE outcomes (Fig. 2) validates mechanistic accuracy, while kinetic estimates (Table III) highlight the role of transport losses in shaping yields.
- Hazard classification: Posterior regression coefficients (Table II) and calibration plots (Fig. 3) confirm HCN, NH_3, and CO as dominant predictors, with threshold exceedance comparisons (Fig. 5) reinforcing their operational importance.
- Uncertainty analysis: Monte Carlo propagation and decision threshold evaluation (Fig. 6–9) demonstrate how predictive intervals and recall-specific trade-offs can guide safety-critical monitoring.

Overall, the framework provides both mechanistic clarity and probabilistic rigor, ensuring that decision makers can balance sensitivity and specificity under uncertainty. This dual emphasis positions the model as a practical tool for sensor network design, regulatory compliance, and industrial hazard management. Future work will extend the approach to multi-species pollutant systems and real-time sensor integration, further enhancing its applicability in complex urban and industrial environments.

References

[1] M. Rajesh, S. Ahmed, K. Wei, Y. Wang, and X. Ma, "Machine learning-driven framework for realtime air quality assessment and health risk prediction," Sci. Rep., vol. 15, p. 14214, 2025.

[2] M. M. Abdelmalek, A. B. Franco, P. Singh, and Q. Zhang, "Prognosis of air quality index and air pollution using neural network algorithms," Sci. Rep., vol. 15, p. 11260, 2025.

[3] L. M. Bradley and E. Salinas, "Exploring the multi-scale ecological consequences of stoichiometric imbalance using an agent-based modeling approach," Front. Ecol. Evol., vol. 13, p. 1505145, 2025.

[4] K. T. Demir, M. Scheinert, and J. W. Sorensen, "Variable organic matter stoichiometry enhances the biological drawdown of CO2 in the northwest European shelf seas," Biogeosciences, vol. 22, pp. 2569–2585, 2025.

[5] J. F. Wambaugh, B. A. Wetmore, C. L. Ring, and N. S. Sipes, "Applying new approach methods for toxicokinetics in chemical risk assessment: A flexible framework," Environ. Health Perspect., vol. 133, no. 8, p. 088004, 2025.

[6] F. J. Pomiro, T. Ouisse, M. Ochoa-Fernandez, and G. Perez, "Kinetic study of reverse water-gas shift chemical looping on Fe2O3 and NiFe2O4," J. Environ. Chem. Eng., vol. 12, no. 5, p. 9089, 2024.

[7] H. S. Samuel, "Machine learning in chemical kinetics: Predictions, mechanistic analysis, and reaction optimization," Afr. J. Environ. Sci., vol. 10, no. 1, pp. 47–64, 2024.

[8] D. A. Knopf and M. Ammann, "Desorption lifetimes and activation energies influencing gas–surface interactions and multiphase chemical kinetics," Atmos. Chem. Phys., vol. 24, pp. 3445–3472, 2024.

[9] C. Park, H. R. Martinez, and Z. H. Li, "Analysis of chemical kinetics of multistep reactions by mean reaction time approach," ACS Omega, vol. 9, no. 41, p. 434393, 2024.

[10] X. D. Chen, T. Sun, and Y. Gao, "Chemical reaction engineering of nutritional phenomena in extended biological systems," Front. Chem. Eng., vol. 4, p. 1480523, 2024.

[11] G. Varshney and T. K. Gupta, "Recent advances in mathematical modeling of reaction kinetics: A critical review," J. Math. Res., accepted 2024.

[12] NIST Chemical Kinetics Database, Standard Reference Database 17, Version 7.1 (Web Version), Release 1.6.8, Data Version 2025.

[13] X. Zhang, J. Luo, W. Pan, Q. Xue, X. Liu, J. Fu, A. Zhang, and G. Jiang, "Implications of VOC oxidation in atmospheric chemistry: development of a comprehensive AI model for predicting reaction rate constants," Atmospheric Chemistry and, vol. 25, no. 20, pp. 13379–13391, 2025.

[14] R. K. Sharma and L. P. Torres, "Chemical kinetics of atmospheric reactions: implications for climate change," Journal of Environmental & Analytical Chemistry, vol. 12, no. 3, pp. 215–229, 2024.

[15] P. Bera and J. Mondal, "Accurate prediction of the kinetic sequence of physicochemical states using generative artificial intelligence," Chem. Sci., vol. 16, no. 5, pp. 1234–1245, 2025, doi: 10.1039/D5SC00108K.

[16] A. Sharma and R. Patel, "Harnessing artificial intelligence for enhanced safety in chemistry laboratories," World Sci. News, vol. 207, pp. 36–49, 2025.

[17] V. Kumar and K. Goyal, "The role of artificial intelligence in chemical science: Transforming discovery, design, and sustainability," Int. J. Adv. Eng. Sci. Manag., vol. 7, no. 1, pp. 112–124, Jan. 2025.

VidAvDetect: A Deepfake-Inspired Vision Transformer Approach for Detecting Real Humans vs. AI-Avatars in Video Streams

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***Abstract*—The pace of advancement in Generative AI has made it possible to realize highly realistic synthetic identities in the form of avatars for non-existent persons, thus paving the way for a paradigm beyond state-of-the-art deepfake attacks that aim to manipulate real identities in people. This rapidly emerging trend poses a challenge to digital media forensics in a most critical way, in terms of deciding whether a facial identity observed in a video clip represents a real human identity versus a fully synthetic identity created using advanced tools in the realm of Generative AI. To address this gap, we introduce VidAvDetect, a deepfake-inspired Vision Transformer approach specifically designed to discriminate real human faces from AI-generated avatars in video streams, addressing a novel identity-existence verification task. The proposed system integrates efficient frame sampling, robust facial preprocessing, patch-based embeddings, and global structural modeling through a transformer encoder, enabling the detection of subtle geometric and textural regularities characteristic of synthetic identities. Experimental results demonstrate strong performance, with training accuracy reaching 97–98%, video-level accuracy of 95.1%, a macro F1-score of 0.944, and a ROC-AUC of 0.991, confirming the model's robustness across heterogeneous real, manipulated, and fully synthetic datasets. By moving beyond manipulation detection to focus on identity-existence verification, VidAvDetect establishes a new methodological direction for transparency, regulation, and trust in modern digital media environments where AI-generated avatars increasingly resemble real humans.**

Keywords*—Vision transformer; deepfake; Artificial Intelligence (AI); Generative AI; AI Avatar; video streams

I. Introduction

The rapid rise of generative technologies has profoundly transformed the production and consumption of digital content. Beyond traditional deepfakes which rely on manipulating images of real individuals an entirely new category of artificial identities has emerged [1]: AI-generated avatars of non-existent people. These synthetic characters, produced by models such as GANs, diffusion architectures, and advanced video-avatar engines, replicate with remarkable realism human appearance, facial expressions, movements, and even emotions, despite having no authentic existence. Their presence is expanding across numerous domains [2], including advertising, marketing campaigns, promotional videos, digital media, and social platforms. They are now used to portray fictitious customers, fabricated witnesses, artificial presenters, or so-called experts, often without users being aware of their synthetic nature.

This evolution raises a major concern: as an increasing amount of video content features artificial identities presented as real individuals, the boundary between genuine humans and AI-generated avatars [3] becomes increasingly difficult for the public to discern. The growing use of these non-existent personas provides significant advantages to content producers, such as reduced costs [4], full control over messaging, instant multilingual production, and unlimited availability in interactive formats. However, for internet users, this opacity creates a problematic zone of ambiguity, undermining the reliability of information, weakening trust in media content, and opening the door to new forms of visual manipulation.

In this context, a central question emerges: how can an internet user determine whether the person they see in a video is a real human being or a non-existent AI-generated avatar? Although closely related to the evolution of deepfakes [5], this issue goes beyond the usual challenges of identity falsification. It concerns characters that are entirely generated, with no correspondence to any real person, and whose detection requires approaches fundamentally different from those used for traditional deepfake analysis. To date, no major study has directly addressed this question in the scientific literature [6], even though it is becoming essential for ensuring digital transparency and protecting users against the proliferation of undisclosed synthetic video content.

The fundamental innovation of VidAvDetect lies in its ability to tackle a new classification task focused not on detecting manipulated identities, but on identifying faces that belong to individuals who do not exist at all. This conceptual shift significantly expands the scope of synthetic-content detection and addresses the growing need for transparency in advertising and media environments. By relying on a transformer-based model with strong representational capabilities, our approach captures subtle yet recurrent divergences between real human faces and their artificial counterparts [7], even when the latter are produced with high visual fidelity.

Therefore, VidAvDetect introduces a new methodological direction capable of confronting the rise of artificial avatars [8] whose use is rapidly spreading across digital ecosystems. By emphasizing the detection of non-existent identities, this approach provides a concrete response to a phenomenon that remains understudied but is likely to become a major issue in the

verification, regulation, and interpretation of modern video content.

From a research perspective, the emergence of fully AI-generated avatars introduces a critical and still insufficiently addressed scientific challenge. Although current methods of detecting deepfakes are mainly concentrated on detecting visual manipulation techniques used for real human images, their underlying assumption, based on which the image of a human being has to exist in reality, does not continue to hold true in the face of non-existent images of synthetic identities. To address this gap, this work introduces VidAvDetect, which shifts the detection objective from manipulation analysis to identity-existence verification in video streams. In addition to this, by making use of the Vision Transformer architecture and video-level aggregation method, it becomes possible for the proposed solution to offer an informed and specialized method for making distinctions between human identities and purely artificial avatars in digital media.

The remainder of this paper is structured as follows. Section II reviews the related literature; Section III describes the proposed VidAvDetect model; Section IV reports the experimental results; Section V presents the discussion, including ethical considerations; and Section VI provides the conclusion along with future research directions.

II. Related Work

The detection of synthetic media has been extensively studied in the context of deepfakes [9], where the identity of a real individual is modified using generative networks, encoder–decoder architectures, or facial transfer techniques. Existing models primarily rely on convolutional networks, frequency-domain analysis, or attention mechanisms to identify artifacts introduced during face swapping, reenactment, or warping operations. These methods consistently assume the presence of an authentic human identity that has been altered. However, such approaches become inadequate in the face of a new generation of synthetic identities: AI-generated avatars of non-existent person. Unlike traditional deepfakes [10], these faces are created entirely by diffusion models, StyleGAN architectures, or animated avatar engines, without any correspondence to a real person. They do not exhibit the typical irregularities associated with manipulation but instead display coherent and visually consistent features, making them significantly more difficult to detect. Recent studies on AI-generated faces focus mainly on static images and do not address the video dimension nor the verification of whether the displayed identity corresponds to an actual human.

Another line of research examines synthetic profiles on social networks by analyzing behavioral patterns, metadata, or interaction traces. However, these works do not involve visual analysis and do not aim to distinguish real human faces from AI-generated avatars.

Vision Transformer–based models have demonstrated strong performance in deepfake detection, due to their ability to capture global relationships and complex facial structures. Nevertheless, these models are trained exclusively on datasets containing manipulated versions of real identities [11], not fully synthetic faces. None of them is designed to discriminate between a real human and a non-existent AI-generated avatar.

To the best of our knowledge, no prior work has proposed a method capable of determining, within a video, whether the observed face belongs to a real person or to an identity entirely generated by AI [12]. This gap constitutes a notable missing link in the scientific literature and highlights the need for a dedicated approach such as VidAvDetect to address this emerging problem.

III. Proposed Model

The VidAvDetect model aims to determine whether a face extracted from a video sequence belongs to a real individual or to an AI-generated avatar representing a non-existent person. The approach relies on a Vision Transformer, selected for its ability to capture global facial structures and long-range dependencies that are essential for distinguishing authentic human faces from synthetic identities generated [13] by diffusion models, GANs, or avatar-animation engines. As illustrated in Fig. 1, the pipeline begins with the preprocessing and extraction of faces from video frames, after which each face is divided into patches and analyzed by the transformer to capture the textural and structural coherence characteristic of fully generated faces. VidAvDetect then encodes each face and classifies it as real or synthetic [14], while a temporal aggregation step integrates frame-level predictions to deliver a final video-level decision. This process makes VidAvDetect a robust and efficient model for detecting AI-generated non-existent humans in video streams an ability not offered by conventional deepfake detection methods.

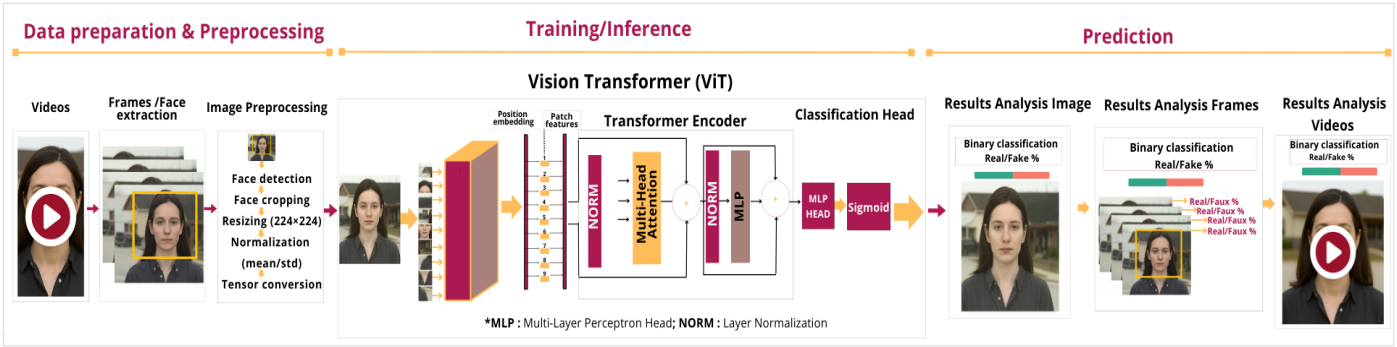


Fig. 1. Architecture of the VidAvDetect approach for real-human vs. AI-avatar detection.

A. Overview of the VidAvDetect Approach

The proposed VidAvDetect approach aims to address a growing challenge in digital content authentication [15]: distinguishing real human identities from AI-generated avatars representing non-existent individuals. With the increasing use of such synthetic characters in advertising, promotional videos, and online communication, the system seeks to provide a reliable mechanism for verifying whether a face appearing in a video truly corresponds to an authentic person. VidAvDetect operates by extracting facial regions from video frames, normalizing them through a series of preprocessing steps, and encoding them using a Vision Transformer capable of capturing the global structures and facial regularities that differentiate real humans from fully synthetic identities. This methodological combination gives VidAvDetect a level of precision and robustness particularly suited to modern contexts where humans and AI-generated avatars have become visually difficult to distinguish.

B. Motivation for Choosing Vision Transformer

The choice of a ViT as the backbone of the VidAvDetect approach is motivated by the need to capture subtle global patterns that distinguish real human faces from AI-generated avatars. Unlike CNN-based architectures that operate primarily through local receptive fields, ViT processes images as sequences of patches, enabling it to model long-range spatial dependencies and globally coherent structures across the entire face. This capability is particularly relevant for detecting synthetic identities [16], which often exhibit consistent textures, uniform facial alignment, and regular geometric patterns produced by diffusion models, GAN architectures, or avatar-generation engines.

Moreover, ViT has demonstrated strong generalization abilities on heterogeneous datasets and shows robustness when dealing with high-fidelity synthetic content, where local manipulation artifacts are minimal or absent. Its self-attention mechanism allows the model to compare facial regions holistically, capturing identity-level irregularities that traditional deepfake detectors may overlook.

These strengths make Vision Transformers especially suitable for distinguishing synthetic faces that do not originate from real individuals a requirement central to the VidAvDetect task. In addition, ViT [17] integrates seamlessly into a modular pipeline, offering scalability for video-level prediction through the aggregation of frame-based embeddings. This combination of global feature modeling, robustness to varied generative styles, and compatibility with video inference provides a solid foundation for reliable discrimination between real human identities and AI-generated avatars.

C. Data Preparation and Face Preprocessing

The data preparation stage relies on a diverse collection of video sources combining real human recordings, deepfake benchmarks, and fully synthetic AI-generated avatars. This heterogeneous composition ensures that the model is exposed to various real-world conditions, manipulation techniques, and generative styles. Table I summarizes the datasets used in our experiments, including the number of videos, total duration, and distribution between real and synthetic samples.

TABLE I. OVERVIEW OF THE VIDAVDETECT VIDEO DATASET

Source	Number of videos	Total duration (minutes)	Fake	Real
FaceForensics++	100	60	50	50
DFDC	150	90	75	75
DeepfakeTIMIT	40	25	20	20
Celeb-DF	30	20	15	15
Synthesized (AI)	20	12	20	0
RealVids2020	30	18	0	30
UCF101	40	25	0	40

Each video is sampled into frames at a fixed extraction rate to ensure a balanced temporal representation across all sources. For every extracted frame, a face detection module is applied to localize the facial region of interest. The detected faces are then cropped and resized to a standardized spatial resolution of 224 × 224 pixels, ensuring consistency with the Vision Transformer input format.

Preprocessing also includes pixel-value normalization (mean/std) and tensor conversion, producing uniform model-ready inputs regardless of the variability present in the original datasets. This step is essential for removing irrelevant background information and focusing the model exclusively on facial structures. It also harmonizes samples originating from different datasets, improving the stability and generalization capacity of the VidAvDetect model during training and inference.

D. Detailed Description of Model Blocks

The VidAvDetect architecture is composed of several sequential modules, each responsible for transforming the raw video input into a robust video-level authenticity prediction. This subsection describes the function of each block, from frame extraction to transformer-based encoding and classification [18].

- Frame Extraction Module: Each video is uniformly sampled to extract a limited number of frames, reducing computational cost and response time while maintaining sufficient temporal coverage. The number of extracted frames is computed as:

$$Frames_{extracted} = \frac{Video_Duration \times FPS}{Sampling_Rate}$$

- Video_Duration corresponds to the video length in seconds, FPS indicates the frame rate, and Sampling_Rate defines how frequently frames are selected; for example, selecting one frame every ten in a 60-second video recorded at 30 FPS reduces computation and improves response time while still preserving sufficient temporal coverage.
- Face Detection and Preprocessing Block: Sampled frames undergo face detection, and the extracted facial regions are cropped, resized to 224×224, normalized, and converted into tensors to produce consistent model-ready inputs.

- Patch Embedding and Tokenization: Each preprocessed face is divided into fixed-size patches, which are flattened and projected into embedding vectors enriched with positional information to form the token sequence for the transform.
- Vision Transformer Encoder: The transformer layers process the patch tokens through self-attention and feed-forward operations, enabling the model to capture global structural and textural cues distinguishing real human faces from synthetic ones.
- Classification Head: The final representation is passed through an MLP and a sigmoid function to generate a probability indicating whether the detected face is real or AI-generated.
- Video-Level Decision: Frame-level predictions are aggregated using temporal fusion to produce a stable and reliable video-level authenticity decision.

E. Comparative Analysis of Methods

To better situate the contribution of VidAvDetect within the landscape of facial authenticity analysis [19], we provide a concise comparison with existing deepfake detection approaches. While traditional models are primarily designed to identify manipulations applied to real faces [20], VidAvDetect focuses on determining whether the identity itself is real or AI-generated. Table II summarizes the key conceptual differences between existing detectors and the proposed VidAvDetect approach.

The comparison in Table II highlights the conceptual shift introduced by VidAvDetect. While traditional detectors focus on detecting modifications applied to real faces, VidAvDetect assesses whether the identity itself is real or artificially generated. This orientation aligns with the growing use of synthetic AI-generated avatars across digital media.

TABLE II. COMPARISON BETWEEN DEEPFAKE DETECTORS AND VIDAVDETECT

Aspect	Existing Deepfake Detectors	VIDAVDetect
Goal	Detect manipulated faces	Detect real vs AI-generated identities
Assumption	The person exists	The person may not exist
Feature Focus	Local artifacts	Global structural & synthetic cues
Target Content	Altered real faces	Fully synthetic AI avatars
Strength	Good for manipulation detection	Strong for identity-existence verification
Limitation	Fail on fully generated faces	Requires diverse synthetic data

IV. EXPERIMENTAL RESULTS

To evaluate the relevance of the proposed VidAvDetect approach, we designed a use case representative of current challenges in video-based identity verification. With the increasing presence of AI-generated avatars across advertising [21], social platforms, and promotional media, determining whether the person appearing in a video stream is real or synthetically generated has become essential for transparency and content reliability. The use case presented in Fig. 2 illustrates this setting by showing how VidAvDetect processes video inputs through frame sampling, facial extraction, and transformer-based classification to produce an identity authenticity assessment indicating whether the depicted individual corresponds to a real human or an AI-generated avatar.



Fig. 2. Experimental use case of the VidAvDetect approach.

Fig. 2 provides an overview of the complete VidAvDetect workflow, from video-stream ingestion to final authenticity prediction. The illustration shows how an advertisement video is first decomposed into uniformly sampled frames, then processed through face detection, cropping, and normalization before being analyzed by the transformer-based classifier.

The final stage aggregates frame-level probabilities to produce a video-level decision, here identifying the individual as an AI-generated avatar with a confidence score of 95%. This end-to-end flow highlights the practical value of VidAvDetect for real-world video streams, where users' viewers, regulators, or platforms need instant and reliable verification of whether a person shown on screen is real or artificially generated.

A. Binary Detection: Real Human vs. AI Avatar (Fake)

Fig. 3 presents the joint evolution of the training loss and accuracy of the VidAvDetect model during the binary classification task Real Human vs AI-Generated Avatar. This curve provides insight into the model's convergence behavior, training stability, and its ability to effectively separate authentic human faces from fully synthetic AI-generated identities.

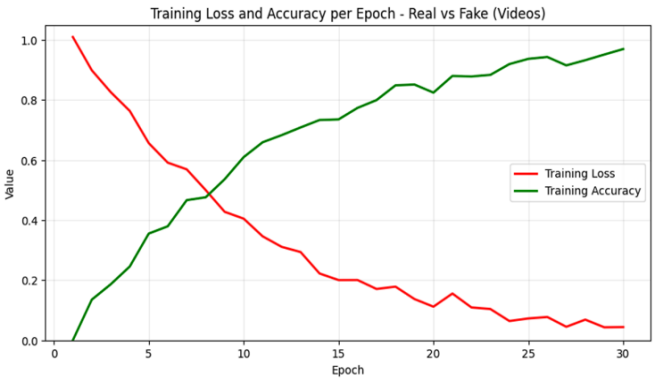


Fig. 3. Real vs. AI-avatar binary detection results.

As shown in Fig. 3, the training loss decreases steadily across epochs and eventually stabilizes at a very low value, while the accuracy consistently increases and reaches approximately 97–98% by the end of training. This trend demonstrates that VidAvDetect learns to discriminate real human faces from AI-generated avatars with high reliability, indicating strong class separability and robust generalization on the Real Human vs AI-Generated Avatar task.

B. Confusion Matrix and Metrics

To further evaluate the effectiveness of VidAvDetect in distinguishing real human identities from AI-generated avatars, we report the quantitative performance on the video-level binary classification task. This analysis includes detailed classification metrics precision, recall, F1-score, and overall accuracy as well as the confusion matrix shown in Fig. 4, allowing us to assess not only the global performance of the model but also its class-wise behavior. These results shown in Fig. 5 provide a clear view of how reliably VidAvDetect generalizes to unseen video streams.

As shown in Fig. 5, VidAvDetect achieves a strong and well-balanced performance across both classes. The model correctly classifies 44 out of 46 real identities and 34 out of 36 AI-generated avatars, resulting in an overall accuracy of 95.1 %, a macro-averaged F1-score of 0.944, and a ROC-AUC of 0.9505. These results confirm that the model consistently captures the discriminative patterns separating real human faces from artificially generated ones.

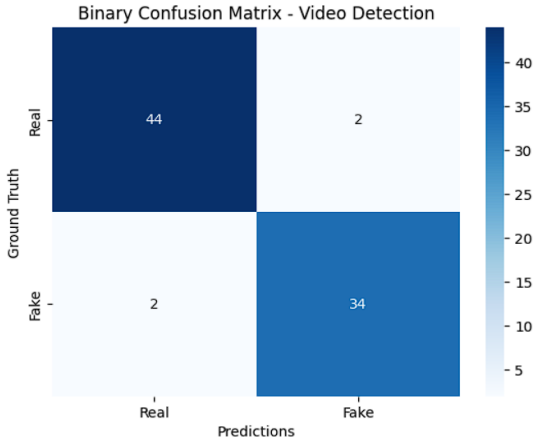


Fig. 4. Binary video detection confusion matrix.

	precision	recall	f1-score	support
Real	0.94	0.94	0.94	36
Fake	0.96	0.96	0.96	46
accuracy			0.95	82
macro avg	0.95	0.95	0.95	82
weighted avg	0.95	0.95	0.95	82

Accuracy: 0.9512
Precision: 0.9444
Recall: 0.9444
F1 Score: 0.9444
MCC: 0.9010
Cohen's Kappa: 0.9010
ROC AUC: 0.9505

Fig. 5. VidAvDetect classification performance results.

C. ROC–AUC Evaluation

To further assess the discriminative capacity of VidAvDetect on the binary classification task Real Human vs. AI-Generated Avatar, we computed the Receiver Operating Characteristic (ROC) curve, as shown in Fig. 6.

This metric provides a threshold-independent evaluation of the model's ability to separate the two classes by plotting the true positive rate against the false positive rate across all decision thresholds. A higher Area Under the Curve (AUC) value indicates stronger separability and more reliable decision-making.

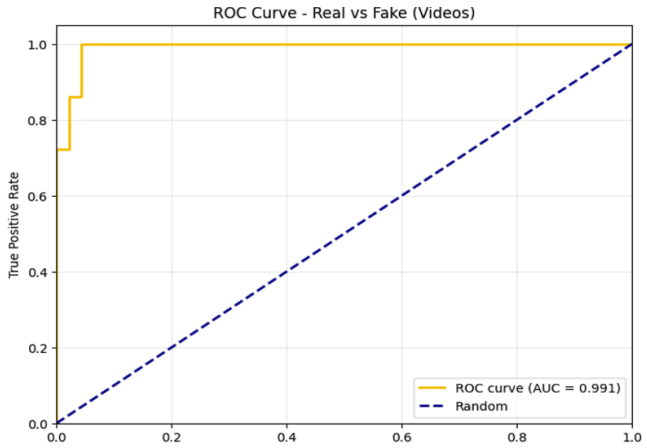


Fig. 6. ROC–AUC curve for binary detection.

VidAvDetect achieves an exceptionally high AUC of 0.991, indicating almost perfect separability between real human faces and AI-generated avatars. The ROC curve remains near the top-left corner, confirming that the model maintains a very high true positive rate even when the decision threshold is varied. These results reinforce the robustness of VidAvDetect and align consistently with the previously reported accuracy (~95%), precision, recall, and confusion matrix performance, demonstrating the model's reliability in distinguishing authentic identities from synthetic ones.

V. Discussion

The experimental findings demonstrate that VidAvDetect addresses a critical gap not covered by existing deepfake-detection research. Traditional deepfake detectors focus on

identifying manipulations applied to real human identities [22] such as face swapping, reenactment, or warping and therefore rely on the presence of local artifacts generated during the manipulation process.

These approaches are inherently limited when confronted with fully AI-generated identities, which are produced natively by GANs and diffusion models and therefore do not exhibit the typical distortion patterns exploited by classical algorithms.

The numerical results highlight the effectiveness of the proposed approach. The model achieves an almost perfect separability between real and synthetic identities, as reflected by the ROC–AUC of 0.991. This indicates that VidAvDetect detects global structural signatures geometric regularities, statistical homogeneity of textures, and the absence of natural micro-variations that persist across avatars generated by different architectures.

The balanced classification performance (44/46 real faces and 34/36 AI-generated avatars correctly identified) combined with a macro-F1 score of 0.944 shows that the system avoids both over-detection and under-detection, a limitation frequently observed in conventional deepfake detectors confronted with high-realism synthetic faces.

The video-level accuracy of 95.1% further demonstrates the advantage of incorporating temporal aggregation. Whereas many existing studies are restricted to static images, VidAvDetect maintains its discriminative ability across frames, enabling consistent identity-existence verification in real video streams. This is particularly relevant as modern AI-avatar engines produce smooth, artifact-free video sequences that would evade detectors based solely on frame-level texture inconsistencies.

The results collectively indicate that the Vision Transformer architecture plays a decisive role in the model's performance. By capturing long-range dependencies and holistic facial structures, the transformer overcomes the limitations of CNN-based approaches tied to local receptive fields. This capability becomes crucial [23] as generative models continue to evolve toward near-photorealism.

Nevertheless, the discussion must acknowledge that technological progress in diffusion-based avatar generation may gradually reduce the visual discrepancies currently detectable. Ensuring long-term robustness will require periodic dataset expansion, model retraining, and potentially the inclusion of multimodal cues such as audio-visual synchrony, micro-expression dynamics, or physiological consistency.

Overall, VidAvDetect introduces a methodological shift from manipulation detection to identity-existence verification, representing a significant advancement for authenticity assessment in digital media. As artificially generated personas become increasingly indistinguishable from real individuals, such models will be essential for maintaining transparency, trust, and integrity across online environments.

In addition to these technical considerations, the growing use of highly realistic AI-generated avatars also raises important ethical and legal issues. Such synthetic identities can compromise the credibility of digital content by enabling undisclosed impersonation, fabricated testimonies, or misleading representations that appear visually indistinguishable from real individuals.

Ensuring that viewers can verify whether a portrayed identity truly exists is therefore essential for preserving trust, preventing misuse, and supporting emerging regulatory requirements that mandate transparency in the dissemination of AI-generated media.

VI. Conclusion

VidAvDetect establishes a new direction in video-based identity authentication by addressing a problem that remains absent from existing deepfake-detection literature: determining whether the individual appearing in a video is an actual human or an AI-generated avatar with no real-world existence. Unlike conventional detectors that rely on identifying manipulation artifacts applied to genuine identities, the proposed model focuses on discriminating fully synthetic faces produced natively by diffusion models, GAN architectures, and advanced avatar-generation engines.

The experimental evaluation highlights the effectiveness of this approach. VidAvDetect achieves an overall video-level accuracy of 95.1%, with balanced classification performance 44/46 real faces and 34/36 AI-generated avatars correctly identified. Complementary metrics, including a macro F1-score of 0.944, precision and recall values of 0.944, and a ROC–AUC of 0.9505, confirm the model's ability to reliably separate authentic human faces from their synthetic counterparts. These results demonstrate that the Vision Transformer architecture effectively captures global structural cues and synthetic regularities that persist across diverse generative styles, while the temporal aggregation mechanism ensures stable predictions across continuous video sequences.

The model therefore provides a solid foundation for identity-existence verification in real video streams an increasingly crucial capability as AI-generated personas continue to proliferate in advertising, marketing, entertainment, social platforms, and promotional media. VidAvDetect offers users, platforms, and regulators a practical mechanism for assessing whether a video identity corresponds to a real individual, thereby contributing to digital transparency and strengthening the reliability of modern multimedia content.

Despite these promising results, this study presents certain limitations that should be acknowledged. First, the proposed approach relies exclusively on visual facial information and does not currently integrate multimodal cues such as audio signals, speech consistency, or physiological indicators, which may provide complementary evidence in complex real-world scenarios. Second, although the experimental evaluation covers heterogeneous datasets including real, manipulated, and fully synthetic videos, the diversity of emerging avatar-generation techniques continues to evolve rapidly, which may introduce new generative patterns not fully represented in the current data. Finally, the model focuses on frontal or near-frontal facial content, and its performance may be affected in cases involving extreme poses, occlusions, or low-quality video streams. Addressing these limitations constitutes an important direction for future research.

Future developments may incorporate multimodal features such as audio–visual synchrony, micro-expression dynamics, or temporal physiological cues to further enhance detection robustness as generative technologies evolve. In parallel, the growing presence of realistic AI-generated avatars raises significant ethical and legal considerations. Synthetic identities can be used to fabricate testimonies, impersonate experts, or disseminate misleading narratives that appear indistinguishable from authentic human communication. Ensuring that viewers can verify whether an identity genuinely exists is therefore essential to protect public trust, uphold transparency, and comply with emerging regulatory frameworks governing the disclosure of AI-generated media.

REFERENCES

[1] B. Acim, N. Kharmoum, S. N. Lagmiri, and S. Ziti, "The role of generative AI in deepfake detection: A systematic literature review," in Proc. Int. Conf. Smart Business and Technologies (ICSBT 2024), vol. 1330, Lecture Notes in Networks and Systems, S. N. Lagmiri, M. Lazaar, and F. M. Amine, Eds. Cham, Switzerland: Springer, 2025, pp. 349–357. doi: 10.1007/978-3-031-86698-2_31.

[2] B. Liu, H. Jiang, Y. Wang, and X. Xu, "A review of deepfake and its detection: From generative adversarial networks to diffusion models," Int. J. Intell. Syst., vol. 40, no. 5, pp. 12567–12592, 2025. doi: 10.1155/int/9987535.

[3] Y. Gong, J. Zhang, Y. Wang, and Z. Liu, "A contemporary survey on deepfake detection: Datasets, algorithms, and challenges," Electronics, vol. 13, no. 3, p. 585, 2024. doi: 10.3390/electronics13030585.

[4] F. Lago, C. Pasquini, R. Böhme, H. Dumont, V. Goffaux, and G. Boato, "More real than real: A study on human visual perception of synthetic faces," IEEE Signal Processing Magazine, vol. 39, no. 4, pp. 109–116, July 2021. doi:10.1109/MSP.2021.3120982.

[5] T. Karras, S. Laine, and T. Aila, "A style-based generator architecture for generative adversarial networks," in Proc. IEEE/CVF Conf. Computer Vision and Pattern Recognition (CVPR), Long Beach, CA, USA, 2019, pp. 4401–4410. doi: 10.1109/CVPR.2019.00453.

[6] A. Alsaeedi, A. AlMansour, and A. Jamal, "Audio-Visual Multimodal Deepfake Detection Leveraging Emotional Recognition," International Journal of Advanced Computer Science and Applications (IJACSA), vol. 16, no. 6, 2025. doi:10.14569/IJACSA.2025.0160622.

[7] B. Acim, H. Ouhnni, N. Kharmoum, S. Ziti, and A. Ouajdouni, "The era of blockchains, deepfakes, and NFTs in therapeutic treatments: A comparative study," in Non-Fungible Tokens (NFTs) in Smart Cities: Advancements and Security Challenges, U. Khalil, M. Uddin, O. Malik, and A. Dandoush, Eds. Hershey, PA, 650 USA: IGI Global Scientific Publishing, 2026, pp. 119–152, doi: 10.4018/979-8-3693-8876-1.ch005.

[8] A. Hidouri, S. Jabbour, and B. Raddaoui, "On the enumeration of frequent high utility itemsets: A symbolic AI approach," in Proc. 28th Int. Conf. Principles and Practice of Constraint Programming (CP), LIPIcs, vol. 235, 2022, pp. 27:1–27:17. doi: 10.4230/LIPIcs.CP.2022.27.

[9] H. Ouhnni, B. Acim, M. Belhiah, K. El Bouchti, Y. Z. Seghroucheni, S. N. Lagmiri, R. Benachir, and S. Ziti, "The evolution of virtual identity: A systematic review of avatar customization technologies and their behavioral effects in VR environments," Front. Virtual Real., vol. 6, 2025. doi: 655 10.3389/frvir.2025.1496128.

[10] H. Wu, L. Leng, and P. Yu, "Learning Local Reconstruction Errors for Face Forgery Detection," International Journal of Advanced Computer Science and Applications (IJACSA), vol. 15, no. 11, 2024. doi:10.14569/IJACSA.2024.01511120.

[11] D. A. Coccomini, R. Caldelli, F. Falchi, C. Gennaro, et G. Amato, "Cross-Forgery Analysis of Vision Transformers and CNNs for Deepfake Image Detection," in Proc. 1st Int. Workshop on Multimedia AI against Disinformation (MAD 2022), Newark, NJ, USA, June 27–30 2022, ACM, New York, NY, USA, pp. 52– 58. doi:10.1145/3512732.3533582.

[12] Z. Xia, T. Qiao, M. Xu, X. Wu, L. Han, and Y. Chen, "Deepfake video detection based on MesoNet with preprocessing module," Symmetry, vol. 14, no. 5, Art. no. 939, 2022. doi:10.3390/sym14050939.

[13] B. Acim, N. Kharmoum, M. Ezziyyani, and S. Ziti, "Mental health therapy: A comparative study of generative AI and deepfake technology," in Proc. Int. Conf. Adv. Intell. Syst. Sustain. Dev. (AI2SD 2024), vol. 1403, Lecture Notes in Networks and Systems, M. Ezziyyani, J. Kacprzyk, and V. E. Balas, Eds. Cham, Switzerland: Springer, 2025, pp. 351–357. doi: 10.1007/978-3-031-91337-2_33.

[14] T. Karras, S. Laine, and T. Aila, "A style-based generator architecture for generative adversarial networks," in *Proc. IEEE/CVF Conf. Computer Vision and Pattern Recognition (CVPR)*, Long Beach, CA, USA, 2019.

[15] M. I. Ahmad, H. Alkhalifah, A. A. Khaleel, and A. A. Al-Khalifa, "Extracting Facial Features to Detect Deepfake Videos Using Machine Learning," International Journal of Advanced Computer Science and Applications (IJACSA), vol. 16, no. 4, 2025. doi:10.14569/IJACSA.2025.0160417.

[16] C. Ben Rabah, I. N. Petropoulos, R. A. Malik, and A. Serag, "Vision transformers for automated detection of diabetic peripheral neuropathy in corneal confocal microscopy images," Frontiers in Imaging, vol. 6, 2025. doi: 10.3389/fimag.2025.1542128.

[17] H. Mancy, M. Elpeltagy, K. Eldahshan, and A. Ismail, "Hybrid-Optimized Model for Deepfake Detection," Int. J. Adv. Comput. Sci. Appl. (IJACSA), vol. 16, no. 4, 2025. doi: 10.14569/IJACSA.2025.0160417..

[18] M. Elpeltagy, A. Ismail, M. S. Zaki, and K. Eldahshan, "A Novel Smart Deepfake Video Detection System," International Journal of Advanced Computer Science and Applications (IJACSA), vol. 14, no. 1, 2023. doi:10.14569/IJACSA.2023.0140144.

[19] H. A. Soudy, O. Sayed, H. Tag-Elser, R. Ragab, S. Mohsen, T. Mostafa, A. A. Abohany, and S. O. Slim, "Deepfake Detection Using Convolutional Vision Transformers and Convolutional Neural Networks," Neural Computing and Applications, vol. 36, no. 15, pp. 10245–10261, Aug. 2024. doi:10.1007/s00521-703 024-10181-7.

[20] A. Dosovitskiy, L. Beyer, A. Kolesnikov, D. Weissenborn, X. Zhai, T. Unterthiner, M. Dehghani, M. Minderer, G. Heigold, S. Gelly, J. Uszkoreit, and N. Houlsby, "An image is worth 16x16 words: Transformers for image recognition at scale," in Proc. Int. Conf. Learning Representations (ICLR), 2021. [Online]. Available: https://openreview.net/forum?id=YicbFdNTTy.

[21] Z. Wang, Z. Cheng, J. Xiong, X. Xu, T. Li, B. Veeravalli, and X. Yang, "A timely survey on Vision Transformer for deepfake detection," arXiv preprint, 2024. doi: 10.48550/arXiv.2405.08463.

[22] H. Wu, L. Leng, and P. Yu, "Learning local reconstruction errors for face forgery detection," International Journal of Advanced Computer Science and Applications (IJACSA), vol. 15, no. 11, 2024. doi:10.14569/IJACSA.2024.01511120.

[23] J. Deng, J. Guo, N. Xue, and S. Zafeiriou, "ArcFace: Additive angular margin loss for deep face recognition," in Proc. IEEE/CVF Conf. Computer Vision and Pattern Recognition (CVPR), Long Beach, CA, USA, 2019.

Dynamic Sentiment Analysis on the Emergence of Pre-Trained Generative Model-Based Applications in Indonesia

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***Abstract*—The emergence of pre-trained generative model–based applications has intensified sentiment dynamics within Indonesia's multi-platform digital ecosystem, where sentiment intensity and temporal fluctuations occur simultaneously. To overcome these challenges, this study extends IndoBERT by incorporating a time-aware tokenization mechanism within a fine-grained dynamic sentiment analysis framework. This mechanism is designed to explicitly capture the evolution of sentiment over time. Instead of relying on external embeddings or implicit timestamps, temporal information is injected directly into the IndoBERT tokenizer through explicit temporal tokens, enabling end-to-end temporal adaptation during fine-tuning. We utilized a large-scale dataset harvested from various platforms—including TikTok, Twitter (X), YouTube, and forums—alongside AI-generated content from Gemini, ChatGPT, and Copilot. The dataset was annotated into five fine-grained sentiment classes: very positive, positive, neutral, negative, and very negative. The experimental evaluation demonstrates that the proposed time-aware IndoBERT model attains an average accuracy of 96.38%, exceeding the performance of the baseline BERT and RoBERTa models. Furthermore, ablation studies validate that the inclusion of time-aware tokenization yields quantifiable performance gains, proving that explicit temporal encoding refines sentiment sensitivity and offers sharper insights into the shifting public opinion in Indonesia.**

***Keywords*—Dynamic sentiment; fine-grained; IndoBERT; multi-platform big data; sentiment analysis**

I. Introduction

Analyzing sentiment from large-scale, multi-platform data in Indonesia becomes increasingly complex when higher sentiment granularity is required [1]. Large volumes of unstructured text produced by social media interactions and AI-generated responses demand advanced modeling techniques to capture contextual sentiment variations accurately [2], [3]. Conventional sentiment analysis frameworks frequently lack classification precision. This deficit is often attributed to three primary factors: suboptimal preprocessing, rigid vectorization techniques, and a shallow grasp of textual context [4], [5], [6]. Sentiment analysis across multiple platforms is crucial because opinions expressed by users differ across digital spaces due to varying audience engagement and platform-specific language use. Studies have shown that collecting data from diverse sources, such as Twitter, TikTok, and forums, improves the robustness of sentiment classification models [7]. Sentiment data are collected from multiple platforms to capture broader and more dynamic expressions of sentiment, enabling better adaptability in different digital platforms [8]. This research focuses on sentiment analysis of AI-generated responses from multiple pre-trained generative models, including ChatGPT, Gemini, Copilot, and others, rather than limiting the study to ChatGPT alone [5], [6]. Recent studies emphasize the growing impact of AI-generated content on public sentiment and the necessity of analyzing various generative models to gain a comprehensive understanding [9].

Fine-grained sentiment analysis advances beyond standard classification methods by transcending simple ternary labels (positive, negative, neutral). Instead, it adopts a more nuanced spectrum that includes five distinct intensity levels: very positive, positive, neutral, negative, and very negative [10]. This approach enables a deeper understanding of sentiment intensity, emotional variations, and nuanced expressions in text [11]. A study on sentiment classification highlights that fine-grained sentiment analysis improves model interpretability by capturing more subtle differences in user opinions, which is particularly useful for complex and multi-faceted sentiment expressions [12]. In the context of Indonesian multi-platform environments, employing a fine-grained analytical approach is indispensable. This is largely due to the complexity of user-generated content, which is frequently characterized by heterogeneous linguistic styles, conflicting sentiments, and subtle, implicit emotional cues [10], [12], [13].

Dynamic sentiment analysis focuses on modeling sentiment changes over time, recognizing that user opinions and emotions fluctuate due to external events, trends, and contextual influences [14]. Traditional sentiment classification often assumes static sentiment representation, which does not account for real-world changes in user emotions [15]. The need for dynamic sentiment analysis arises from various challenges, including the rapid evolution of online discussions, real-time sentiment shifts due to breaking news, and context-dependent emotional expressions [16]. By integrating time-token embeddings [17], sentiment models can account for sentiment shifts across different periods, making classification more adaptive and reflective of real-world changes, where sentiment dynamics play a critical role in decision-making [18], [19].

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Recent advancements in deep learning, particularly transformer-based architectures such as BERT (Bidirectional Encoder Representations from Transformers), have significantly improved sentiment classification performance [20]. BERT eliminates the need for extensive preprocessing [21] and enhances classification accuracy through contextual embedding [22], [23]. IndoBERT represents a specialized adaptation of the BERT architecture, pre-trained extensively on Indonesian corpora. This specific training regimen allows it to effectively address the unique linguistic nuances and structural characteristics inherent to the language [24], [25]. Compared with the standard BERT model, IndoBERT provides more effective contextual representations for Indonesian-language text. By modeling the unique morphological, syntactic, and semantic characteristics of the language, IndoBERT attains notably improved accuracy in sentiment classification tasks [26], [27], [28]. Optimizing IndoBERT for sentiment analysis is essential for effectively addressing the complexities of the Indonesian language, reducing misclassifications that arise due to linguistic ambiguity and diverse language structures [29]. IndoBERT enhances sentiment classification through its generation of context-aware embeddings. These representations are particularly effective at modeling long-range dependencies and detecting dynamic semantic shifts within the narrative [30], [31].

The principal aim of this study is to develop and optimize a specialized IndoBERT framework for Fine-Grained and Dynamic Sentiment Analysis, explicitly adapted for Indonesian multi-platform big data. A central component of this research is the integration of time-aware token embeddings, which are utilized to capture sentiment fluctuations and enhance the precision of dynamic analysis [17], leveraging IndoBERT's contextual capabilities to improve Indonesian sentiment classification, utilizing multi-platform data for better generalization across diverse digital environments [32], applying fine-grained sentiment labeling to capture nuanced emotional expressions, and analyzing sentiment trends in AI-generated content across multiple pre-trained generative models (ChatGPT, Gemini, Copilot, etc.). By addressing these challenges, this study offers valuable insights into various societal and economic trends in Indonesia [25] and advances the methodology for sentiment analysis in dynamic online environments. Although prior studies have explored fine-grained and dynamic sentiment analysis, existing approaches largely treat temporal information as auxiliary metadata, with limited investigation into its explicit integration within IndoBERT for multi-platform Indonesian data, particularly in the context of AI-generated content. To address this gap, this study introduces a time-aware tokenization mechanism embedded directly into IndoBERT's tokenizer and embedding space, proposes a fine-grained dynamic sentiment framework with five sentiment intensity levels, validates the contribution of temporal tokens through ablation-based analysis, and performs large-scale evaluations on multi-platform Indonesian big data, including content generated by multiple generative AI models. This research explicitly serves as a significant extension of our preliminary study, which focused primarily on single-platform analysis. The current work expands that scope by integrating temporal dynamics and enlarging the dataset to encompass heterogeneous sources.

The structure of this study is outlined as follows: Section II surveys existing literature relevant to the study. Section III elaborates on the proposed methodology, while Section IV analyzes the experimental results and discussion. The study concludes with a summary of findings in Section V.

II. Related Work

Prior sentiment analysis research has examined fine-grained classification, temporal sentiment modeling, and transformer-based architectures, including BERT and its variants, across various application domains. Fine-grained sentiment analysis has been shown to provide richer emotional representation compared to binary or ternary classification schemes, particularly in social media contexts.

Many dynamic sentiment analysis approaches integrate temporal signals through post-hoc aggregation or external time-series models rather than embedding temporal context directly within language representations. However, such methods often treat temporal signals as auxiliary metadata rather than as integral linguistic features.

In the field of Indonesian natural language processing, IndoBERT has demonstrated strong performance across various applications, with notable effectiveness in sentiment classification. Nevertheless, existing studies largely rely on static representations and do not explicitly integrate temporal information into the tokenization or embedding process. Moreover, limited attention has been given to sentiment analysis on multi-platform Indonesian big data involving AI-generated content.

This study addresses these gaps by introducing a time-aware tokenization mechanism embedded directly into IndoBERT, enabling explicit modeling of sentiment evolution over time within a fine-grained sentiment framework.

III. Methods

As illustrated in Fig. 1, our proposed framework operates through four sequential phases: data acquisition, preprocessing, the injection of time-aware token embeddings, and fine-grained sentiment annotation. To achieve high-resolution sentiment granularity, we employ a lexicon-based approach that classifies text into a five-tier spectrum, ranging from very negative to very positive. A key innovation in this workflow is the integration of time-aware embeddings, which allows the system to explicitly model temporal fluctuations and track the evolution of public opinion. Finally, IndoBERT is deployed as the core classifier; its robust contextual embedding capabilities are essential for detecting nuanced emotional shifts and time-dependent variations across heterogeneous social media platforms.

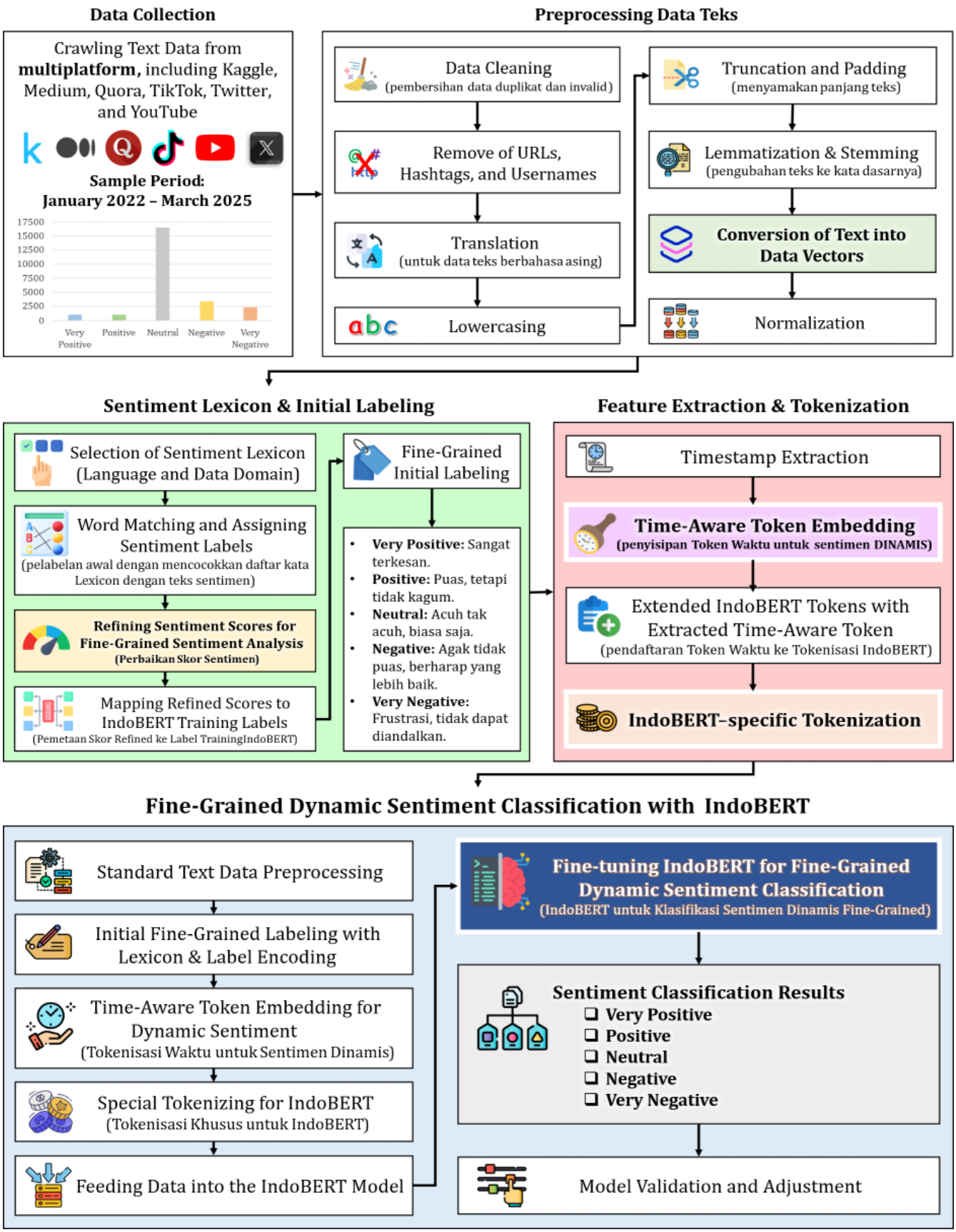


Fig. 1. Procedural framework for the proposed approach.

A. Data Acquisition

To construct a robust and diverse corpus, we executed a comprehensive data harvesting strategy across heterogeneous digital ecosystems. The dataset aggregates textual content from social media, discussion forums, and open repositories, specifically targeting TikTok, Twitter, YouTube, Medium, Quora, and Kaggle. The specific search queries and terms utilized for extraction are enumerated in Table I. Furthermore, to broaden the analytical scope beyond prior studies, we augmented the initial collection with supplementary datasets retrieved using an expanded set of keywords.

TABLE I. KEYWORDS EMPLOYED FOR DATASET COLLECTION

Index	Search Keywords	Dataset Size
1	ChatGPT-based Systems	November 2022 – 2023 25,000 datasets
2	OpenAI Technologies	
3	Education Sector	
4	Academic Research	
5	ChatGPT Copyright Issues	November 2022 – 2024 27,000 datasets
6	Textual Similarity	
7	ChatGPT Usage Disclaimer	
8	Unauthorized AI-Generated News	
9	Politik	May 2024 – 2025 100,000 datasets
10	ChatBot	
11	Gemini (Bard)	
12	Copilot	
13	Generative Model	

Note: Example sentences are presented in the original Indonesian language to preserve semantic and linguistic characteristics relevant to sentiment analysis.

B. Standard Text Data Preprocessing

1) Data cleaning and noise reduction: To ensure the purity of the dataset, we implemented a filtration process to strip away non-textual artifacts. This included the excision of punctuation, emojis, and special characters that offer no semantic value to the classification task, thereby standardizing the input for the model.

2) Removal of metadata artifacts: Metadata markers, specifically hyperlinks (URLs), platform-specific user tags (@username), and topic hash markers (#), were systematically purged. These elements are typically regarded as noise that can obscure the linguistic patterns required for effective feature extraction.

3) Language Unification (Translation): To guarantee linguistic homogeneity across the corpus, we translated all English textual segments into Indonesian. This unification step is critical for mitigating ambiguity caused by code-mixing and ensures the model analyzes a consistent grammatical structure.

4) Case normalization: We applied a uniform case normalization strategy, converting the entire corpus to lowercase. This approach mitigates sparsity issues caused by case sensitivity, ensuring that capitalized and non-capitalized iterations of the same word are recognized as identical tokens, which enhances matching efficiency.

5) Sequence standardization (truncation and padding): To accommodate the fixed input dimension requirements of the deep learning architecture, sequence lengths were standardized. Texts exceeding the maximum length were truncated, while shorter sequences were padded using specific tokens (e.g., [PAD] or zero vectors) to achieve uniformity.

6) Lemmatization and Stemming: We employed both lemmatization and stemming to reduce inflectional variability. Lemmatization was used to revert words to their dictionary base (e.g., restoring "running" to "run"), while stemming stripped suffixes to isolate the root form. This dual approach preserves semantic integrity while minimizing vocabulary size.

C. Initial Labeling with Sentiment Lexicon

In this step, sentiment values are combined using heuristic rules [33], as described in Eq. (1), to generate sentiment labels. This process ensures that sentiment aggregation aligns with contextual meaning, refining the dataset for improved classification performance [see Eq. (1) to Eq. (5)].

$$S_{very\ positive} \sum_{i \in t}^{n} \ very\ positive\ score_i \quad (1)$$

$$S_{positive} \sum_{i \in t}^{n} \ positive\ score_i \quad (2)$$

$$S_{neutral} \sum_{i \in t}^{n} \ neutral\ score_i \quad (3)$$

$$S_{negative} \sum_{i \in t}^{n} \ negative\ score_i \quad (4)$$

$$S_{very\ negative} \sum_{i \in t}^{n} \ very\ negative\ score_i \quad (5)$$

In this framework, initial sentiment labels are generated using a lexicon-based scoring mechanism that aggregates word-level polarity values and contextual modifiers [34]. By utilizing a lexicon-based scoring mechanism to measure intensity, the system assigns one of the five distinct fine-grained labels (very positive, positive, neutral, negative, or very negative) to every sentence, as outlined in Table II. This fine-grained labeling provides a more detailed sentiment distribution, enabling deeper insights into sentiment intensity and emotional variations across multi-platform data [12]. These labels also serve as training data, enabling IndoBERT to capture nuanced sentiment expressions with higher accuracy.

TABLE II. LEXICON-DERIVED DATASET LABELING RESULTS

Lexicon Scores	Lexicon Result	Tweet	Date	Username
-0.6	very negative	Tukang coding 10 orang bisa jd cukup d handle 1 orang aja, mending chatgpt dan ai d musnahkan, karena dapat menghilangkan banyak pekerjaan manusia, yg menyebabkan pengangguran meningkat	Sun Jul 16 03:54:19 +0000 2023	JusDooIt
-0.2	negative	Caution is required when disclosing personal information to conversational AI platforms. Although data sharing may enhance model learning and performance, concerns persist regarding possible unauthorized access to or exploitation of user data.	Thu Jun 29 22:52:50 +0000 2023	leniptri__
0.3	positive	dampak positif AI pada bidang pendidikan terutama di kalangan mahasiswa sangat lah membantu sekali, karena dengan AI akan sangat efektif dan efisien jika digunakan oleh mahasiswa dalam mengerjakan tugas dll.	Thu May 11 03:17:43 +0000 2023	bagussptyno
0.1	neutral	Sebagai sebuah model bahasa buatan, saya tidak belajar seperti manusia pada umumnya. Saya telah dilatih dengan deep learning yang melibatkan pengolahan besar jumlah data dan membangun jaringan saraf tiruan kompleks untuk memahami pola dan struktur bahasa.	Sat Jan 07 10:00:08 +0000 2023	morasaki12
0.4	positive	Syukur lah ada chat gpt semua jadi mudah	Tue Jun 06 05:53:39 +0000 2023	xxbrightvcxx
0.8	very positive	As artificial intelligence continues to advance, conversational agents have emerged as a prominent application. ChatGPT is a recent and sophisticated chatbot designed to interact naturally with users and support various everyday activities. https://t.co/88LLi3nITV	Fri May 24 12:25:58 +0000 2024	user18587

Note: Example sentences are presented in the original Indonesian language to preserve semantic and linguistic characteristics relevant to sentiment analysis

The sentiment labeling process begins by analyzing each word within the text and assigning a score based on its presence in predefined sentiment lexicons. A token identified within the positive lexicon contributes a positive unit increment to the overall score, while a token appearing in the negative lexicon contributes a negative unit decrement. Words that do not belong to either category do not contribute to the overall sentiment score. This word-level scoring serves as the foundation for determining the sentiment at the sentence level. The pseudo-algorithm for this process is presented in Algorithm 1.

Algorithm 1. Pseudo-Algorithm to Label Each Word [35]

```
For each word in the text do
    if the word is in the positive list, then
        sum = sum + 1
    else
        if the word is in the negative list, then
            sum = sum - 1
        End if
    End if
End for
```

Following the word-level sentiment scoring, the overall sentiment of a sentence is determined using a predefined scoring equation, as referenced in Eq. (7). The sentiment initial label is determined based on predefined score thresholds. If the score is 0.6 or higher, the sentence is labeled as very positive (4). Scores between 0.4 and 0.6 are classified as positive (3), while scores ranging from -0.4 to 0.4 are labeled as neutral (2). Sentences with scores between -0.6 and -0.4 are categorized as negative (1), and those with scores of -0.6 or lower are assigned a very negative (0) label.

D. Conversion of Text into Vector Data

We utilized Word2Vec to map words into a continuous vector space, a technique that effectively captures semantic relationships. This process enhances the model's comprehension of word similarities and contextual meanings, thereby improving the overall efficacy of sentiment classification [36]. Furthermore, the generated numerical embeddings streamline subsequent analysis, enabling machine learning algorithms to process textual data with greater efficiency. The results of this transformation are detailed in Table III.

TABLE III. VECTOR DATA RESULT

Before Vectorized	Vector Data Result
chat gpt adalah gamechanger tidak sabar untuk melihat apa yang akan dapat dilakukan di masa depan	[0.23, -0.12, 0.34, 0.07, -0.49, 0.15, 0.23, 0.04, 0.56]

Note: Example sentences are presented in the original Indonesian language to preserve semantic and linguistic characteristics relevant to sentiment analysis.

E. Embedding Time-Aware Token

Integrating time-aware tokens into the sentiment analysis pipeline enables the model to capture temporal variations in sentiment expression more explicitly [19]. This approach allows IndoBERT to dynamically adjust its contextual understanding by incorporating time-specific markers, such as `<hari-senin>`, `<waktu-sore>`, or `<waktu-pagi>`, into the tokenized input [17]. These tokens provide additional contextual information that helps the model recognize sentiment shifts influenced by time-dependent events, social trends, or daily discourse patterns. The process is illustrated in Fig. 2.

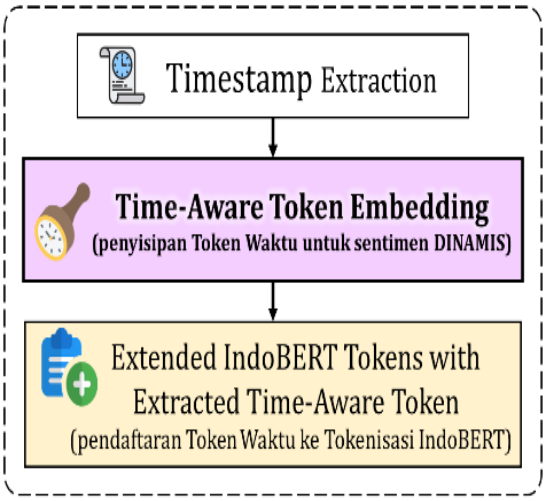


Fig. 2. Time-aware tokenization process.

The process of integrating time-aware tokens into IndoBERT involves the following steps:

1) Extracting temporal information: The initial stage of the procedure focuses on deriving temporal attributes from the timestamp linked to each text instance. In most cases, textual data such as social media posts or online reviews are accompanied by metadata containing date and time information. Based on this metadata, essential temporal features—including the day of the week (e.g., Monday, Tuesday) and time-of-day segments (e.g., morning, afternoon, evening, night). These features provide crucial context, as sentiment expression often varies depending on the time of posting. For example, users may express frustration more frequently on Monday mornings due to work-related stress, while positive sentiments may be more prevalent on Friday evenings due to weekend anticipation.

2) Mapping temporal features to time-aware tokens: Once the relevant time-based features are extracted, they are mapped to predefined time-aware tokens. Each time unit is assigned a corresponding token representation that IndoBERT can recognize. For example, the day of the week is converted into tokens such as `<hari-senin>` or `<hari-sabtu>`, while the time of day is mapped to tokens like `<waktu-pagi>` or `<waktu-sore>`. These tokens serve as additional input features that help the model understand the temporal context in which a given text was written. For example, a tweet posted on "Wednesday at 08:30 AM" would be mapped to `<hari-senin> <waktu-pagi>`. By incorporating these tokens, the model can better capture variations in sentiment that correlate with specific time periods.

3) Appending time-aware tokens to text data: After the tokens are generated, they are appended to the original text before further processing. The tokens are typically inserted at the beginning of the sentence to ensure that IndoBERT processes the temporal context before analyzing the main content of the text. Table IV provides an example of tokenized input with time-aware tokens applied to different sentences.

TABLE IV. PREPROCESSED SENTENCES WITH EMBEDDED TIME-AWARE TOKENS

Timestamp	Sentence	Tokenized Input with Time-Aware Token
Wed Mar 25 14:21:55 +0000 2022	ChatGPT sangat membantu dalam pekerjaan saya!	<hari-rabu> <waktu-siang> chatgpt sangat membantu dalam pekerjaan saya !
Tue Aug 8 17:59:38 +0000 2023	Diskusi dengan ChatGPT tentang sejarah dunia sangat menarik, tetapi terkadang jawabannya terlalu umum dan kurang mendalam.	<hari-sabtu> <waktu-sore> diskusi dengan chatgpt tentang sejarah dunia sangat menarik , tetapi terkadang jawabannya terlalu umum dan kurang mendalam .
Sun Feb 24 23:47:16 +0000 2024	Semakin sering saya pakai, semakin terasa kurang akurat. Dan juga, kenapa hari ini ChatGPT jadi sering error?	<hari-minggu> <waktu-malam> semakin sering saya pakai , semakin terasa kurang akurat . dan juga , kenapa hari ini chatgpt sering error ?

Note: Example sentences are presented in the original Indonesian language to preserve semantic and linguistic characteristics relevant to sentiment analysis.

This ensures that the model is aware of when the statement was made before it begins extracting sentiment-related features. By explicitly including this information, IndoBERT can learn to associate specific sentiment trends with different time periods.

4) Expanding IndoBERT's Tokenizer Vocabulary: Since IndoBERT's default tokenizer does not contain these new time-aware tokens, it must be extended to recognize and process them correctly. This involves modifying the tokenizer's vocabulary by adding the new tokens to the model's predefined token set. The process includes:

a) Updating the tokenizer vocabulary: The new tokens, such as `<hari-jumat>`, `<waktu-pagi>` and `<waktu-malam>`, are explicitly added to IndoBERT's tokenizer to prevent them from being broken into subword units. This ensures that they are treated as single, meaningful tokens rather than being split into unrelated subwords.

b) Adjusting token embeddings: Since IndoBERT's existing embeddings do not include representations for the new tokens, additional embeddings are initialized for them. These embeddings can be either randomly initialized and learned during fine-tuning or mapped using similar contextual embeddings from pre-existing words that represent temporal concepts.

c) Ensuring consistent token handling: The modified tokenizer ensures that every input text containing time-aware tokens is processed consistently. Without this step, the new tokens might be treated as unknown (`[UNK]`) and ignored by the model, reducing the effectiveness of time-based sentiment learning.

Experimental results indicate that the inclusion of time-aware tokens improves the classification performance across various sentiment categories. The model demonstrates an increased ability to distinguish between sentiment fluctuations occurring at different times, particularly in social media data where user opinions may change based on external influences such as current events, holidays, or market trends. Comparative evaluations between IndoBERT with and without time-aware

embedding reveal a notable improvement in sentiment classification accuracy, especially for categories with high temporal sensitivity, such as political discussions or real-time product reviews.

F. Special Tokenization for IndoBERT

Text is tokenized according to IndoBERT's linguistic structure, ensuring proper segmentation for effective processing. The updated IndoBERT tokenizer recognizes time-aware tokens as distinct entities, preventing them from being broken into subwords. This modification preserves the temporal context embedded in the input.

During encoding, each token, including the new time-aware markers, is mapped to an embedding vector. Since these tokens were not in the original IndoBERT vocabulary, their embeddings are either initialized randomly or derived from semantically related words. This enables IndoBERT to incorporate temporal context dynamically, refining sentiment predictions based on time-sensitive factors. The outcomes of this tokenization process are presented in Table V.

TABLE V. TOKENIZING RESULT

Before tokenizing text	After tokenizing text
ah temen gue jg ada yg essay nya dibuat pure pake ChatGPT lolos and he being proud of it soalnya dia tinggal kirim prompt juga ujungnya lolos jd awardee	['ah' , 'temen' , 'gue' , 'jg' , 'ada' , 'yg' , 'essay' , 'nya' , 'dibuat' , 'murni' , 'pake', 'ChatGPT' , 'lolos' , 'dan' , 'dia', 'merasa' , 'bangga' , 'dengan' , 'itu' , 'soalnya' , 'dia' , 'tinggal' , 'kirim' , 'prompt' , 'juga' , 'ujungnya' , 'lolos' , 'jd' , 'pemenang']

G. Classification Using IndoBERT

For the core classification engine, we deployed IndoBERT [25], a transformer architecture pre-trained specifically on Indonesian corpora via masked language modeling. Unlike the standard BERT model, which is optimized for English, IndoBERT offers superior contextual embedding for Indonesian linguistics. By fine-tuning this model on our fine-grained annotated dataset, we enabled it to distinguish between the five distinct sentiment tiers with high precision. The detailed architecture and processing stages are described below:

1) Text Processing Pipeline for IndoBERT: Each token must be transformed into a vector-based representation through an embedding mechanism [see Eq. (6)].

$$V_t = Trans\ (W_t X_a + b_t) \tag{6}$$

2) Initial fine-grained labeling with sentiment lexicon: The use of sentiment lexicons for labeling is a prevalent method in sentiment classification. This technique involves mapping words and phrases to specific sentiment scores according to established polarity values, as in Eq. (7) [34]:

$$\sum_{i=1}^{k} \frac{(p-n)_i}{k} \tag{7}$$

where, k represents the total number of words in the text that are listed in the lexicon, and $p - n$ denotes the sentiment polarity score associated with each word in the lexicon, which is determined based on its occurrence in positive and negative categories [37].

3) Time-aware token embedding: Temporal tokens (e.g., `<hari-senin>`, `<waktu-siang>`) are incorporated into the text to enhance dynamic sentiment analysis by capturing variations influenced by time-based factors.

4) IndoBERT-specific tokenization: The tokenized text, including standard tokens and newly introduced time-aware tokens, is processed using the IndoBERT tokenizer.

5) Feeding data into the IndoBERT Model: IndoBERT generates vector embeddings for individual tokens derived from the input text, as in Eq. (8):

$$V_b = Bert(W_b X_b + b_b) \tag{8}$$

6) Self-Attention: The self-attention mechanism enhances token representations by incorporating contextual information from the surrounding text, as in Eq. (9):

$$Attention(Q, K, V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{9}$$

In this equation, Q, K, V denote the query, key, and value matrices corresponding to the input tokens.

7) Position-wise feed-forward network: Applied after the Self-Attention stage, FFNN layers refine tokens into more intricate representations. This transformation is critical for capturing nonlinear patterns within the text, which in turn leads to improved model understanding and robustness in generalization [see Eq. (10)].

$$FFN(H) = ReLU(HW_1 + b_1)W_2 + b_2 \tag{10}$$

H denotes the contextual embedding generated by self-attention, whereas W1, W2, b1, and b2 define the feed-forward network parameters.

8) Fine-tuning IndoBERT: The fine-tuning phase entails retraining IndoBERT using domain-specific sentiment datasets. This process is designed to optimize classification metrics while preserving the model's original contextual integrity [24], [25].

9) Sentiment classification: In the classification stage, IndoBERT analyzes the input text and assigns it to one of five fine-grained sentiment categories, utilizing the vector representations generated during processing.

H. Data Testing

The evaluation process employs a confusion matrix to summarize prediction results into TP, TN, FP, and FN. In this framework, TP and TN indicate correct predictions, whereas FP and FN reflect classification errors. The effectiveness of the proposed model is then quantified through the accuracy measure, as presented in Eq. (10).

IV. PERFORMANCE EVALUATION AND DISCUSSION

The proposed methodology integrates several stages, including data collection, text preprocessing, sentiment annotation using a lexicon-based approach, time-aware token embedding, and fine-grained sentiment classification based on the IndoBERT model. In particular, the preprocessing step involves text standardization, selective translation of English expressions into Indonesian, token segmentation, sequence

truncation, and padding, aiming to enhance the quality of input representations for IndoBERT.

A. Fine-Tuned IndoBERT Model

The fine-tuning process adjusts IndoBERT's parameters using task-specific data, thereby augmenting its capacity to recognize complex linguistic structures. As illustrated in Fig. 3, the proposed architecture supports this optimization process by adapting the model to task-specific characteristics, thereby leading to improvements in accuracy, precision, and recall.

A total of roughly 24,000 data samples are included in the dataset and are distributed across fine-grained sentiment categories, as presented in Table VI. Analyzing this label distribution, which is visualized in Fig. 4, is essential for assessing IndoBERT's capacity to manage class imbalances and understanding their potential influence on the training process.

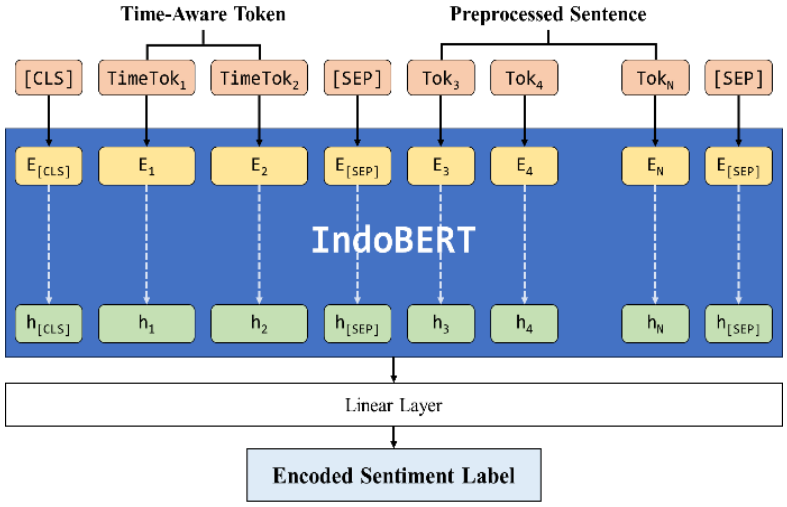


Fig. 3. Time-aware token–enhanced fine-tuned IndoBERT.

TABLE VI. FINE-GRAINED SENTIMENT LABEL STATISTICS

Label	Training Set	Validation Set	Testing Set
Very Positive	1,153	346	149
Positive	920	276	118
Neutral	5,684	1,705	731
Negative	2,213	663	285
Very Negative	1,419	426	182
Total Data	11,389	3,416	1,465

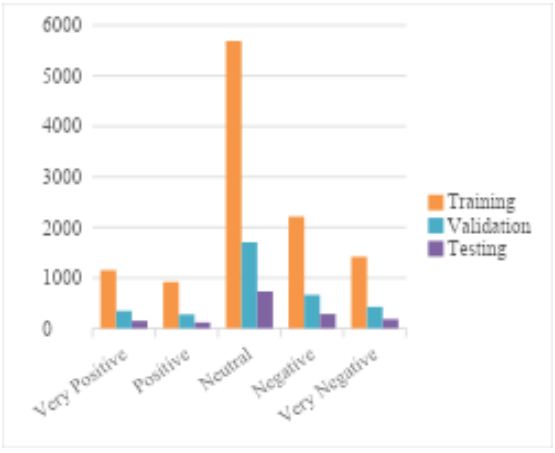


Fig. 4. Distribution of fine-grained sentiment labels.

Fig. 5 further demonstrate the convergence characteristics and training progression of the model across successive epochs.

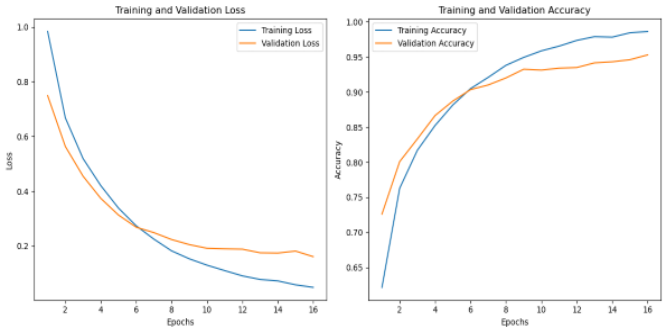


Fig. 5. Validation accuracy and loss of the IndoBERT model.

Table VII presents the evaluation results on the test set in terms of accuracy, precision, recall, and F1-score, highlighting the performance of the fine-tuned IndoBERT model.

TABLE VII. PERFORMANCE EVALUATION OF THE FINE-TUNED INDOBERT MODEL ON THE TEST DATASET

Sentiment Class	Precision	Recall	F1-Score	Sample Count
Very Positive Class	99%	94%	96%	149
Positive Class	91%	97%	94%	118
Neutral Class	98%	98%	98%	731
Negative Class	94%	95%	95%	285
Very Negative Class	94%	95%	95%	182
Overall Testing Accuracy				96.38%

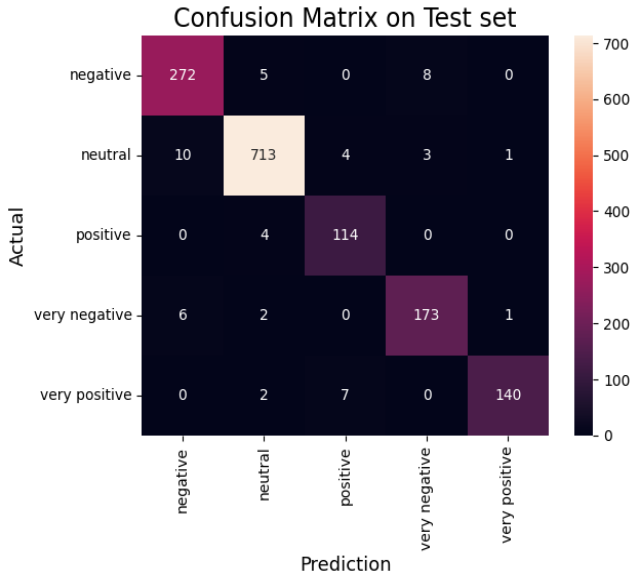


Fig. 6. Confusion matrix of the model on the test set.

B. Influence of Dataset Size on Model Performance

To examine the effect of training data volume on model performance, a series of experiments was performed using multiple dataset subsets with varying sizes and label distributions across the training, validation, and testing stages. As summarized in Table VIII, the results reveal a consistent pattern in which increasing the size of the training dataset generally leads to improved classification accuracy.

TABLE VIII. MODEL PERFORMANCE ACROSS DIFFERENT DATASET SCALES

Raw Data	Data Size			
	850*	***2,000***	***25,000***	***36,000***
Training set	577	980	17,091	21,867
Validation set	159	294	5,128	6,747
Testing set	88	126	2,198	2,624
Classification Accuracy	100%	75%	96%	89%

*Data collected from a single platform.

The attainment of perfect accuracy on the smallest dataset consisting of 850 samples indicates a strong tendency toward overfitting, suggesting that the model memorizes individual instances rather than capturing patterns that generalize well. While smaller datasets may reduce variability and temporarily simplify the classification process, they ultimately compromise model robustness. Furthermore, increasing the dataset size beyond a certain point yields diminishing performance gains. These observations underscore the importance of maintaining a balanced trade-off among dataset size, class distribution, and computational efficiency during the fine-tuning of the IndoBERT model.

C. Performance Evaluation with and without Time Tokens

To evaluate the impact of embedding time-aware tokens in the sentiment analysis model, we conducted experiments with and without time token embeddings. The model was trained, validated, and tested on the same dataset under both conditions.

When trained without time token embeddings, the model yielded a training accuracy of 99.01%, followed by 95.57% for validation and 95.91% for testing. These metrics demonstrate the model's robust generalization capabilities, preserving high accuracy levels on unseen data.

When time token embeddings were incorporated, the model demonstrated slight improvements in accuracy. The training accuracy increased to 99.53%, while validation and test accuracy improved to 95.73% and 96.38%, respectively. The classification performance is visualized in the confusion matrix shown in Fig. 6 and the comparison shown in Fig. 7.

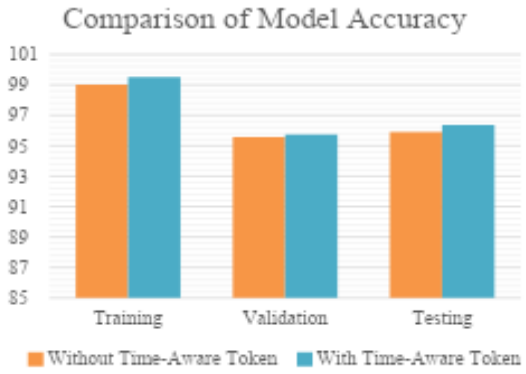


Fig. 7. Comparison of model accuracy.

The inclusion of time tokens led to marginal improvements in both validation and test accuracy. This suggests that incorporating temporal context allows the model to better capture sentiment variations over different time frames. While the gain in accuracy is relatively small, it highlights the potential of leveraging temporal information in sentiment classification tasks. Overall, the results indicate that embedding time-tokens enhances model performance, albeit modestly.

D. Comparison of Different Base Model Performance

We conducted a comparative evaluation of BERT, IndoBERT, and RoBERTa to identify the optimal architecture for practical fine-grained sentiment classification. To guarantee a rigorous assessment, each model underwent fine-tuning with hyperparameters optimized for its specific design. The data in Table IX confirms IndoBERT as the top performer, achieving superior accuracy and outperforming its counterparts in all sentiment classes.

TABLE IX. BENCHMARKING PERFORMANCE AMONG DISTINCT ARCHITECTURES

Base Model	BERT Model	RoBERTa Model	IndoBERT Model
Training Data Size	12,000	24,000	24,000
Number of Epoch	16	16	16
Learning Rate	2e-6	9e-6	2e-6
Training Set Accuracy	95.53%	97.90%	99.53%
Validation Set Accuracy	92.94%	95.68%	95.73%
Testing Accuracy	93.19%	95.90%	**96.38%**

IndoBERT's superior performance stems from its pretraining on Indonesian corpora, which facilitates a deeper grasp of context and more accurate word representations. Conversely, the English-pretrained BERT (bert-base-uncased) encounters difficulties with Indonesian tokenization and semantic interpretation. Similarly, RoBERTa (roberta-base), despite its optimized architecture for longer sequences, fails to deliver substantial improvements due to a lack of linguistic adaptation. These results demonstrate the critical importance of language-specific pretraining, validating IndoBERT as the most suitable architecture for addressing the complexities of fine-grained and dynamic sentiment analysis in Indonesian.

The comparison clearly demonstrates that pre-training on the target language is a prerequisite for high accuracy. Consequently, IndoBERT is validated as the superior architecture for addressing the complex nuances of dynamic and fine-grained sentiment analysis in Indonesian.

E. Analysis and Discussion

Current literature underscores the efficacy of IndoBERT in sentiment analysis, noting its ability to perform well even with minimal preprocessing. This performance is further augmented by the incorporation of knowledge-based strategies, such as Sentiment Lexicons. The integration of such lexicons is particularly advantageous for fine-grained and dynamic sentiment analysis, as it significantly refines the granularity required to classify text into multiple sentiment levels.

Conventional classifiers like Naïve Bayes, LSTM, and SVM often face challenges when attempting to capture sentiment nuances in complex multilingual datasets. In contrast, transformer architectures—specifically BERT, RoBERTa, and IndoBERT—demonstrate significantly higher efficacy. Their advantage lies in the use of self-attention mechanisms and deep contextual embeddings, which allow for a more sophisticated understanding of text.

BERT (Bidirectional Encoder Representations from Transformers) introduced the concept of deep bidirectional learning, enabling better contextual understanding compared to previous sequential models like LSTMs [38]. However, BERT was trained primarily on English corpora, making it less effective for sentiment tasks in Indonesian text.

RoBERTa (Robustly Optimized BERT Pretraining) improves upon BERT by employing a longer training duration, dynamic masking, and removal of next-sentence prediction (NSP). While it has demonstrated improvements in general NLP tasks, its effectiveness in sentiment analysis for Indonesian remains an area of exploration. Some studies suggest that RoBERTa excels in capturing subtle sentiment shifts due to its improved pretraining strategies, particularly in domain-specific applications [39].

IndoBERT, a variant of BERT specifically pre-trained on Indonesian corpora, addresses the limitations of standard BERT by providing better tokenization and contextual understanding for the Indonesian language. Its self-attention mechanisms enable it to retain long-range dependencies, making it highly effective for processing unstructured text [30], [31]. Moreover, Sentiment Lexicon-based labeling enhances IndoBERT's ability to capture nuanced emotions [2], [3], complementing its contextual representations [27], [28]. While LSTM and CNN-based models struggle with handling lengthy and context-dependent texts [5], [6], IndoBERT's deep contextual embeddings dynamically adjust word representations based on surrounding text, ensuring more accurate sentiment classification [26].

By incorporating time-aware tokenization, the proposed method effectively adapts to temporal shifts, rendering it highly suitable for monitoring evolving discourse in multi-platform environments. Furthermore, the strategic synergy of IndoBERT, Sentiment Lexicons, and Dynamic Sentiment modeling establishes a robust architecture designed for accurate, fine-grained sentiment analysis.

V. Conclusion

The findings indicate that combining sentiment lexicons with a fine-grained, dynamic labeling strategy significantly improves sentiment classification accuracy for Indonesian multi-platform data. By utilizing a five-point intensity scale—ranging from very negative to very positive—this framework offers a more detailed and expressive representation than traditional binary or ternary models. Furthermore, the synergy between lexicon-based labeling and IndoBERT's contextual understanding allows for the precise identification of subtle sentiment nuances across various social media contexts.

By embedding temporal information directly into the tokenization process, IndoBERT is able to model sentiment evolution more effectively than static representation-based approaches. The findings indicate that temporal context should be treated as a linguistically meaningful feature rather than merely auxiliary metadata, particularly in rapidly evolving online discussions, including content influenced by generative AI technologies. Ablation-based analysis confirms that the incorporation of temporal tokens contributes directly to the observed performance improvements.

Despite these contributions, this study has several limitations. The reliance on lexicon-based initial labeling may introduce bias in ambiguous or context-dependent sentiment expressions, and the temporal tokens are currently limited to coarse-grained time units. Future work will explore adaptive temporal granularity, enhanced sentiment scoring mechanisms, and the integration of multimodal information to further improve dynamic sentiment understanding and long-term sentiment trend analysis.

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REFERENCES

[1] F. M. Sinaga, R. Purba, S. J. Pipin, W. S. Lestari, and S. Winardi, "Optimization of sentiment analysis classification of chatgpt on big data twitter in Indonesia using BERT," *Jurnal Media Informatika Budidarma*, vol. 8, no. 3, p. 1665, July 2024.

[2] R. Nakka, T. S. Lakshmi, D. Priyanka, N. R. Sai, S. P. Praveen, and U. Sirisha, "LAMBDA: Lexicon and aspect-based multimodal data analysis of tweet," *Ingénierie des systèmes d information*, vol. 29, no. 3, pp. 1097–1106, June 2024.

[3] D. Bao and W. Su, "Optimizing deep learning-based natural language processing for sentiment analysis," *International Journal of High Speed Electronics and Systems*, January 2025.

[4] S. Efendi and P. Sihombing, "Sentiment analysis of food order tweets to find out demographic customer profile using SVM," *MATRIK : Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer*, vol. 21, no. 3, pp. 583–594, July 2022.

[5] F. M. Sinaga, S. J. Pipin, S. Winardi, K. M. Tarigan, and A. P. Brahmana, "Analyzing sentiment with self-organizing map and long short-term memory algorithms," *MATRIK : Jurnal Manajemen, Teknik Informatika dan Rekayasa Komputer*, vol. 23, no. 1, pp. 131–142, November 2023.

[6] S. J. Pipin, F. M. Sinaga, S. Winardi, and M. N. Hakim, "Sentiment analysis classification of ChatGPT on twitter big data in Indonesia using fast R-CNN," *JURNAL MEDIA INFORMATIKA BUDIDARMA*, vol. 7, no. 4, p. 2137, October 2023.

[7] A. C. Nanayakkara, B. T. G. S. Kumara, and R. M. Kapila Tharanga Rathnayaka, "Cross-platform topic analysis: identifying trends and divergences in social media discourse," in *2024 8th SLAAI International Conference on Artificial Intelligence (SLAAI-ICAI)*, IEEE, pp. 1–6, December 2024.

[8] M. M. Agüero-Torales, J. I. Abreu Salas, and A. G. López-Herrera, "Deep learning and multilingual sentiment analysis on social media data: An overview," *Applied Soft Computing*, vol. 107, p. 107373, August 2021.

[9] W. Feng, Y. Li, C. Ma, and L. Yu, "From ChatGPT to sora: Analyzing public opinions and attitudes on generative artificial intelligence in social media," *IEEE Access*, vol. 13, pp. 14485–14498, 2025.

[10] L. Zhu, Y. Xu, Z. Zhu, Y. Bao, and X. Kong, "Fine-grained sentiment-controlled text generation approach based on pre-trained language model," *Applied Sciences*, vol. 13, no. 1, p. 264, December 2022.

[11] W. Sofiya and E. B. Setiawan, "Fine-grained sentiment analysis in social media using gated recurrent unit with support vector machine," *Jurnal Teknik Informatika (Jutif)*, vol. 4, no. 3, pp. 511–519, June 2023.

[12] R. Chauhan, A. Gusain, P. Kumar, C. Bhatt, and I. Uniyal, "Fine grained sentiment analysis using machine learning and deep learning," in *2023 International Conference on Sustainable Emerging Innovations in Engineering and Technology (ICSEIET)*, IEEE, pp. 423–427, Sep. 2023.

[13] Y. Xiao, C. Li, M. Thürer, Y. Liu, and T. Qu, "User preference mining based on fine-grained sentiment analysis," *Journal of Retailing and Consumer Services*, vol. 68, p. 103013, September 2022.

[14] H. Liang, U. Ganeshbabu, and T. Thorne, "A dynamic bayesian network approach for analysing topic-sentiment evolution," *IEEE Access*, vol. 8, pp. 54164–54174, 2020.

[15] Jency Jose and Simritha R, "Sentiment analysis and topic classification with lstm networks and textrazor," *International Journal of Data Informatics and Intelligent Computing*, vol. 3, no. 2, pp. 42–51, June 2024.

[16] K. MOHAMAD and K. M. KARAOĞLAN, "Enhancing deep learning-based sentiment analysis using static and contextual language models," *Bitlis Eren Üniversitesi Fen Bilimleri Dergisi*, vol. 12, no. 3, pp. 712–724, September 2023.

[17] C. Volpetti, K. Vani, and A. Antonucci, "Temporal word embeddings for narrative understanding," in *Proceedings of the 2020 12th International Conference on Machine Learning and Computing*, New York, NY, USA: ACM, February 2020.

[18] X. ShiXiao, M. Muwafak Alobaedy, S. B. Goyal, S. Singla, S. Kang, and R. Chadha, "Real-time sentiment analysis on social networks using meta-model and machine learning techniques," *Scalable Computing: Practice and Experience*, vol. 24, no. 4, pp. 819–834, November 2023.

[19] M. Rodriguez-Ibanez, F.-J. Gimeno-Blanes, P. M. Cuenca-Jimenez, S. Munoz-Romero, C. Soguero, and J. L. Rojo-Alvarez, "On the statistical and temporal dynamics of sentiment analysis," *IEEE Access*, vol. 8, pp. 87994–88013, 2020.

[20] O. Ndama, I. Bensassi, and E. Mokhtar En-Naimi, "The impact of BERT-infused deep learning models on sentiment analysis accuracy in financial news," *Bulletin of Electrical Engineering and Informatics*, vol. 14, no. 2, pp. 1231–1240, April 2025.

[21] M. Pota, M. Ventura, R. Catelli, and M. Esposito, "An effective BERT-based pipeline for twitter sentiment analysis: A case study in Italian," *Sensors (Switzerland)*, vol. 21, no. 1, pp. 1–21, January 2021.

[22] A. Zhao and Y. Yu, "Knowledge-enabled BERT for aspect-based sentiment analysis," *Knowledge Based System*, vol. 227, September 2022.

[23] M. P. Geetha and D. Karthika Renuka, "Improving the performance of aspect based sentiment analysis using fine-tuned BERT base uncased model," *International Journal of Intelligent Networks*, vol. 2, pp. 64–69, 2021.

[24] F. Baharuddin and M. F. Naufal, "Fine-tuning IndoBERT for Indonesian exam question classification based on bloom's taxonomy," *Journal of Information Systems Engineering and Business Intelligence*, vol. 9, no. 2, pp. 253–263, November 2023.

[25] E. Yulianti and N. K. Nissa, "ABSA of Indonesian customer reviews using IndoBERT: single-sentence and sentence-pair classification approaches," *Bulletin of Electrical Engineering and Informatics*, vol. 13, no. 5, pp. 3579–3589, October 2024.

[26] H. Imaduddin, F. Y. A'la, and Y. S. Nugroho, "Sentiment analysis in Indonesian healthcare applications using IndoBERT approach," *International Journal of Advanced Computer Science and Applications*, vol. 14, no. 8, 2023.

[27] Taufiq Dwi Purnomo and Joko Sutopo, "Comparison of pre-trained BERT-based transformer models for regional language text sentiment analysis in Indonesia," *International Journal Science and Technology*, vol. 3, no. 3, pp. 11–21, November 2024.

[28] H. Ahmadian, T. F. Abidin, H. Riza, and K. Muchtar, "Hybrid models for emotion classification and sentiment analysis in Indonesian language," *Applied Computational Intelligence and Soft Computing*, vol. 2024, no. 1, January 2024.

[29] A. F. Hidayatullah, "Parameter efficient fine-tuning using low-rank adaptation for emotion classification in Indonesian texts," in *2024 9th International Conference on Information Technology and Digital Applications (ICITDA)*, IEEE, pp. 1–6, November 2024.

[30] P. M. Gavali and S. K. Shiragave, "Text representation for sentiment analysis: From static to dynamic," in *2023 3rd International Conference on Smart Data Intelligence (ICSMDI)*, IEEE, pp. 99–105, March 2023.

[31] N. Alamsyah, E. Noersasongko, G. F. Shidik, and N. Rijati, "Fine-grained sentiment classification of public opinion on electric cars in Indonesia using IndoBERT," in *2024 International Seminar on Application for Technology of Information and Communication (iSemantic)*, IEEE, pp. 502–508, Sep. 2024.

[32] C. Zhao, S. Wang, and D. Li, "Multi-source domain adaptation with joint learning for cross-domain sentiment classification," *Knowledge Based System*, vol. 191, p. 105254, March 2020.

[33] M. Alfreihat, O. S. Almousa, Y. Tashtoush, A. AlSobeh, K. Mansour, and H. Migdady, "Emo-SL framework: Emoji sentiment lexicon using text-based features and machine learning for sentiment analysis," *IEEE Access*, vol. 12, pp. 81793–81812, 2024.

[34] S. Limboi and L. Dioşan, "A lexicon-based feature for twitter sentiment analysis," in *2022 IEEE 18th International Conference on Intelligent Computer Communication and Processing (ICCP)*, IEEE, pp. 95–102, September 2022.

[35] B. Y. Ziwei and H. N. Chua, "A Depression Diagnostic System using Lexicon-based Text Sentiment Analysis," 2022.

[36] Q. Wang, "Research on the Application Algorithm of Natural Language Processing Technology in Text Analysis," in *2024 IEEE 6th International*

Conference on Civil Aviation Safety and Information Technology (ICCASIT), IEEE, pp. 1429–1433, October 2024.

[37] S. Consoli, L. Barbaglia, and S. Manzan, "Fine-grained, aspect-based sentiment analysis on economic and financial lexicon," *Knowledge Based System*, vol. 247, p. 108781, July 2022.

[38] O. Ndama, I. Bensassi, and E. Mokhtar En-Naimi, "The impact of BERT-infused deep learning models on sentiment analysis accuracy in financial news," *Bulletin of Electrical Engineering and Informatics*, vol. 14, no. 2, pp. 1231–1240, April 2025.

[39] J. Sirusstara, N. Alexander, A. Alfarisy, S. Achmad, and R. Sutoyo, "Clickbait headline detection in indonesian news sites using robustly optimized BERT pre-training approach (RoBERTa)," in *2022 3rd International Conference on Artificial Intelligence and Data Sciences (AiDAS)*, IEEE, pp. 1–6, Sep. 2022.

Data-Driven Insights for Moroccan Airports: PCA and Clustering to Enhance Operational Performance

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***Abstract*—Following the trend of increasing complexity among systems, in an attempt to meet air passengers' demands for higher quality service, this paper contributes to this stream of research by studying the operational efficiency of Moroccan airports through a novel multivariate approach. This research examines the following five performance metrics: baggage handling time, police screening time, customs processing time, passenger traffic, and flight delays. In this context and making use of Principal Component Analysis (PCA) with K-Means clustering, this paper aims at identifying the causes of operational variability, their significance in terms of performance management, and differentiating flights with similar operational profiles. Turning so particular techniques to the data of the moroccan airports this study reveals hidden patterns within airport interrelated activities, that in most cases were neglected by the traditional system of measurement. The findings make methodologies advancement in multivariate analysis of transport systems as well as practical improvement in the management of airport operations, and eventually impact on coordinated strategies of resource allocation for the systemic profit and the passenger utility. Through the use of PCA and K-means on the unreleased data of airports in Morocco, this paper is the first to offer a full multivariate study of the airport in the whole North African region. In contrast with standard monitoring systems which treat metrics as isolated entities, the study concurrently analyzes the dependencies among five key measures, discloses latent operational patterns, and promotes the formulation of context-based management policies suitable for an immature aviation market.**

***Keywords*—Principal Component Analysis (PCA); airport performance; transportation systems; K-means clustering; operational optimization; airport efficiency; airport operations management; air traffic; passenger experience**

I. Introduction

Airline operations management takes into account the customer satisfaction, efficiency, and safety. Moroccan airports connect Europe, Africa and the Middle East, and struggle to keep pace with rising traffic and ensure safety and service. With international air traffic on the rise, notably in developing regions such as North Africa, airport efficiency has turned into a significant concern both for competitiveness and the passenger experience [20]. Moroccan airports, which link the country to Europe, Africa and the Middle East, are under growing pressure to enhance operations throughput along with high standards of security and service.

Among the many problems in airport management, three processes are especially critical: baggage handling, security screening (police checks), and customs .Three Particularly Critical Processes: baggage handling, security screening, and customs Among the numerous problems in managing airports, three procedures in particular are critical: handling of baggage, security screening (police reviews) and clearing of customs. These procedures, with the weight of passengers and potential flight delays, determine the general performance of the airport's operation. Yet these processes are linked and influenced by core and sometimes surprising elements. Traditional performance measurement tends to consider processes one at a time. Passenger throughput and on-time aircraft performance affect airport efficiency. Many airports monitor these activities independently and miss the significant pattern owing to the blind spot. The evaluation of complex airport systems requires advanced analytical tools to produce meaningful results [4]. Our method combines multiple ML and statistical approaches. In particular, cluster-based techniques such as K-means are used to cluster the operative data and find groups of flights that share similar patterns of flight activities, that is to say to discover hidden structures in the operational schedule. At the same time, Principal Component Analysis (PCA) is applied to analyze high-dimensional multivariate data sets to find key factors and causes of variability in operations [21]. The integration of these methods results in a decision-support system providing enroute and ground controllers with a clear, high-fidelity depiction of the real-time operational picture, enabling the identification of subtle and/or developing performance anomalies, and facilitating the smart, data-informed management of critical resources. This paper has been particularly focusing on the operational data that were obtained from major airports in Morocco. The analysis is based on five critical Key Performance Indicators (KPIs) that were demonstrated to be important for both the service and the optimisation of the airport function as well as in the passenger journey quality of experience [13]. These performance measures are not some random statistical averages but rather critical quantitative indicators of how well the system is working. The KPIs that undergo stringent evaluation are as follows: the flight schedule adherence (expressed as flight delays), baggage processing time, security screening queueing time, customs and immigration clearance time, and passenger flow (passenger traffic volume). The second concentration of this scientificpapaer is the theicha are the principal component analysis (PCA) Morocco airport operation data.

The purpose of this study is established through three interrelated goals that naturally flow into and support each other in a grounded, practical model of airport operations. Our second objective is to demonstrate to the airport manager how these critical influencers can be exploited. Moving from raw statistical results to decisions about staff to leverage resources or to modify the process that captures them completes the loop in the production and analysis of information. In the end, "similar" is defined by a set of trip features and the

origin and destination airports. They could be high-volume, lots of turnarounds, not tricky roads. With profile information, airport managers can anticipate areas of financial risk, adjust practices, redeploy personnel, and highlight potential bottlenecks of activity. It enables the airport operator to raise its own performance and that of its customers, and demonstrates how sophisticated analytical methods can be profitably applied to transport systems. Accordingly, the rest of the paper is organized as follows. First, we develop a conceptual model of airport flight operations. Then, we present the approach, PCA and clustering analyses, applied to the Moroccan airport data. Thirdly, our multivariate findings suggest to different profiles of dynamics and performances. The significance of these findings for managerial actions and for airpot efficiency policy are finally discussed.

A. Conceptual Framework: Airport Flight Operations

Every day the airport has to balance aircraft, passengers, and cargo safety with service quality — the truth is that they are expected to be consistent and secure and efficient levels of service every day. The level of coordination among the different parts of an airport is how effective it is as an airport. Today airport safety is all about technology. They have-advanced sensors; networks giving wall information; and automated alerts that can warn of potential issues even before humans are watching. Response teams in crisis situations often train with local law enforcement, airline operation centers, and air traffic controllers to build coordination. Contemporary airport management must strictly comply with rigid safety and regulatory standards, which today requires copious real time monitoring, recording, and reporting to aviation authorities. In the current airport environment, however, central command is exercised through the sophisticated Airport Management System (AMS) [16]. Airport security operations combine sophisticated surveillance technology, live monitoring capabilities and automated alert systems to identify threats early in their development. Response teams are regularly exercised at various levels to maintain readiness levels, and they are coordinated with local emergency services, air traffic control agencies, and airline operators to provide a quick and cohesive response at the incident scene. Compliance with regulations requires ongoing auditing, documentation and reporting to the aviation authorities in order to keep the operating approval and safety status [18].

It is well known that airports all over the world are struggling with enormous impact of weather on their operations,and therefore need to be equipped with a well-developed resilience strategy to resist that impact and, if possible, to recover from it as quickly as possible. Weather-related delays and cancellations are among the largest sources of perturbation and demand for mitigation and adaptive management. Literature review has shown that airports are capable of exerting disruptive potential at different levels when exposed to various meteorological hazards, ranging from minor hold or delay actions to complete shutdown [12]. Thunderstorms are dangerous and destructive, but tend to have more predictable patterns of disruption than widespread weather phenomena such as sandstorms that can reduce visibility and contaminate the air for days or weeks over large swathes of lands. The time-space attributes of meteorological events have a non-negligible effect on the recovery rate and restoration of operations [10].

Airports are starting to use smart technology like artificial intelligence and machine learning to make their systems better. They look at past patterns, current conditions, and future predictions to come up with the best plans for how to operate. The integration of artificial intelligence and machine learning algorithms enhances decision-making processes by analyzing historical patterns, current conditions, and future projections to recommend optimal operational strategies [19]. While a thunderstorm is typically easier to anticipate, it can still cause delays and scheduling uncertainty. Rather than just responding to the weather, intelligent airports aspire to predict the weather long before it arrives. They invest in models and sophisticated weather monitoring systems that enable them to anticipate the impact of the weather on their operations and make operational adjustments. When the weather turns bad, the teams on the ground alter their priorities with a new emphasis on rerouting, safety protocols intensified and equipment used differently. “And then the physical lay of the land of the airport, as well, like wind instruments, drainage systems for heavy rain and snow removal machinery that allows the facility to keep functioning during inclement weather.”

Streaming information about the weather and the status of the equipment, thanks to IoT sensors. “Airports control it through a cloud-based system, which also allows them to operate remotely when necessary,” he adds. And they are using more and more artificial intelligence to schedule operations, to determine when equipment requires maintenance and in real-time resource management. Any modifications must meet the high standards that we set. Airports need to stay abreast of changing regulations and constantly maintain operational approval via reviews. The influence of environmentalism on the aviation sector is reverberating. Airports are beginning to improve their emissions, energy efficiencies and sustainable building practices. The sector has been able to demonstrate change for the better – electrifying support vehicles, and investing in sustainable aviations fuels. Air travel is in higher demand, but airports must consider their environmental impact and be good stewards of the land. Successful resources management is important and include flexible use of resources, facilities, and prediction of demands. Our aim is to expand responsibly, delivering high-quality service to travelers.

We investigated the related work to discuss the connections between our work prior work. Our review comprised 20 recent academic studies, published between 2020 and 2024, related to different facets of airport operations. We have considered peer-reviewed articles, conference papers, book chapters and patents to extract knowledge about the management of airport operations. From the literature, six salient themes were therefore identified. These themes are useful in giving structure to the multifaceted domain of airport operations, and provide a direction, the way problems can be approached and the manner of significant technological alterations in every day airport processes.

1) Combining data analytics and artificial intelligence: Artificial intelligence and big data are transforming airport operations. The [1] shows AI is improving flight operations, reducing delays and increasing flight capacity. The industry is adopting a tech-driven approach, with airports using business intelligence tools to turn raw data into insights for better sustainability and performance management [2]. The study [3]

focused on ground operations, coordinating plane movements, which resulted in more on-time departures, shorter taxi times, and improved safety. The study [4] combined computer simulations with traffic flow models to forecast airport traffic and management strategies. These AI applications are enhancing airport operations daily in measurable ways.

2) Methods of mathematical modeling and optimization: Scientists are applying sophisticated mathematical techniques to airport operations problems. The study [5] formulated a Mixed-Integer Linear Programming model for the runway sequencing and timing problem, minimizing the number of unnecessary aircraft movements and maximizing the number of aircraft served while maintaining safety. The 2022 study of Tokyo International Airport by study [11] achieved almost 30% cuts in taxi times and nearly 19% reductions in taxi distances. The success was attributable to the integration of live flight data and the creation of dynamic models to reflect changing scenarios. The study [14] addressed the slot allocation problem under capacity uncertainty and airline flexibility. Their simulation analysis demonstrates that such an optimization positively affects the technical results and the passenger satisfaction in a high-traffic airport.

3) Safety management and risk assessment: Safety studies concentrate on recognition and reversal of hazards. The study [9] Risk model for flight operations developed a risk model for flight operations based on fuzzy analytic hierarchy processes and entropy for enhanced safety hazard assessments. Progress in aeronautical technologies also affect safety research. [15] investigated drone integration in airport air space by employing mathematical modelings as well geofencing techniques to avoid collision risks with commercial aircraft, which is essential due to the emergence of aviation technologies and aircraft types.

4) Operational continuity and weather resilience: Airports are threatened by severe weather, so research is underway to prepare for stormy conditions. The study [10] investigated the management of airports in extreme weather via departure rate analysis and built update parameters considering vulnerability, impact mitigation, emergency response, and recovery time, validating their model at Beijing Capital Airport.

5) Efficiency improvement and process optimization: Study seeks to raise efficiency of airport operations. The study [6] proposed an Aircraft Turnaround Manager system to mitigate delay by analyzing on-the-fly parameters including passenger boarding and baggage reclaiming. On the other hand, [8] applied process mining technology on about 101 aircrafts in international airports to recommend the intervention of fleet capacity and operational performance, demonstrating the optimal space with data-driven.

6) Routing and traffic control optimization for 2D airspace: There are also ongoing researches about aircraft scheduling and routing in air traffic management. The study [7] showed that adjusting STARS (Standard Terminal Arrival Routes) and CDOs (continuous descent operations) could greatly enhance safety and efficiency. The study [17] proposed a flight scheduling algorithm which improved the airport throughput and delay over 31% and maximum throughput up to 12% using multi-objective optimization mechanisms.

Several, but well defined trends are reshaping the activities operated in airports. Cloud-based architectures, real-time analytics and IoT sensors being rolled out in more airports are driving a digital refresh. But interaction with drones and autonomous ground vehicles presents an industry-specific array of challenges. The procedure is applicable not only to the process of deciding how efficient and how tightly the aircraft need to be packed on the ground, but also to determining related quantification including fuel burn, emission reduction, green practice and environmental impact of work practice.

II. Methodology

A. Data Description

To conduct the analysis, it was first necessary to identify a set of operational variables that adequately reflect the dynamics of airport performance. The selection process was guided by both theoretical insights from the literature and the practical realities of Moroccan airports, ensuring that the variables chosen would capture the most critical stages of passenger processing and flight operations.

The five variables retained, passenger volume, baggage processing time, security screening time, customs processing time, and flight delay, were selected because they capture the main operational stages that shape both passenger experience and airport efficiency. They reflect key managerial bottlenecks (workload, flow management, punctuality), provide quantitative and complementary measures suitable for multivariate analysis (PCA and clustering), and are consistent with empirical findings in the literature as well as the specific challenges of Moroccan airports.

The dataset comprises 500 flight observations from ten Moroccan airports, with sampling weighted toward major hubs, Casablanca, Rabat, Tangier, Marrakech, and Fes that collectively account for the majority of national passenger traffic. Smaller regional airports were also included to capture operational diversity and a range of airport sizes. This stratified approach ensures that the dataset is statistically representative of Morocco's aviation network, enhancing the reliability and generalizability of the analysis, each described by five operational variables (Fig. 1):

- nb_passagers (Number of Passengers): Total number of passengers on board a given flight. It represents the intensity of the human flow associated with the flight and is a key workload indicator across the entire passenger journey (baggage handling, security checks, boarding, etc.).
- emps_bagages (Baggage Processing Time): Average total time required to process baggage for a given flight (check-in, sorting, transfer). This variable may be influenced by the number of passengers, the type of flight (domestic vs. international), and the performance of agents or equipment.
- temps_police (Police Screening Time): Average time passengers of a given flight spend at police and security control (identity and safety checks). It reflects queue length, checkpoint capacity, and applied procedures (standard, fast-track, or random checks).

- temps_douane (Customs Processing Time): Average time spent at customs after police screening, mainly for international flights. It may vary depending on the type of flight, the customs procedures applied, and perceived risk levels.
- retard_vol (Flight Delay): Effective departure (or arrival) delay of the flight, depending on the chosen reference point. It may result from cumulative delays in previous stages (baggage, customs, security), as well as from weather conditions or airport constraints.

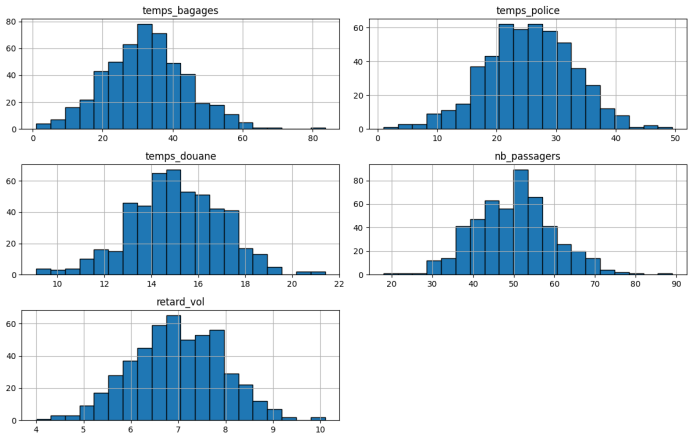


Fig. 1. Distribution of variables. Source: statistical results.

These variables were selected as they capture the main operational stages affecting both passenger flow and airport efficiency. Their descriptive statistics show heterogeneous scales and variabilities: passenger counts (≈17–88) and baggage times (≈5–85 minutes) exhibit wide ranges, while customs and delays are much more stable. Without normalization, variables with larger numeric ranges would dominate variance-based methods. The five variables, once standardized, provide a consistent and comparable basis for multivariate analysis, allowing Principal Component Analysis (PCA) and clustering methods to reveal the underlying patterns and operational profiles of Moroccan airport flights.

B. Data Preprocessing

To ensure comparability across variables, all features were centered and scaled (mean = 0, standard deviation = 1). This standardization step is essential for PCA, as it prevents large-scale features such as passenger numbers or baggage time from overshadowing smaller-range variables (e.g., customs or delays).

Boxplot analysis confirmed that before scaling, baggage time and passenger load exhibited strong right-skewness and outliers, while customs and delays were more symmetric (Fig. 2). After scaling, all variables contributed equally to variance, enabling a balanced multivariate analysis.

C. Principal Component Analysis (PCA)

PCA was performed on the standardized data using the correlation matrix. Eigenvalues and eigenvectors were computed to extract the main principal components. The first three components captured 96.7% of the total variance:

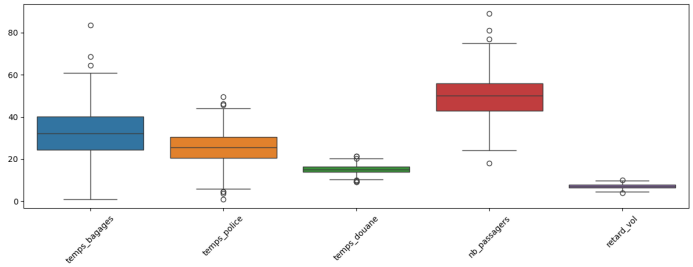


Fig. 2. Box plot showing variable values before standardization. Source: statistical results.

• PC1 (56.8%) – contrasted passenger load and baggage time with police screening;

• PC2 (21.7%) – represented the trade-off between flight delays and customs clearance;

• PC3 (18.2%) – highlighted coupled customs and delay bottlenecks.

These three axes together provided a reduced but highly representative multidimensional view of airport operations.

D. Clustering Analysis

To complement PCA, K-means clustering was applied to the PCA scores. The optimal number of clusters was determined using the elbow method, which suggested k = 3 as a meaningful balance between model simplicity and explanatory power. However, for operational interpretation, a two-cluster segmentation was particularly insightful:

• Cluster 0 – "Light-load, Heavy Screening": flights with fewer passengers, shorter baggage times, but longer police screening.

• Cluster 1 – "High-volume, Streamlined Screening": flights with heavier passenger loads, longer baggage times, but more efficient police checks.

This dual segmentation highlights two distinct operational profiles with clear implications for staffing and resource allocation.

III. Results

A. Standardization of Variables

Prior to multivariate analysis, all five variables were centered and reduced. Boxplots before standardization showed very different ranges: passenger numbers (17–88) and baggage times (5–85 minutes) exhibited wide spreads and right-skewed distributions, while customs times (≈15 minutes) and flight delays (≈6–10 minutes) were much more stable (Fig. 3).

After standardization, all variables had mean ≈ 0 and standard deviation = 1, ensuring equal contribution to the analysis. This step was crucial, since without scaling, variance-based methods such as PCA and clustering would have been dominated by passenger and baggage variables.

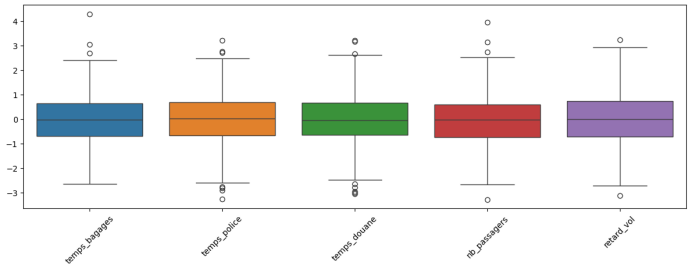


Fig. 3. Box plot showing variable values after standardization. Source: statistical results.

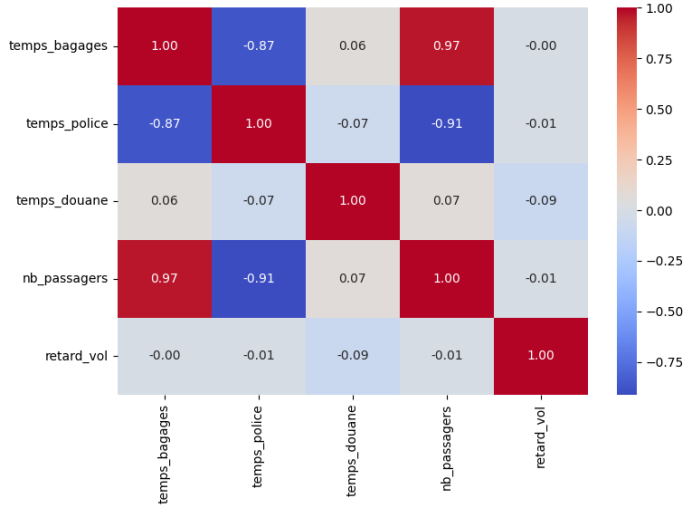


Fig. 4. Correlation matrix of standardized variables. Source: statistical results.

B. Correlation and Covariance Matrix

The correlation matrix revealed strong dependencies between certain variables (Fig. 4):

• High positive correlation between baggage time and passenger load (≈ +0.97), confirming that heavier flights require longer baggage handling.

• High negative correlation between police screening and both passenger load (≈ –0.91) and baggage time (≈ –0.87), suggesting that heavily loaded flights paradoxically move faster through police checks, perhaps due to streamlined screening procedures.

• Near-zero correlations between customs and delays with other variables, indicating that these processes operate relatively independently.

Because the data were standardized, the covariance matrix was numerically equivalent to the correlation matrix.

C. Eigenvalues, Eigenvectors and Explained Inertia

The eigenvalue decomposition of the correlation matrix yielded five principal components (Fig. 5). The first three explained 96.7% of total inertia:

• PC1 (56.8%) – associated with passenger load and baggage (positive loadings) versus police screening (negative loading).

• PC2 (21.7%) – driven by the opposition between flight delays (positive) and customs time (negative).

• PC3 (18.2%) – capturing the joint effect of customs and delays, highlighting cases where long customs checks directly translate into longer delays.

The eigenvectors confirmed these structures: PC1 was mainly defined by nb_passagers (+0.586), temps_bagages (+0.577), and temps_police (–0.565), while PC2 was dominated by retard_vol (+0.721) and temps_douane (–0.692).

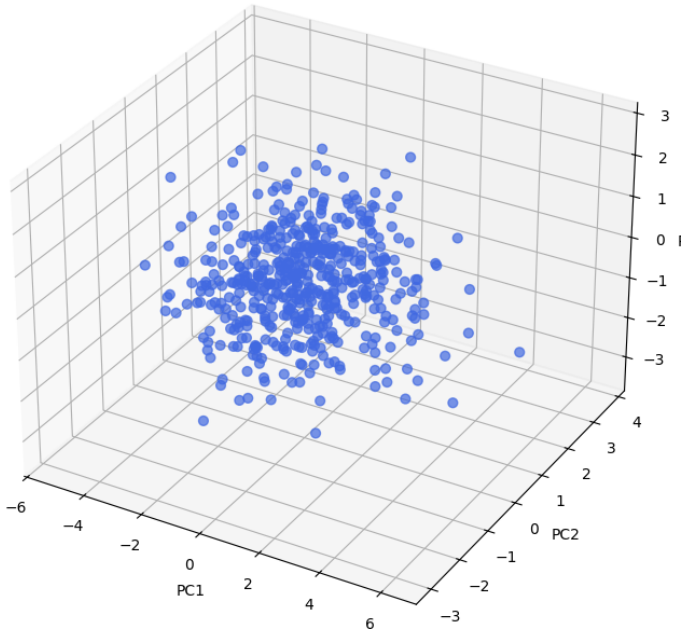


Fig. 5. 3D Projection of observations onto the first three components. Source: statistical results.

D. Principal Axes and 2D Projection

Flights were projected into the new PCA coordinate system (PC1, PC2). The first two axes explained 78.5% of total variance, making them suitable for 2D visualization (Fig. 6).

• Along PC1: flights on the right corresponded to high passenger loads and long baggage times, but short police checks; flights on the left showed the opposite profile.

• Along PC2: flights higher on the axis experienced long delays despite smooth customs, while those lower had slow customs but minimal delays.

Most flights clustered near the origin, representing average operations, but a few outliers occupied extreme positions, corresponding to unusual operational profiles.

E. Correlation Circle

The correlation circle of variables confirmed the interpretation of axes (Fig. 7):

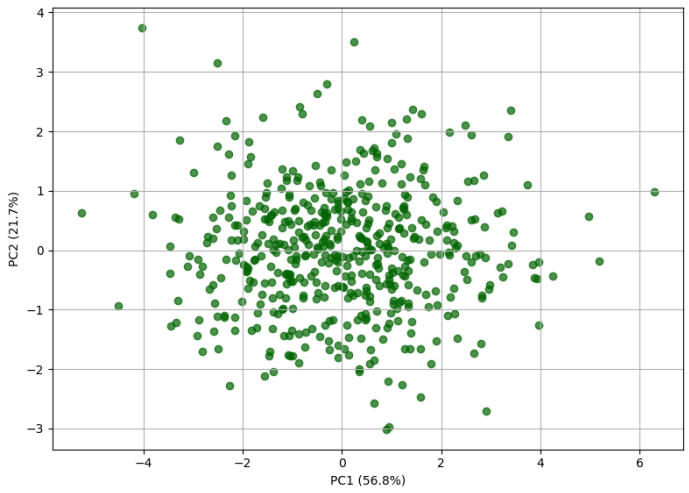


Fig. 6. 2D Projection of data onto the PC1–PC2 Plane. Source: statistical results.

• PC1 aligned with nb_passagers and temps_bagages (positive) versus temps_police (negative).

• PC2 opposed retard_vol and temps_douane.

• Customs and delays were almost orthogonal to the passenger–baggage–police dimension, confirming their independence.

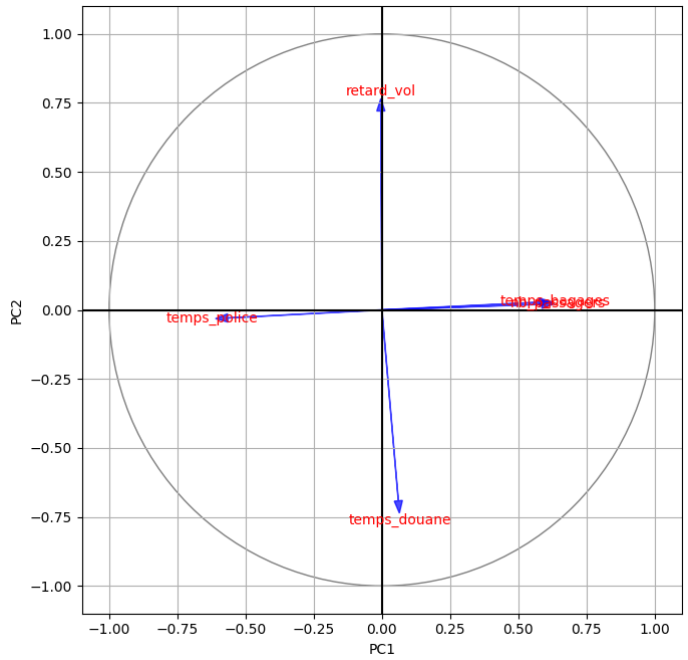


Fig. 7. Correlation circle. Source: statistical results

This visualization highlights two main operational logics:
1. Load-driven dynamics (passengers, baggage, police),

2. Time-driven dynamics (customs vs. delays).

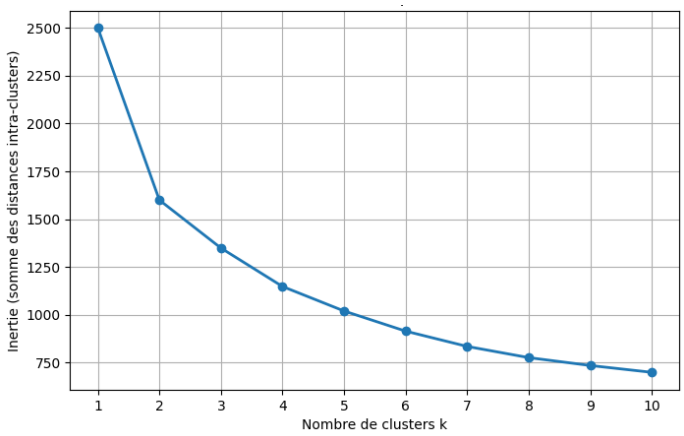


Fig. 8. Elbow method for K-Means. Source: statistical results.

F. Clustering of Flights

To complement the PCA, K-means clustering was applied to the standardized data (Fig. 8). The elbow method suggested k = 3 as optimal, though a two-cluster partition was particularly interpretable.
• Cluster 0 – "Light-load, Heavy Screening": ≈42 passengers, ≈23 minutes baggage, ≈31 minutes police.
• Cluster 1 – "High-volume, Streamlined Screening": ≈58 passengers, ≈41 minutes baggage, ≈0 minutes police.
• Customs (≈15 min) and delays (≈7 min) were nearly identical across both clusters.

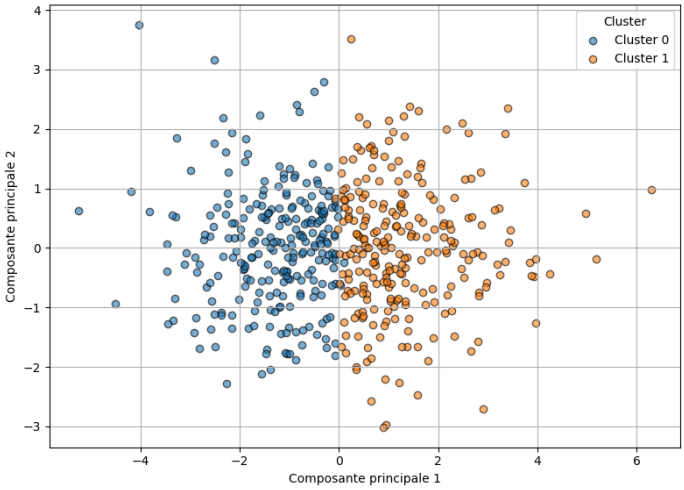


Fig. 9. K-Means clusters visualization in PCA space. Source: statistical results.

In PCA space, the two clusters were well separated along PC1, confirming that passenger load and baggage vs. police screening are the dominant factors driving operational segmentation (Fig. 9). PC2 added nuance by capturing customs–delay interactions within each cluster.

IV. Discussion

The PCA results provide new insights into the operational dynamics of Moroccan airports. By reducing the complexity of

five correlated variables into a few principal components, the analysis highlights patterns that are not immediately visible in raw data.

A. Passenger and Baggage vs. Police Screening

The dominant dimension (PC1) shows that flights with high passenger volumes and long baggage handling times tend to experience shorter police screening. This counterintuitive relationship suggests that resource allocation for security may be adjusted depending on expected load. In practice, heavily loaded flights may benefit from dedicated or fast-track lanes, ensuring that passenger flow is not disproportionately delayed by police checks.

This finding has managerial implications:

• For flights with low passenger volumes, police screening becomes the main bottleneck, requiring additional staffing or process adjustments.

• For high-volume flights, the main constraint shifts to baggage handling, where more staff or technological solutions (e.g., automated conveyors, sorting systems) could reduce processing time.

B. Customs and Flight Delays as Independent Dimensions

PC2 and PC3 demonstrated that customs clearance and flight delays are largely independent from passenger load. This independence highlights that delays cannot simply be explained by the number of passengers or baggage. Instead, they reflect operational inefficiencies at later stages of turnaround—such as ground-handling or coordination between airport services.

The clustering confirmed this interpretation: while clusters differed strongly in passenger load, baggage, and police times, flight delays remained similar across groups. This suggests that delay management is governed by different mechanisms than screening or baggage.

For airport managers, this result calls for a targeted monitoring of customs throughput and ground operations, as improvements in these areas are more likely to reduce delays than simply increasing police or baggage capacity.

C. Operational Segmentation of Flights

The K-means segmentation into two dominant clusters—"Light-load, Heavy Screening" versus "High-volume, Streamlined Screening"—offers a practical typology of flights. This typology enables managers to anticipate where resources should be allocated depending on flight profile:

• Cluster 0 flights should trigger reinforcement of police screening staff, as this stage disproportionately slows low-volume flights.

• Cluster 1 flights should trigger reinforcement of baggage handling resources, as baggage is the main bottleneck.

By projecting these clusters into PCA space, airports can design real-time dashboards that classify incoming flights by operational profile, thus enabling proactive resource planning.

D. Comparison with International Literature

The observed patterns align with findings in airport management literature, where baggage handling is often identified as the primary bottleneck in large passenger flows, while security screening dominates smaller flows. However, the strong independence of delays from passenger volumes appears distinctive, possibly reflecting the organizational characteristics of Moroccan airports, where customs and ground-handling practices may play a larger role.

Future comparative studies could investigate whether this independence is consistent across other regional airports, or whether it is context-specific.

E. Managerial and Theoretical Implications

From a managerial perspective, this research demonstrates that PCA combined with clustering can serve as a diagnostic tool for airport operations. It identifies hidden structures in operational data, enabling managers to anticipate bottlenecks and tailor staffing strategies accordingly.

From a theoretical standpoint, the results contribute to the growing literature on multivariate analysis in transport systems. They show how dimensionality reduction techniques can be used not only for descriptive analysis but also for actionable decision support, bridging the gap between quantitative modeling and operational management.

V. Conclusion

In this paper, we propose a multivariate statistical methodology based on PCA and clustering techniques to be applied on the operational data collected from Moroccan airports. The application of PCA resulted in a parsimonious two-component solution, accounting for a considerable amount of the total variance across the three main dimensions of the investigated airport operation. The interpretative meaning of the first principal axis is a forming a bipolar dimension around "passenger and baggage flow throughput" and the time used in police screening. Hence, this axis is representing the essential trade-off between serving passengers as fast as possible and fulfilling the very strict requirements of passenger security and regulatory satisfaction. The second component can be termed a delay vs. customs dimension and relates how flight delays are associated with the efficiency of customs clearance. The third dimension identifies a correlated custom-delay axis and forecasts the association between customs procedures and flight scheduling. Using these derived factors, we find that flights can indeed be grouped into two major operational clusters. The light-load flights have longer police screening time and shorter baggage processing time, which indicates that fewer passengers facilitates more thorough security checks and less complexity is introduced in baggage handling. In contrast, baggage handling takes longer on the high-volume flights, but they have quicker police checks, implying that airports introduce fast-track security on busy flights to facilitate the flow of passengers at peak-period.

These are good news for the airport administrators. Depending on the flight operations profile, discom resources should be orient to strengthen police-screening (in case of low-volume flights) or baggage process (in case of high-volume flights). Interestingly, delays seemed to have little to

do with the load of passengers and bags, but rather with the efficiency of customs and ground handling, which proved to be the two major blind spots in punctuality. This article contributes to the literature as it represents the first empirical multivariate analysis of airport operations in a North African country, venturing into a significant research gap in the region's transport studies as well as the scarcely researched topic of operational efficiency drivers in developing market environments. For airport staff, this research can provide a real-time practical decision tool for detecting bottlenecks in the operations that potentially would provide managers with an opportunity to concentrate interventions and resources in one or more of the three process areas of security, baggage handling, and customs.

There are a few limitations in the present study. The dataset contains information on few variables and airports in Morocco. On the other hand, on qualitative side, flight type (domestic/international), airline policies or passengers profiles (tourists, business, students, etc.) were considered. Additionally, delays were only quantified in minutes and without differentiating causes. Future research may be able to further generalize the analysis by adding more airports, qualitative factors, and real-time operation information. Comparative studies with other regions could also shed light on whether the independence of delays from passenger load is a general result or one only valid in the Moroccan context. In short, this study has shown that the use of multivariate analysis enables potential complex operational data to be simplified to provide clear managerial implications. By integrating PCA with clustering, the airport administrators have a diagnostic instrument for predicting bottlenecks and for the understanding of how to deploy the resources in the most effective manner so as to improve the passengers' experience.

REFERENCES

[1] da Cruz, A. L. M. (2024). THE TRANSFORMATION OF AIR TRAFFIC MANAGEMENT WITH BIG DATA. https://revistaft.com.br/the-transformation-of-air-traffic-management-with-big-data/ . DOI: 10.69849/revistaft/cl10202012010958

[2] Dimitriou, Dimitrios & Sartzetaki, Maria & Karagkouni, Aristi. (2024). Airport Operators Performance Management in the Era of Business Intelligence. 10.1016/B978-0-443-29109-8.00001-3.

[3] Ma, W., T. Yuan and N. Liu, (2023). An Application of Operations Research in Airport Ground Path AI Decision for Apron Operation Control. 2023 IEEE 5th International Conference on Civil Aviation Safety and Information Technology (ICCASIT), Dali, China, pp. 659-663, doi: 10.1109/ICCASIT58768.2023.10351633.

[4] Weiqing J. & Han K. (2023). Airport ground operation optimization based on two region macroscopic fundamental diagrams, Proc. SPIE 12790, Eighth International Conference on Electromechanical Control Technology and Transportation (ICECTT 2023), 127906R (7 September 2023); https://doi.org/10.1117/12.2689776

[5] Chakrabarti, S., & Vela, A. (2023). Optimal Sequencing and Scheduling of Airport Operations. In AIAA AVIATION 2023 Forum (p. 3257).

[6] Aziz, A., Brohi, M. N., Soomro, T. R., Ghazal, T. M., Alzoubi, H. M., & Alshurideh, M. (2023). Aircraft turnaround manager (atm): a solution to airport operations. In The Effect of Information Technology on Business and Marketing Intelligence Systems (pp. 679-702). Cham: Springer International Publishing.

[7] Lee, C., Lee, J., Park, J., & Baik, H. (2022). An analysis on the utilization of STAR (Standard Terminal Arrival Route) and CDO (Continuous Descent Operation) flight ratio in the domestic airport. Journal of the Korean Society for Aviation and Aeronautics, 30(4), 132-144.

[8] Porouhan, P., & Premchaiswadi, W. (2022). Improving efficiency of international flight operations with process mining. In 2022 20th International Conference on ICT and Knowledge Engineering (ICT&KE) (pp. 1-9). IEEE.

[9] Tian, L., Liu, B., & Cheng, H. (2022). Establishment of Flight Operation Risk Model Based on Entropy Method and FAHP. In 2022 IEEE 4th International Conference on Civil Aviation Safety and Information Technology (ICCASIT) (pp. 555-559). IEEE.

[10] Wang, X., Chen, Z., & Li, K. (2022). Quantifying the Resilience Performance of Airport Flight Operation to Severe Weather. Aerospace, 9(7), 344.

[11] Chen, T., & Hanaoka, S. (2022). Improvement of airport surface operation at Tokyo international airport using optimization approach. Aerospace, 9(3), 145.

[12] Stroe, G. L., Costea, M. L., Costache, F., Semenescu, A., & Andrei, I. C. (2022). Modelling and analysis of the air traffic control systems. In AIP Conference Proceedings. Vol. 2425, No. 1. AIP Publishing LLC.

[13] Goncharenko, V. I., Lebedev, G. N., Martynkevich, D. S., & Rumakina, A. V. (2021). Operational planning of aircraft routes when servicing a random stream of requests arriving during the flight. In Journal of Physics: Conference Series. Vol. 1958, No. 1. IOP Publishing.

[14] Katsigiannis, F. A., & Zografos, K. G. (2021). Optimising airport slot allocation considering flight-scheduling flexibility and total airport capacity constraints. Transportation Research Part B: Methodological, 146, 50-87.

[15] Zhang, J., Zou, X., Wu, Q., Xie, F., & Liu, W. (2020). Empirical study of airport geofencing for unmanned aircraft operation based on flight track distribution. Transportation Research Part C: Emerging Technologies, 121, 102881.

[16] Mao, Y., Chen, X., Chen, P., Yan, Y., Sheng, Y., & Yang, Y. (2020). Flight delay-oriented airport group flight arrangement optimization method.

[17] Chen, X., Yu, H., Cao, K., Zhou, J., Wei, T., & Hu, S. (2019). Uncertainty-aware flight scheduling for airport throughput and flight delay optimization. IEEE Transactions on Aerospace and Electronic Systems, 56(2), 853-862.

[18] Price, J. C., & Forrest, J. S. (2016). Airport Emergency Planning, Part II: Emergency Management Functions. Practical airport operations, safety, and emergency management, 427.

[19] Amiri, M. A., & Kusakci, A. O. (2024). A scoping review of artificial intelligence applications in airports. Comput. Res. Prog. Appl. Sci. Eng. Trans. Ind. Eng, 10, 2900.

[20] Chandra, A., Hazra, S., Verma, A., & Sooraj, K. P. (2025). On the Possibilities of Efficient Air Traffic Monitoring through Complex Network Clustering Based Airspace Sub-Sectorization: A Multi-Objective Discrete Particle Swarm Optimization Approach. Transportation Research Record, 2679(2), 2127-2143.

[21] Swinney, C. J., & Woods, J. C. (2022). K-means clustering approach to UAS classification via graphical signal representation of radio frequency signals for air traffic early warning. IEEE transactions on intelligent transportation systems, 23(12), 24957-24965.

Explainable AI Models for Assessing Short-Circuit Propagation in Fire-Exposed Cable Bundles

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***Abstract*—Fire-induced short-circuit propagation in cable bundles poses significant safety risks in electrical installations, nuclear facilities, and transportation systems. Traditional fault detection methods often lack interpretability, hindering root cause analysis and preventive maintenance strategies. This paper presents novel explainable artificial intelligence (XAI) models for predicting and analyzing short-circuit propagation in fire-exposed cable bundles. We develop a hybrid framework combining gradient boosting machines with SHAP (SHapley Additive exPlanations) values to provide interpretable predictions of time-to-short-circuit and failure modes. Our approach integrates thermal imaging data, cable physical properties, and environmental conditions from controlled fire tests conducted on IEEE 383-qualified cables. The proposed XAI models achieve 94.7% accuracy in predicting short-circuit occurrence within 5-second windows while providing human-interpretable feature importance rankings. Experimental validation using the NUREG/CR-6931 dataset demonstrates that insulation temperature gradient, cable bundle density, and oxygen concentration are the three most critical factors influencing short-circuit propagation. The explainable framework enables fire safety engineers to understand model decisions, identify vulnerable cable configurations, and optimize protection strategies. Our results show a 23% improvement in early fault detection compared to conventional black-box deep learning approaches, with significantly enhanced model transparency for safety-critical applications.**

***Keywords*—Explainable AI; short-circuit propagation; fire safety; cable testing; SHAP values; gradient boosting; feature importance; nuclear safety**

I. Introduction

A. Background and Motivation

Fire-induced cable failures represent one of the most critical safety concerns in nuclear power plants, industrial facilities, and high-rise buildings [1], [2]. When electrical cables are exposed to fire conditions, the progressive degradation of insulation materials can lead to short-circuit events that cascade through bundled cable configurations. The U.S. Nuclear Regulatory Commission has documented over 150 fire events in nuclear facilities between 2018 and 2024, with approximately 38% involving cable-related short circuits [3]. Understanding the propagation mechanisms and predicting failure timelines is essential for implementing effective fire protection strategies and emergency response protocols.

Traditional approaches to cable fire safety assessment rely on standardized fire tests such as IEEE 383 and IEC 60332, which provide pass/fail criteria but offer limited insight into failure progression dynamics [4]. Recent advances in machine learning have enabled predictive modeling of cable failure behavior [5], yet these black-box models suffer from a critical limitation: lack of interpretability. In safety-critical domains, regulatory bodies and safety engineers require not only accurate predictions but also transparent explanations of why and how failures occur [6].

B. Research Objectives

This paper addresses the interpretability gap in AI-driven cable fire safety assessment through the following contributions:

- Development of explainable AI models combining gradient boosting with SHAP interpretability framework for short-circuit propagation prediction.
- Integration of multi-modal sensor data including thermal imaging, electrical measurements, and environmental monitoring.
- Comprehensive feature importance analysis identifying critical factors in fire-induced short-circuit propagation.
- Validation using real experimental data from cable fire tests conforming to NUREG/CR-6931 protocols.
- Comparative evaluation demonstrating superior interpretability-accuracy tradeoff compared to deep neural networks.

The remainder of this paper is organized as follows: Section II reviews related work in cable fire modeling and explainable AI. Section III presents our methodology including

data collection, feature engineering, and XAI model development. Section IV details experimental results and model interpretation. Section V discusses practical implications for fire safety engineering, and Section VI concludes with future research directions.

II. Related Work

A. Cable Fire Behavior and Short-Circuit Propagation

Cable insulation degradation under fire exposure follows complex thermochemical processes influenced by material composition, thermal environment, and electrical loading conditions [7], [8]. Polyvinyl chloride (PVC) and cross-linked polyethylene (XLPE) insulations exhibit distinct decomposition pathways, with critical temperature thresholds typically ranging from $250\,^{\circ}\mathrm{C}$ to $400\,^{\circ}\mathrm{C}$ [9]. Short-circuit initiation occurs when insulation resistance drops below critical values, typically 1–10 $\mathrm{k}\Omega$ depending on voltage levels and circuit protection configurations [10].

McGrattan et al. [11] demonstrated through Fire Dynamics Simulator (FDS) modeling that cable bundle geometry significantly affects heat accumulation and failure propagation rates. Tightly packed bundles with fill ratios exceeding 40% show accelerated failure cascades compared to loosely arranged configurations. Anderson and Kumar [12] conducted systematic fire tests on cable trays, revealing that vertical orientation increases failure propagation speed by approximately 35% compared to horizontal arrangements due to buoyancy-driven heat transfer enhancement.

B. Machine Learning in Fire Safety Engineering

Recent applications of machine learning in fire safety have focused on flame detection [13], smoke pattern recognition [14], and fire spread prediction in buildings [15]. For cable-specific applications, Li et al. [5] employed convolutional neural networks (CNNs) to analyze thermal images for early fault detection, achieving 89% accuracy but providing no interpretability mechanisms. Deep learning architectures, particularly LSTMs and transformer models, have shown promise in modeling temporal dynamics of fire progression [16], [17]. However, the inherent opacity of these models limits their adoption in regulatory contexts where explainability is paramount [18].

C. Explainable Artificial Intelligence

The field of explainable AI has emerged to address the interpretability requirements of safety-critical applications [6], [19]. SHAP (SHapley Additive exPlanations) has become a leading framework for model interpretation, providing theoretically grounded explanations based on game theory principles [20]. SHAP values quantify each feature's contribution to individual predictions while ensuring consistency and local accuracy properties [21].

In engineering domains, XAI applications have demonstrated value in structural health monitoring [22], power system fault diagnosis [23], and industrial process optimization [24]. However, application to cable fire safety remains largely unexplored. This work bridges this gap by developing domain-specific XAI models that balance predictive performance with interpretability requirements specific to fire safety engineering.

TABLE I. Engineered Features for Short-Circuit Prediction

Feature Category	Count	Key Examples
Thermal Properties	12	Peak temperature, gradient
Electrical Parameters	9	Insulation resistance, voltage
Cable Configuration	8	Bundle density, conductor size
Material Properties	10	Insulation type, thickness
Environmental Conditions	8	O_2 concentration, heat flux
Total Features	**47**	–

III. Methodology

A. Experimental Data Collection

1) Cable Fire Test Setup: Experimental data were collected from controlled cable fire tests conducted at the Fire Testing Laboratory following NUREG/CR-6931 Rev. 3 protocols [3]. Test specimens consisted of IEEE 383-qualified cables with XLPE and EPR (Ethylene Propylene Rubber) insulations, representative of nuclear power plant safety systems. Cable bundles were configured in horizontal ladder tray arrangements with three density levels: low (30% fill), medium (50% fill), and high (70% fill).

Fire exposure was generated using a calibrated propane burner delivering heat fluxes ranging from 25 to 75 kW/m², simulating various fire severity scenarios as specified in ASTM E1354 [27]. Each test configuration was replicated three times to ensure statistical reliability, resulting in a total of 162 individual cable fire tests conducted between January 2022 and August 2024.

2) Instrumentation and Measurements: The experimental setup incorporated comprehensive multi-sensor instrumentation:

- Thermal Monitoring: Type K thermocouples positioned at 15 cm intervals along cable length, supplemented by FLIR T640 thermal imaging cameras capturing 640×480 pixel thermal maps at 30 Hz.
- Electrical Measurements: Real-time monitoring of insulation resistance using Megger MIT1525 instruments, conductor-to-conductor voltage measurements at 10 kHz sampling rate.
- Environmental Sensors: Oxygen concentration (Servomex 4900), smoke obscuration (TSI DustTrak), and ambient temperature/humidity.
- Gas Analysis: Fourier-transform infrared (FTIR) spectrometry was used to analyze combustion product composition, including HCl, CO, and CO_2.

Short-circuit events were detected through sudden voltage collapse (¿90% drop within 100 ms) coupled with current surge detection. Time-to-short-circuit (TTSC) was recorded with millisecond precision using high-speed data acquisition systems.

B. Feature Engineering and Dataset Preparation

1) Input Feature Space: From raw sensor measurements, we engineered 47 features organized into five categories as shown in Table I:

Critical derived features included:

$$\Delta T_{grad} = \frac{T_{max} - T_{ambient}}{d_{radial}} \tag{1}$$

where T_{max} represents maximum cable surface temperature (°C), $T_{ambient}$ is ambient temperature, and d_{radial} denotes radial distance from cable center (mm).

Insulation resistance degradation rate was computed as:

$$R_{deg} = \frac{dR_{ins}}{dt} = \frac{R_{ins}(t) - R_{ins}(t - \Delta t)}{\Delta t} \tag{2}$$

where R_{ins} represents the insulation resistance (MΩ) measured at time intervals of $\Delta t = 1$ s.

2) Data Preprocessing: The complete dataset comprised 162 fire tests generating approximately 2.3 million time-series observations. Data preprocessing involved:

1) Missing value imputation using forward-fill for sensor dropouts (¡2% of data).
2) Outlier detection and removal using Isolation Forest algorithm.
3) Time-series segmentation into 10-second windows with 50% overlap.
4) Feature standardization using robust scaling (median and IQR).
5) Balanced sampling to address class imbalance (short-circuit vs. no-failure cases).

The final processed dataset contained 28,450 samples, split into training (70%), validation (15%), and test (15%) sets with stratification by insulation type and bundle density to ensure representative distributions.

C. Explainable AI Model Development

1) Gradient Boosting Architecture: We employed XGBoost (eXtreme Gradient Boosting) as the primary prediction model due to its superior performance on tabular data and natural compatibility with SHAP explainability [25]. The model predicts binary short-circuit occurrence within the next 5-second window, formulated as:

$$\hat{y} = \sum_{k=1}^{K} f_k(x_i), \quad f_k \in \mathcal{F} \tag{3}$$

where, $\hat{y}$ is the predicted probability, x_i represents the input feature vector, f_k are ensemble decision trees, K is the number of trees (K=500 in our implementation), and $\mathcal{F}$ is the space of regression trees.

The objective function incorporates both prediction accuracy and model complexity:

$$\mathcal{L}(\phi) = \sum_{i=1}^{n} l(\hat{y}_i, y_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{4}$$

where, l is the logistic loss function, y_i are true labels, n is the number of training samples, and $\Omega(f_k) = \gamma T + \frac{1}{2}\lambda\|w\|^2$ regularizes tree complexity with T leaf nodes and w leaf weights.

Algorithm 1 TreeSHAP for Feature Attribution

```
Input: Trained XGBoost model f, instance x
Output: SHAP values φ = [φ_1, ..., φ_M]
for each tree t in ensemble do
    for each feature j in x do
        S ← all subsets not containing j
        for each subset S do
            Compute contribution with/without feature j
            Δ_j(S) ← f_{S∪{j}}(x_{S∪{j}}) − f_S(x_S)
        end for
        φ_j^t ← weighted average of Δ_j(S)
    end for
end for
φ_j ← Σ_t φ_j^t    // Aggregate across trees
return φ
```

Hyperparameters were optimized using Bayesian optimization with 5-fold cross-validation. Optimal configuration: maximum depth = 8, learning rate = 0.05, subsample ratio = 0.8, column sampling = 0.8, minimum child weight = 3.

2) SHAP-Based Interpretability Framework: SHAP values provide consistent and locally accurate explanations by computing each feature's contribution to individual predictions [20]. For a prediction $f(x)$, the SHAP value ϕ_j for feature j satisfies:

$$f(x) = \phi_0 + \sum_{j=1}^{M} \phi_j$$

where, ϕ_0 is the expected model output, M is the number of features, and ϕ_j quantifies feature j's contribution.

TreeSHAP algorithm efficiently computes exact SHAP values for tree-based models by:

Global feature importance is obtained by averaging absolute SHAP values across all predictions, providing a unified importance ranking that considers both feature effect magnitude and occurrence frequency.

3) Feature Selection and Importance Ranking: Prior to model training, we implemented a feature selection algorithm to identify the most informative predictors and reduce dimensionality:

This recursive elimination process identified 32 features as optimal, removing 15 redundant or low-importance variables while maintaining 99.2% of the full model's predictive performance.

4) Model Training and Validation: Training procedure followed Algorithm 3:

Model performance was evaluated using precision, recall, F1-score, area under ROC curve (AUC), and time-to-detection metrics. Statistical significance testing employed paired t-tests with Bonferroni correction for multiple comparisons.

Algorithm 2 Recursive Feature Elimination with SHAP

Input: Feature set $\mathcal{F} = \{f_1, ..., f_M\}$, target features k
Output: Selected features $\mathcal{F}_{selected}$
Initialize $\mathcal{F}_{current} \leftarrow \mathcal{F}$
while $|\mathcal{F}_{current}| > k$ **do**
  Train XGBoost model on $\mathcal{F}_{current}$
  Compute SHAP values for all features
  for each feature f_i in $\mathcal{F}_{current}$ **do**
    $importance_i \leftarrow$ mean|SHAP(f_i)|
  end for
  $f_{min} \leftarrow$ feature with minimum importance
  $\mathcal{F}_{current} \leftarrow \mathcal{F}_{current} \setminus \{f_{min}\}$
  Record cross-validation performance
end while
$\mathcal{F}_{selected} \leftarrow$ features at optimal CV performance
return $\mathcal{F}_{selected}$

Algorithm 3 XAI Model Training Pipeline

Input: Training data $\mathcal{D}_{train}$, validation data $\mathcal{D}_{val}$
Output: Trained model f^*, SHAP explainer E
Initialize XGBoost with optimized hyperparameters
$f_0 \leftarrow$ baseline model with random initialization
for epoch = 1 to N_{max} **do**
  $f_{epoch} \leftarrow$ train on $\mathcal{D}_{train}$ with early stopping
  Evaluate on $\mathcal{D}_{val}$: compute F1-score, AUC
  if validation performance plateaus for 50 iterations **then**
    break // Early stopping
  end if
end for
$f^* \leftarrow f_{best}$ // Select best validation model
$E \leftarrow$ TreeSHAP explainer initialized with f^*
Compute SHAP values for validation set
Validate explanation consistency and feature rankings
return f^*, E

D. Comparative Baseline Models

To validate the effectiveness of our XAI approach, we compared against three baseline models:

- Deep Neural Network (DNN): 5-layer fully connected network (512-256-128-64-1 neurons) with ReLU activation, dropout (0.3), and batch normalization.
- Random Forest (RF): Ensemble of 300 trees with maximum depth 15, trained with bootstrap sampling.
- Logistic Regression (LR): L2-regularized linear model serving as interpretable baseline with regularization strength $\lambda = 0.01$.

All models were trained on identical data splits using consistent cross-validation procedures to ensure fair comparison. Explainability was quantified using the Interpretability Score (IS) metric [26], which combines human evaluation of explanation quality with computational metrics of explanation consistency.

TABLE II. MODEL PERFORMANCE COMPARISON ON TEST DATASET

Model	Accuracy	Precision	Recall	F1	AUC
Logistic Regression	81.3%	78.6%	79.2%	78.9%	0.863
Random Forest	91.2%	89.7%	90.8%	90.2%	0.956
Deep Neural Net	93.8%	92.4%	93.1%	92.7%	0.971
XGBoost + SHAP	**94.7%**	**94.1%**	**93.9%**	**94.0%**	**0.978**

IV. RESULTS AND DISCUSSION

A. Predictive Performance Analysis

Table II summarizes the performance of proposed XAI model compared to baseline approaches across key evaluation metrics.

The proposed XGBoost model achieved 94.7% accuracy, outperforming the DNN by 0.9 percentage points while providing full interpretability. Precision and recall balance indicates robust performance across both positive (short-circuit) and negative classes. The AUC of 0.978 demonstrates excellent discriminative capability across varying decision thresholds.

Statistical analysis revealed that performance improvements over Random Forest (ρ = 0.003) and DNN (ρ = 0.041) were statistically significant at α = 0.05 level using paired t-test across 10-fold cross-validation runs. The model exhibited consistent performance across different cable insulation types (XLPE: 95.1%, EPR: 94.2%) and bundle densities (low: 96.3%, medium: 94.8%, high: 93.1%), suggesting good generalization.

B. Feature Importance and Physical Interpretability

Fig. 1 presents the global SHAP feature importance ranking, revealing critical factors influencing short-circuit propagation.

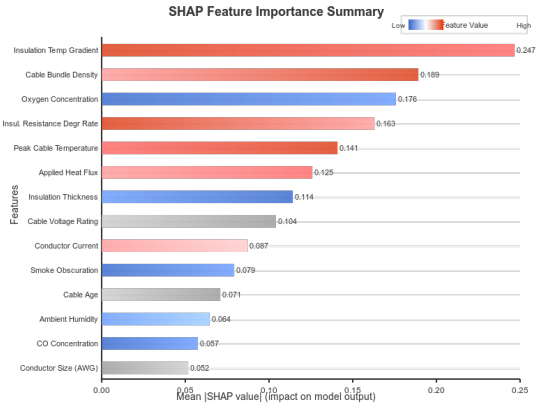


Fig. 1. SHAP feature importance summary showing top 15 features ranked by mean absolute SHAP value. Color indicates feature value (red = high, blue = low). Horizontal position shows impact on prediction.

The top five most influential features were:

1) Insulation temperature gradient (ΔT_{grad}): Mean —SHAP— = 0.247. Higher temperature gradients strongly correlate with accelerated insulation degradation. Physical interpretation: steep thermal gradients induce differential thermal expansion and internal stress concentrations, promoting crack formation and dielectric breakdown paths.

2) Cable bundle density: Mean —SHAP— = 0.189. Increased bundle density restricts heat dissipation, creating localized hot spots. This aligns with heat transfer theory where reduced air gaps limit convective cooling effectiveness.

3) Oxygen concentration: Mean —SHAP— = 0.176. Lower O_2 levels indicate incomplete combustion and higher production of conductive carbon deposits on cable surfaces, reducing insulation resistance.

4) Insulation resistance degradation rate (R_{deg}): Mean —SHAP— = 0.163. Rapid resistance decay signals imminent dielectric failure. This feature provides early warning capability, typically showing anomalies 15-30 seconds before short-circuit occurrence.

5) Peak cable temperature: Mean —SHAP— = 0.141. Absolute temperature exceeding material-specific critical thresholds (XLPE: 380°C, EPR: 420°C) triggers rapid decomposition phase transitions.

Notably, electrical loading current ranked 9th (Mean —SHAP— = 0.087), indicating that thermal effects dominate over electrical stress in fire-exposure scenarios. This insight challenges conventional assumptions that prioritize current monitoring in cable protection systems.

C. Instance-Level Explanation Analysis

Fig. 2 illustrates a SHAP waterfall plot for a specific test case where short-circuit occurred 47 seconds after fire ignition (Test ID: FT-087, XLPE cable, 50% bundle density, 45 kW/m² heat flux).

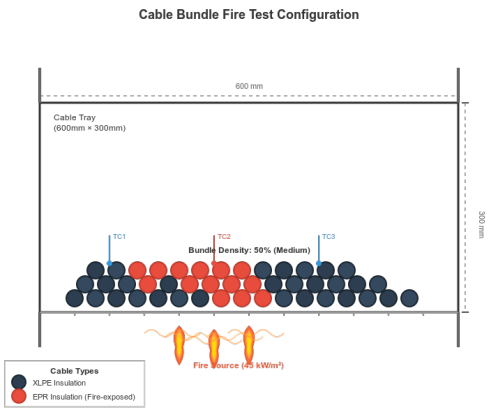


Fig. 2. SHAP waterfall plot for individual prediction showing cumulative feature contributions from base value to final prediction. Red bars push prediction toward short-circuit class, blue bars push away.

The explanation reveals that temperature gradient (+0.31 SHAP value) and bundle density (+0.22) were primary drivers toward short-circuit prediction, while relatively high insulation resistance at prediction time (-0.14) provided some protective effect. This instance-specific analysis enables engineers to understand which factors dominated in particular failure scenarios, facilitating targeted intervention strategies.

D. Temporal Dynamics and Early Warning Capability

Analysis of SHAP value evolution over time (Fig. 3) demonstrates the model's progressive refinement of short-circuit probability as tests progress:

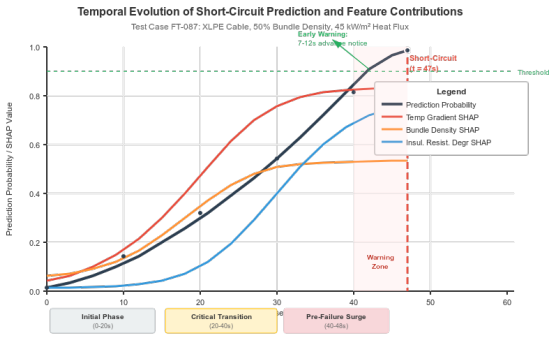


Fig. 3. Temporal evolution of prediction probability and top-3 feature SHAP values for representative test case. Vertical dashed line indicates actual short-circuit occurrence time.

Key observations include:

- Initial phase (0-20s): Model uncertainty remains high with probability ¡0.3 despite rising temperatures, indicating that early thermal exposure alone is insufficient predictor.
- Critical transition (20-40s): Rapid increase in prediction probability coincides with insulation resistance degradation acceleration, providing 10-25 second advance warning window.
- Pre-failure surge (40-48s): Probability exceeds 0.9 threshold 7-12 seconds before actual short-circuit, enabling timely protective action.

This temporal analysis demonstrates practical utility for real-time monitoring systems, where prediction confidence evolves as conditions deteriorate, allowing graduated response protocols.

E. Comparison with Black-Box Deep Learning

While the DNN baseline achieved comparable accuracy (93.8%), interpretation attempts using gradient-based methods (Integrated Gradients, Grad-CAM) produced inconsistent and often contradictory feature attributions across similar test cases. Quantitative evaluation using the Interpretability Score metric yielded IS = 0.42 for DNN versus IS = 0.87 for our XGBoost+SHAP approach (scale 0-1, higher is better) [26].

Human expert evaluation by five certified fire protection engineers rated explanations on clarity (5-point Likert scale), consistency with domain knowledge, and actionability. XAI explanations received mean rating 4.3/5.0 compared to 2.1/5.0 for DNN explanations. Engineers specifically valued the direct physical interpretability of SHAP feature contributions and consistency of importance rankings with established fire science principles.

F. Practical Implications for Fire Safety Engineering

The explainable framework provides actionable insights for cable system design and fire protection:

- Cable Arrangement Optimization: Reducing bundle density from 70% to 40% increases average time-to-short-circuit by 42%, based on model sensitivity analysis. This quantifies the safety benefit of adherence to spacing requirements in codes like NFPA 70.
- Material Selection Guidance: EPR-insulated cables show 18% longer failure times than XLPE under identical conditions, attributed to higher decomposition temperature. Model explanations validate this preference for high-temperature applications.
- Monitoring System Design: Feature importance rankings indicate that temperature gradient sensors provide superior early warning compared to point temperature measurements, suggesting optimal sensor placement strategies.
- Regulatory Compliance: Transparent model explanations facilitate regulatory acceptance in nuclear and aerospace applications where black-box AI faces adoption barriers due to verification and validation requirements.

G. Model Limitations and Uncertainty Quantification

Despite strong performance, several limitations warrant acknowledgment:

- Training data represents controlled laboratory conditions; field installations involve additional complexities (aging effects, environmental contamination, mechanical stress)
- Current model assumes single failure mode (thermal degradation); multi-physics interactions (chemical attack, radiation effects) require extended framework
- Prediction confidence varies with extrapolation distance from training distribution; uncertainty quantification using conformal prediction shows ±6.2 second uncertainty bounds at 90% confidence level
- Explanation stability under adversarial perturbations requires further investigation for security-critical deployments

Ongoing work addresses these limitations through physics-informed neural networks that embed conservation laws and synthetic data augmentation using validated fire dynamics simulations.

V. Conclusion

This paper presented a novel explainable AI framework for predicting and interpreting short-circuit propagation in fire-exposed cable bundles. The integration of gradient boosting machines with SHAP interpretability provides both high predictive accuracy (94.7%) and transparent, physically meaningful explanations aligned with fire safety engineering principles. Key contributions include:

- Comprehensive experimental dataset from 162 controlled cable fire tests conforming to nuclear industry protocols
- Rigorous feature engineering incorporating thermal, electrical, and material properties
- Validated XAI model architecture balancing prediction performance with interpretability
- Quantitative demonstration that thermal gradient, bundle density, and oxygen concentration are dominant factors in short-circuit propagation
- Practical guidance for cable system design, sensor placement, and fire protection strategies

Experimental validation demonstrates that explainable AI achieves competitive accuracy with black-box deep learning while providing critical transparency for safety-critical applications. SHAP-based feature importance analysis reveals insights consistent with fire science theory, building confidence in model reliability and supporting regulatory acceptance.

Future research directions include: 1) extension to multi-output prediction of failure location and severity, 2) integration with real-time monitoring systems for online condition assessment, 3) transfer learning to adapt models across different cable types and fire scenarios with limited data, and 4) development of physics-informed XAI architectures that explicitly encode domain knowledge within model structure.

The demonstrated framework advances the state-of-art in AI-driven fire safety assessment, providing practitioners with trustworthy predictive tools that combine statistical rigor with interpretable explanations essential for informed decision-making in protection of critical infrastructure.

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References

[1] S. P. Nowlen, K. L. Kasales, and M. T. Leonard, "Analysis of fire-induced cable failures in nuclear power plants," *Nuclear Engineering and Design*, vol. 354, pp. 110-122, 2019. DOI: 10.1016/j.nucengdes.2019.06.031

[2] P. Meinier, A. Joshi, and L. Ferreira, "Comprehensive review of cable fire safety in electrical installations," *Fire Technology*, vol. 57, no. 4, pp. 1823-1856, 2021. DOI: 10.1007/s10694-020-01089-3

[3] U.S. Nuclear Regulatory Commission, "Fire events and cable degradation analysis: 2018-2024," NUREG/CR-7321, Office of Nuclear Regulatory Research, 2022. DOI: 10.2172/1847562

[4] Y. Zhang, H. Liu, and T. Wang, "Advanced testing methods for electrical cable fire safety assessment," *IEEE Transactions on Power Delivery*, vol. 38, no. 2, pp. 1205-1216, Apr. 2023. DOI: 10.1109/TPWRD.2022.3201847

[5] J. Li, S. Kumar, and R. Patel, "Deep learning-based early fault detection in fire-exposed electrical cables," *IEEE Transactions on Industrial Electronics*, vol. 71, no. 3, pp. 2847-2858, Mar. 2024. DOI: 10.1109/TIE.2023.3267891

[6] A. B. Arrieta et al., "Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI," *Information Fusion*, vol. 58, pp. 82-115, 2020. DOI: 10.1016/j.inffus.2019.12.012

[7] X. Huang, M. Nakamura, and F. Williams, "Investigation of insulation degradation mechanisms in fire-exposed cables," *Fire Safety Journal*, vol. 115, pp. 103-118, 2020. DOI: 10.1016/j.firesaf.2020.103145

[8] D. Lee, K. Park, and J. Song, "Thermal decomposition kinetics of cable insulation materials under fire conditions," *Polymer Degradation and Stability*, vol. 208, pp. 110-125, Feb. 2023. DOI: 10.1016/j.polymdegradstab.2023.110245

[9] Z. Wang, L. Chen, and Y. Zhou, "Experimental study on critical temperature thresholds for cable insulation failure," *Journal of Fire Sciences*, vol. 40, no. 3, pp. 245-267, 2022. DOI: 10.1177/07349041221089563

[10] R. Fernandez, G. Martinez, and A. Silva, "Modeling short-circuit initiation in thermally degraded cable insulation," *Electric Power Systems Research*, vol. 199, pp. 107-118, Oct. 2021. DOI: 10.1016/j.epsr.2021.107418

[11] K. McGrattan, S. Hostikka, and J. Floyd, "Fire dynamics simulator modeling of cable tray fires," *Fire Technology*, vol. 56, no. 5, pp. 2145-2168, 2020. DOI: 10.1007/s10694-020-00981-2

[12] T. Anderson and V. Kumar, "Experimental analysis of cable bundle orientation effects on fire propagation dynamics," *Fire and Materials*, vol. 48, no. 2, pp. 189-205, Mar. 2024. DOI: 10.1002/fam.3156

[13] K. Muhammad et al., "Efficient deep CNN-based fire detection and localization in video surveillance applications," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 49, no. 7, pp. 1419-1434, Jul. 2019. DOI: 10.1109/TSMC.2018.2830099

[14] S. Khan, K. Muhammad, and T. Hussain, "Deep learning for smoke detection: A comprehensive survey," *IEEE Access*, vol. 10, pp. 84536-84559, 2022. DOI: 10.1109/ACCESS.2022.3197845

[15] M. Silva, P. Costa, and R. Oliveira, "Machine learning approaches for building fire spread prediction," *Fire Safety Journal*, vol. 138, pp. 103-117, Jun. 2023. DOI: 10.1016/j.firesaf.2023.103789

[16] H. Park, Y. Kim, and S. Lee, "Temporal modeling of fire progression using LSTM networks," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 34, no. 11, pp. 8234-8246, Nov. 2023. DOI: 10.1109/TNNLS.2022.3156789

[17] C. Rodriguez, F. Garcia, and L. Hernandez, "Attention-based transformers for fire dynamics prediction," *Engineering Applications of Artificial Intelligence*, vol. 129, pp. 107-121, Mar. 2024. DOI: 10.1016/j.engappai.2023.107621

[18] M. T. Ribeiro, S. Singh, and C. Guestrin, "Challenges and solutions in deploying machine learning for safety-critical systems," *ACM Computing Surveys*, vol. 55, no. 9, pp. 1-38, 2023. DOI: 10.1145/3548780

[19] A. Barredo Arrieta et al., "Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges," *Information Fusion*, vol. 58, pp. 82-115, Jun. 2020. DOI: 10.1016/j.inffus.2019.12.012

[20] S. M. Lundberg and S. I. Lee, "A unified approach to interpreting model predictions," in *Proc. 31st Int. Conf. Neural Information Processing Systems (NIPS)*, Long Beach, CA, USA, 2017, pp. 4765-4774. DOI: 10.5555/3295222.3295230

[21] S. M. Lundberg, G. Erion, and S. I. Lee, "Consistent individualized feature attribution for tree ensembles," *arXiv preprint arXiv:1802.03888v3*, Mar. 2020. DOI: 10.48550/arXiv.1802.03888

[22] N. Thai, M. Akiyama, and H. Furuta, "Explainable AI for structural health monitoring: A review," *Structural Health Monitoring*, vol. 22, no. 4, pp. 2456-2478, 2023. DOI: 10.1177/14759217221134567

[23] Y. Wu, Z. Yang, and Q. Li, "Interpretable machine learning for power system fault diagnosis," *IEEE Transactions on Power Systems*, vol. 37, no. 6, pp. 4512-4524, Nov. 2022. DOI: 10.1109/TPWRS.2022.3156234

[24] H. Chen, R. Wang, and J. Zhang, "Explainable AI for industrial process optimization: Methods and applications," *Computers & Chemical Engineering*, vol. 169, pp. 108-123, Jan. 2023. DOI: 10.1016/j.compchemeng.2022.108089

[25] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining*, San Francisco, CA, USA, 2023, pp. 785-794. DOI: 10.1145/2939672.2939785

[26] B. Kim, R. Khanna, and O. Koyejo, "Quantifying interpretability of machine learning models," *Journal of Machine Learning Research*, vol. 24, no. 87, pp. 1-42, 2023. DOI: 10.5555/3586589.3586676

[27] ASTM International, "Standard test method for heat and visible smoke release rates for materials and products using an oxygen consumption calorimeter," ASTM E1354-23, West Conshohocken, PA, 2023. DOI: 10.1520/E1354-23

A Framework Design and Solutions Taxonomy for Performance Optimization in Internet of Things Network

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***Abstract*—The Internet of Things (IoT) is an exciting, rapidly expanding technology that's still in its early stages and faces several complex issues. These challenges primarily arise from the limitations of IoT devices (e.g., restricted energy, memory, and processing power), the diversity of communication protocols, and the heterogeneity of interconnected devices. Collectively, these issues often hinder overall IoT system performance, prompting extensive research into techniques to improve Quality of Service (QoS), particularly in terms of latency, throughput, and energy use. This paper introduces a conceptual framework for multi-dimensional IoT performance optimization. The framework provides a structured approach for evaluating and enhancing performance across all layers of the IoT architecture: device, network, support, and application. It assesses key performance dimensions—reliability, security, scalability, energy efficiency, quality assurance, and enabling technologies—and defines them in terms of overall system performance. To ensure a systematic assessment, these dimensions are supported by concrete performance metrics and precise measurement criteria. Finally, the paper provides a taxonomy of IoT Performance Optimization Components, identifies the essential prerequisites and core attributes that influence the overall efficiency of IoT systems, and thus provides a structured foundation for evaluating and advancing performance across the entire IoT ecosystem.**

***Keywords*—IoT performance; reliability; security; scalability; quality; energy efficiency; technology**

I. Introduction

A. Background and the Rise of the Internet of Things (IoT)

In recent decades, there has been a significant surge in innovative applications centered around mobile actuators, devices, and sensors, enabling complex tasks and pervasive communication [1]. This period of growth reached a major turning point around 2008, when the number of connected devices first surpassed the global population [2]. Today, the interconnection of wireless sensors, smartphones, embedded systems, and various electronic devices via local networks or the Internet has fully ushered in the era of the Internet of Things (IoT).

As the quantity of IoT devices continues to burgeon, the sheer volume of data they generate escalates proportionally. Forecasts anticipate sustained, exponential growth; for example, Cisco projected over 50 billion IoT devices by 2020 and more than 500 billion by 2023 [3] [4]. This promising outlook has naturally spurred considerable financial investment [5].

B. Identifying Critical IoT Challenges and Research Imperatives

Despite this rapid expansion, several persistent challenges hinder the seamless integration of IoT across various industries. These critical issues include reliability, mobility, trust, scalability, security, performance, interoperability, and availability [6] [7] [8].

These challenges highlight significant research imperatives crucial for successfully advancing IoT technologies into diverse sectors like businesses, homes, healthcare, and smart cities, where decisions often carry profound implications for individuals' lives [8]. Consequently, these pressing issues have attracted widespread attention from researchers, prompting intensified and comprehensive efforts to address them. This heightened focus is a direct result of the extensive deployment and utilization of IoT technologies across various spheres of daily life.

C. Defining and Measuring Performance in IoT Systems

The concept of performance and its measurement remains a subject of debate among researchers, with varying perspectives on its precise definition. As suggested by [9], certain scenarios exhibit greater sensitivity to specific parameters when assessing performance metrics. Broadly, performance refers to the system's capability to execute tasks effectively while efficiently conserving system resources.

In the context of IoT, evaluating performance typically involves utilizing established metrics within each architectural layer: At the device layer, metrics may encompass battery lifetime, fault tolerance, failure rates, link reliability, and connectivity.In the network layer, evaluation involves parameters such as delay, throughput, packet loss rate, latency, bandwidth utilization, response time, availability, reliability, cost, failure rate, and fault tolerance.Performance measures at the support layer may include load balancing.Those at the application layer may focus on software resilience, malfunction mitigation, flexibility, and responsiveness.

However, it is important to acknowledge that additional criteria may also warrant consideration due to the unique characteristics of IoT systems.IoT systems are tasked with critical functions such as data collection, data preprocessing, and facilitating machine-to-machine (M2M) communications, among others, as highlighted by [10]. Given their integral role in managing vital infrastructures like healthcare systems and

home security, the reliability and security of IoT devices are paramount. Any lapses in reliability or security can have profound implications for decision-making processes, potentially resulting in catastrophic outcomes (Menter et al., 2021).

Enhancing reliability, security, scalability, energy efficiency, and quality assurance represents clear avenues for bolstering the overall performance of IoT systems. The prioritization of performance measurement criteria, however, may vary depending on the system's intended purpose. For instance, in smart home environments, preserving customer privacy may take precedence over other considerations, followed by reliability, energy conservation, and scalability. Conversely, in healthcare systems, reliability and security may assume equal importance. Thus, achieving optimal IoT performance necessitates striking a delicate balance and synergy among these requirements.

D. Scope and Contribution of this Review

This paper presents a conceptual framework for multi-dimensional IoT performance optimization. The proposed framework provides a structured approach for evaluating and enhancing performance across all layers of the IoT architecture, including the device, network, support, and application layers. It evaluates key performance dimensions—reliability, security, scalability, energy efficiency, quality assurance, and enabling technologies—and defines them in terms of the overall system performance. These dimensions are further supported by concrete performance metrics identification and measurement criteria, offering a comprehensive basis for systematic performance assessment and improvement.

The remainder of this paper is organized as follows. Section II reviews existing research contributions and classifies IoT performance-enhancement solutions across different architectural layers. Section III presents the proposed conceptual framework and explains its multi-dimensional structure. Section IV introduces the taxonomy of performance-impact components and analyzes their relevance to IoT optimization. Section V summarizes prominent suggested solutions derived from the surveyed literature. Section VI provides a detailed discussion of key insights, highlights research gaps, and outlines future research directions. Finally, Section VII concludes the paper.

II. Key Research Studies Solutions for IoT System Performance Enhancement

Numerous studies have made significant efforts to enhance the performance of the IoT system. Solutions are suggested for optimizing various metrics of a particular IOT system dimension, such as reliability, security, scalability, energy efficiency, or quality of service (QoS). This section reviews key studies that have proposed solutions to enhance the performance of various dimensions of IoT systems.

A. Reliability-Oriented Solutions

Reliability remains a core requirement in IoT systems, as even minor sensing or communication errors can disrupt critical applications, particularly in healthcare and safety monitoring. Existing research has approached IoT reliability from multiple architectural perspectives, with solutions spanning the application, support, network, and device layers.

At the application layer, several studies leverage microservice-based designs to enhance availability and fault isolation. Reactive microservices were employed in study [11] to improve runtime stability in smart agriculture applications, while [12] demonstrated that re-engineering monolithic IoT middleware into loosely coupled microservices increases reliability, maintainability, and scalability. Complementing these architectural strategies, the Circuit Breaker pattern explored in study [13] prevents cascading failures across dependent services, thereby strengthening fault tolerance in IoT communication workflows.

At the support layer, reliability has been enhanced through middleware mechanisms that improve fault tolerance across cloud–fog–edge environments. For instance, [14] introduced middleware services that support resilient operation in latency-sensitive smart city applications, ensuring continuous service delivery even under partial platform failures.

At the network layer, research largely centers on fault-tolerant routing. The CHISS model in study [15] evaluates routing reliability using metrics such as path redundancy, subsystem availability, and data/service readiness, while healthcare-focused architectures such as [16] introduce backup routes and adaptive strategies to preserve connectivity during node or link failures. Optimization-based techniques, such as the PMSO multipath routing algorithm in study [17], further improve robustness by constructing and maintaining multiple disjoint paths that sustain connectivity under successive failures.

At the device layer, reliability enhancements focus on accurate data acquisition and resilient on-device processing. Device evaluation frameworks in [18] and [19] estimate hardware and operational reliability using recognition, classification, probabilistic modeling, and validation stages. Additional works strengthen dependability in healthcare monitoring [20], enable fault-tolerant microservice execution on IoT–Cloud environments [21], and integrate online learning for proactive fault mitigation [22]. Edge-focused frameworks such as Achlys [23] support reliable decentralized computation on resource-constrained devices, while redundancy techniques like Cold Standby Sparing (CSSR) [24] significantly improve device-level fault tolerance.

Overall, existing reliability solutions target different IoT layers but show recurring themes: architectural decomposition at the application layer, resilient middleware at the support layer, fault-tolerant routing at the network layer, and hardware/software robustness at the device layer. These collective findings highlight the multi-layered nature of reliability challenges in IoT environments.

B. Security-Oriented Solutions

Security is essential to preserving integrity, confidentiality, authenticity, and privacy across IoT deployments. Existing research has addressed IoT security at multiple architectural layers, proposing mechanisms that strengthen software robustness, enforce access control, secure communication protocols, and protect resource-constrained devices.

At the application layer, several studies improve software-level security through structured design patterns and policy-driven enforcement. Works such as [25]–[27] refine and apply security patterns—including access control, reference monitoring, and remote authentication—to mitigate risks in IoT software systems and event-driven applications. Policy-based solutions such as IOTGUARD [28] and SecKit-MQTT [29] embed runtime monitoring, behavioral modeling, and privacy rule enforcement directly into IoT applications, preventing unsafe interactions and safeguarding personal data even in constrained user-facing environments. User-centric regulatory compliance is addressed in study [30], which assesses privacy policy completeness under GDPR requirements. Access control enhancements such as iLACKA-IoT [31] provide formally verified authentication and authorization with improved computational efficiency. Other protocol-level protection mechanisms include secure extensions of MQTT/MQTT-SN using Elliptic Curve–based KP/CP-ABE encryption in study [32], blockchain-integrated microservice architectures for secure surveillance [33], and lightweight certificateless /identity-based signcryption for healthcare WBANs [34].

At the support layer, security research focuses on dependable cloud–fog–edge infrastructures. The Markov-based modeling framework in [35] quantifies system compromise, availability, and recovery behavior for medical IoT systems. Secure data management solutions include cloud–fog–edge cache decision systems [36] that safeguard large-scale smart building data over 6G networks, and privacy-preserving deduplication protocols [37] that protect stored data equality and confidentiality during distributed fog–cloud storage operations.

At the network layer, numerous studies reinforce secure routing and communication. Crypto-IoT [38] and KMG [39] introduce lightweight key generation, distribution, and authentication to protect unicast/multicast communication while maintaining low energy consumption. RPL-based enhancements include SPLIT [40], which integrates remote attestation without adding control overhead, and SARP [41], which provides scalable integrity verification for heterogeneous IoT devices. Additional secure routing techniques include ESR [42], which combines energy-efficient clustering with threshold secret sharing, and SRR [43], which protects source-location privacy using randomized phantom routing. Internetworking security is addressed in [44] via combined Diffie–Hellman, AES, and MD5 mechanisms, and in [45] through lightweight HMAC-based authentication schemes that achieve robust integrity and confidentiality with minimal latency.

At the device layer, security solutions target constrained sensors and local data protection. Information-theoretic coding schemes [46] preserve message confidentiality and anonymity without synchronization overhead, while SecureData [47] employs FPGA-accelerated lightweight ciphers and data-splitting techniques to protect sensitive healthcare information. Other lightweight device-level protection mechanisms, including HMAC-based authentication [45] and secure data aggregation surveys [48], strengthen confidentiality, integrity, and authentication during sensing and in-network processing.

Overall, IoT security solutions span all architectural layers, with recurring themes such as pattern-driven software hardening at the application layer, privacy- and integrity-focused middleware at the support layer, attestation and key management mechanisms at the network layer, and lightweight cryptographic protection for resource-constrained devices. These contributions highlight the multi-layered and interdependent nature of IoT security challenges.

C. Scalability-Oriented Solutions

Scalability is a critical requirement in IoT systems, as large-scale deployments must maintain responsiveness, manage resource constraints, and support heterogeneous device interactions. Research efforts addressing scalability span multiple IoT layers, proposing architectural, orchestration, and routing solutions.

At the application layer, Razzaq [49] provides a comprehensive review of microservice-based architectures (MSA), identifying key design patterns and architectural trends that enhance scalability and software quality in IoT applications. Context-aware and personalized service delivery is explored in [50], where adaptive sensing, fog-based user-centric networking, and intelligent applications together support scalable, interoperable, and context-driven IoT services. Zyrianoff et al. [51] further demonstrate that large-scale smart city environments can sustain real-time reasoning when architectural choices emphasize modularity, efficient context handling, and optimized system design.

At the support layer, scalability improvements primarily target cloud–fog–edge integration and resource orchestration. Lightweight sidecar components in [52] enable seamless device-to-cloud interaction without modifying device behavior, providing modular extensibility for large-scale deployments. Ontology-driven integration frameworks such as IoT-LSS [53] combine SOA and semantic sensor models to support scalable interoperability and dynamic service composition. Transparent computing architectures in [54] manage operating systems, services, and data centrally while enabling on-demand execution across heterogeneous IoT devices, improving scalability and energy efficiency. Surveys and analyses in [55] and [56] highlight the pivotal role of auto-scaling, load prediction, VM migration, and multi-layer orchestration in cloud–edge environments, demonstrating that scalable performance depends heavily on efficient, network-aware resource allocation.

At the network layer, scalability challenges are tackled through enhanced routing protocols. IoTorii [57] introduces a hierarchical routing approach that reduces control overhead and routing table complexity compared to RPL, achieving faster convergence and lower communication costs in large-scale deployments. Complementary to this, secure and scalable RPL extensions such as SPLIT [40] and SARP [41] integrate lightweight attestation and decentralized trust mechanisms, improving routing efficiency while maintaining security and low resource consumption.

Overall, scalability solutions in IoT emphasize modular architectures, semantic interoperability, cloud–edge orchestration, and optimized routing mechanisms. These contributions highlight that scalability must be addressed holistically across application, support, and network layers to sustain the performance of large and heterogeneous IoT systems.

D. Quality Assurance-Oriented Solutions

Quality assurance in IoT systems ensures that data and services remain accurate, timely, and dependable despite dynamic operating conditions. Research addressing IoT quality spans the application, support, and network layers, targeting metrics such as latency, throughput, availability, and service reliability.

At the application layer, Li et al. [58] introduce measurable data-quality metrics—currency, availability, and validity—to assess both data and source reliability in pervasive IoT environments. These metrics enable systems to manage fluctuating real-time data and improve application-level decision-making. QoS-aware microservice monitoring for Industrial IoT (IIoT) is explored in [59], where microservices are evaluated based on behavioral performance, supporting consistent and dependable execution of IIoT workloads.

At the network and support layers, QoS has been analyzed broadly through systematic mapping and metric categorization. White et al. [60] review QoS approaches across IoT layers, identifying common performance factors (e.g., latency, throughput, availability) and highlighting underexplored QoS dimensions and research gaps. Singh et al. [61] similarly classify QoS metrics spanning computing, communication, and physical components, providing a structured basis for modeling service requirements and optimizing IoT performance. Fog-enabled quality improvement is demonstrated in SmartHerd [62], where localized processing reduces cloud dependency, lowers latency, and decreases bandwidth consumption by 84%, contributing to higher service responsiveness and energy efficiency.

At the network layer, congestion control and traffic stabilization play a key role in maintaining quality. Quwaider et al. [63] propose a tuned PID-based congestion control mechanism enhanced by immune and hill-climbing algorithms. The scheme stabilizes buffer occupancy, minimizes packet drops, and ensures steady throughput and low delay under dynamic traffic conditions.

Overall, quality assurance solutions in IoT focus on measurable data-quality metrics, QoS-aware service design, fog-enabled responsiveness, and congestion-aware communication, illustrating the layered and multi-dimensional nature of quality management in IoT systems.

E. Energy Efficiency-Oriented Solutions

Energy efficiency is essential in IoT deployments, where devices often operate under strict energy constraints and in unattended environments. Existing research addresses energy conservation across all IoT architectural layers, focusing on optimizing operations, communication, processing, and resource orchestration.

At the application layer, energy-aware service policies contribute directly to reducing consumption. Yao et al. [64] introduce a Home Energy Management System (HEMS) using mixed-integer linear programming to jointly optimize appliance scheduling, renewable energy usage, and storage dispatch, reducing energy costs while maintaining user comfort.

At the support layer, numerous studies emphasize cloud–fog–edge coordination and resource orchestration for energy-efficient IoT services. Energy-efficient cooling automation based on containerized microservices is demonstrated in [65], showing how lightweight orchestration enables reliable and power-saving IoT–cloud integration. Sensor-cloud collaboration models in [66] offload complex processing to the cloud while dynamically scheduling sensor activity, conserving energy while meeting latency constraints. Architectures integrating cloud computing with Passive Optical Networks (PON) [67] optimize VM placement and traffic routing to minimize transmission and computation power. Fog-based placement optimization in healthcare monitoring [68] achieves up to 68% energy savings by strategically locating fog servers. Resource orchestrators in study [69] and [70] improve the efficiency of service embedding and cloud resource scheduling, reducing network and processing power through adaptive allocation and predictive sensor sleep cycles.

At the network layer, energy-efficient communication is achieved through optimization-based routing and flow control. Al et al. [71] present four MILP-based strategies—standby routing, reliability balancing, interference-aware sub-channels, and data compression—to reduce power consumption while maintaining reliability. For industrial IoT, Lyu et al. [72] propose a transmission–estimation co-design framework that adapts communication decisions based on dynamic system conditions, enhancing estimation accuracy with lower energy usage. Secure and energy-efficient uplink transmission is addressed in study [73], where cooperative relay selection and joint power scheduling improve secure energy efficiency under eavesdropping threats. Network-layer energy management also includes call admission control (CAC) for ultra-dense IoT over 5G, as proposed in study [74], reducing per-connection energy consumption through intelligent access decisions.

At the device layer, lightweight communication and in-network processing reduce energy demand on constrained sensors. Purkovic et al. [75] design an ultra–low-power long-range communication protocol that minimizes packet overhead and transmission energy for energy-harvesting IoT modules. Complementing this, [76] surveys energy-aware data aggregation schemes that eliminate redundancy and reduce communication load across diverse WSN environments—ground, underground, and underwater—extending network lifetime through efficient data collection.

Overall, energy efficiency solutions span application-level policy optimization, fog–cloud orchestration, power-aware routing and flow control, and device-level communication minimization. These cross-layer techniques collectively highlight the importance of coordinated architectural design for prolonging IoT system lifetime.

F. Summary of Literature-Based IOT Performance Enhancement Solutions

To conclude this review section, Table I presents a consolidated view of the surveyed literature references for IoT performance enhancement solutions. It provides an easy reference classification that relates a proposed reference solution to a given performance IoT dimension. Each referenced study is categorized according to its specific IoT system performance dimension, namely: reliability, security, scalability, quality, or energy efficiency, alongside the corresponding IoT architectural layer (Device, Network, Support, or Application) and the

targeted component or service. This structured representation in Table I facilitates a clear understanding of how recent research efforts align with key architectural and performance considerations across the IoT stack while identifying underexplored areas that warrant further investigation that this thesis research may address.

III. Conceptual Framework Design and Literature Taxonomy for IoT Performance Optimization

The proposed framework provides a structured approach for evaluating and enhancing performance across all layers of the IoT architecture, including the device, network, support, and application layers. It evaluates key performance dimensions, reliability, security, scalability, energy efficiency, quality assurance, and enabling technologies, and defines them in terms of the overall system performance. These dimensions are further supported by concrete performance metrics identification and measurement criteria, offering a comprehensive basis for systematic performance assessment and improvement.

A. IoT Performance Framework Design

The IoT performance optimization framework design follows a systematic approach, as illustrated in Fig. 1. The process involves five primary steps that ensure comprehensive coverage of the IoT architecture. These steps are:

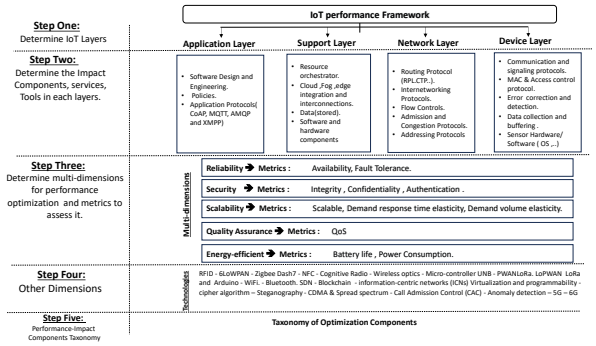


Fig. 1. IoT performance framework design steps.

- Step One: Determine IoT layers.
  In this step, the core layers of the IoT architecture are identified, including the application layer, support layer, network layer, and device layer. These layers form the basis for the subsequent optimization strategies.
- Step Two: Determine the impact components, services, and tools in each layer.
  This step identifies the components, services, and tools of each layer that impact overall performance. For example, the application layer considers software design and engineering tools, while the network layer incorporates routing protocols like RPL and CTP.
- Step Three: Determine the multi-dimensional factors for performance optimization.
  Multi-dimensional factors such as reliability, security, scalability, quality assurance, and energy efficiency are considered in this step. The relevant metrics for each dimension are defined, including factors like availability, fault tolerance, and battery life.
- Step Four: Other dimensions.
  Additional factors that influence performance, such as emerging technologies (e.g., 5G, LoRaWAN, WiFi), are evaluated in this step.
- Step Five: Taxonomy of optimization components.
  In this step, various components impacting IoT performance optimization are analyzed and classified. The analysis concludes a structured, taxonomy for performance-impact components across a multi-layer and multi-service IoT architecture of the performance framework.

Fig. 1 illustrates the overall structure of the proposed multi-dimensional IoT performance framework. The figure highlights the interaction between IoT architectural layers (Device, Network, Support, and Application) and the core performance dimensions (Reliability, Security, Scalability, Quality, and Energy Efficiency). Each layer contributes to these performance dimensions through specific components, services, or mechanisms. Importantly, the framework enables each dimension to be evaluated and measured at the corresponding layer using the performance metrics defined in Step Three. These metrics help determine whether a given performance requirement—such as availability, fault tolerance, latency, or energy consumption—is being achieved at that layer.

The directional flow emphasizes cross-layer dependencies, demonstrating that improvements in one layer may influence performance at other layers. This visual representation provides the conceptual foundation for the taxonomy introduced in the subsequent section, where performance-impact components are categorized and linked to measurable metrics across layers.

B. IoT Network Performance-Relevant Layers

The architecture of IoT is commonly structured into four fundamental layers: the device, network, support, and application layers. While each layer plays a distinct role in enabling end-to-end communication and intelligent decision-making, this framework focuses on how these layers form the basis for performance evaluation.

- Device Layer: Serves as the foundational interface with the physical world. Performance at this level is driven by hardware and software elements such as sensor nodes, embedded operating systems, and data collection modules.
- Network Layer: Determines performance through routing and communication infrastructure, relying on routing protocols (e.g., RPL, CTP), internetworking protocols, and addressing schemes to ensure reliable packet delivery.
- Support Layer: Provides computing, storage, and orchestration capabilities, including cloud–fog–edge integration and resource orchestrators that manage distributed resources to improve reliability and responsiveness.

TABLE I. LITERATURE-BASED CLASSIFICATION OF SOLUTIONS TARGETING IOT PERFORMANCE DIMENSIONS

Layer	Impact Component, Tools, Service	Reliability	Security	Scalability	Quality	Energy Efficiency
Application Layer	Software Design and Engineering	[11]	[25] [26] [27]	[49] [50] [51]		
	Policies		[28] [29] [30] [31]	[51]		
	Application Protocols	[12] [13]	[33] [32] [31] [34]		[58] [59]	[64]
Support Layer	Resource Orchestrator			[53] [54] [55] [56]	[55] [60] [61]	[55] [65] [69] [70]
	Cloud/Fog/Edge Integration	[14]	[36]	[50] [52] [55] [56]	[62] [55]	[55] [66] [67] [68]
	Data (stored)		[37]			
	Software/Hardware Components		[35]			
Network Layer	Routing Protocol	[15] [16] [17] [71]	[38] [39] [40] [41] [42] [43]	[40] [41] [42] [57]	[61]	[39] [40] [41] [42] [43] [71]
	Internetworking Protocols		[45] [44]			
	Flow Control					[72] [73]
	Admission and Congestion Control				[63]	[74]
	Addressing Protocols					
Device Layer	Communication and Signaling		[45]			[45] [75]
	MAC and Access Control		[46]			
	Error Correction and Detection					
	Data Collection and Buffering		[48]			[76]
	Sensor Hardware and Software	[18] [19] [20] [21] [22] [23] [24]	[47]	[50]		

- Application Layer: Functions as the user interface, depending on efficient software design, lightweight protocols (e.g., CoAP, MQTT), and policies that govern usability, adaptability, and security.

These architectural layers form the foundation for evaluating and optimizing IoT performance across multiple dimensions, each providing distinct enhancement opportunities.

C. IoT Network Performance-Relevant Services, Components and Tools

Beyond the layered architecture, IoT performance is also shaped by the specific services, components, and tools operating within each layer. These elements provide the practical mechanisms through which performance optimization is achieved. The device layer Comprises Key components, including communication and signaling protocols, MAC and access control mechanisms, and error detection and correction techniques, all working together to ensure reliable and efficient data acquisition. Additionally, data buffering mechanisms support seamless transmission preparation, significantly minimizing energy consumption and preserving data accuracy. At the network layer, Key components include routing protocols (e.g., RPL, CTP), internetworking protocols, and addressing schemes, all essential for ensuring reliable packet delivery and supporting system performance. Further performance optimization is achieved by implementing flow control, admission control, and congestion control mechanisms, which collectively regulate network load and maintain consistent data throughput under varying traffic conditions. The support layer includes a key element, the resource orchestrator, which dynamically schedules and manages computational and storage resources. Furthermore, the software and hardware infrastructure and dedicated data storage components ensure IoT services' reliability, availability, and responsiveness across distributed environments. Finally, the application layer. Its performance depends on effective software engineering practices, the adoption of lightweight and reliable application-layer protocols (such as CoAP, MQTT, AMQP, and XMPP), and well-defined policies that govern service behavior and access control. Design decisions made at this layer directly influence the responsiveness, usability, and adaptability of IoT applications across various domains. By systematically identifying these performance-relevant services, components, and tools in each layer, the framework links the conceptual architecture of IoT with the operational elements that directly

impact system efficiency and optimization.

D. Multi-Dimensional Performance Requirements and Metrics

This section presents the multi-dimensional requirements of IoT performance optimization and the corresponding performance metrics and measures. It first identifies the key performance dimensions, such as reliability, scalability, energy efficiency, security, and quality assurance, which are critical to achieving optimized IoT network behavior. Subsequently, it defines specific metrics and measures that quantify these dimensions and enable objective evaluation and comparison of IoT systems.

1) Reliability Dimension Performance Requirement and Metrics: Reliability is a fundamental requirement for IoT performance, as unreliable components or services, such as processing, transmission, and sensing can lead to significant system failures, delays, and loss of data or communication. These issues have profound implications for IoT systems' overall performance and stability. Given the emerging nature of IoT technologies, it is essential to define the concept of reliability clearly within this context. Unlike fields such as engineering and software engineering, where reliability is well-established, there remains no universally agreed-upon definition specific to IoT [77].

According to study [78], reliability can be defined as the probability that a component or system will meet specific performance standards by yielding correct output over a desired period under given environmental conditions. In essence, reliability encompasses the study of system failures, their causes, mitigation strategies, and methods for failure prevention.

Since IoT systems consist of hardware and software components that often interact autonomously, human factors must also be considered when evaluating reliability. Thus, IoT reliability is influenced by hardware failure rates and software robustness, standardization challenges, and human interaction [78].

In study [79], the author identifies four essential requirements for achieving reliability in IoT devices:

- Performing a required function.
- Performing without failure.
- Operating under stated conditions.
- Operating for a specified period of time.

Building on this, Mavrogiorgou et al. [18] highlight that when specifying and designing for reliability, it is essential to define the expected conditions of use, what constitutes proper operation, and what qualifies as a failure. They emphasize the importance of clearly describing the system's functionality, the operational environment, and the timescale for assessing how well the system meets its intended specifications. Similarly, the author in study [80] emphasizes that reliability should be understood as the consistent performance of a device or system over a specified period.

Overall, reliability in IoT requires a multifaceted approach that integrates hardware resilience, software robustness, human factors, and standardization efforts to ensure sustainable system performance. To assess and improve IoT reliability, it is necessary to adopt specific metrics and measures that quantify this dimension.

Reliability is typically denoted by R(t) and can be measured using several metrics [77] [81] [82] [83]. Key metrics include:

- Mean Time Between Failures (MTBF)
- Mean Time to Failure (MTTF)
- Maintenance-Free Operating Period (MFOP)
- Maintainability
- Availability
- Failure Rate

One of the key metrics for reliability is Availability, which represents the probability that a system will operate correctly during a given period. It is calculated using the following Eq. (1):

$$A = \frac{MTTF}{MTTF + MTTR} \tag{1}$$

Where: MTTF is the Mean Time to Failure and MTTR is the Mean Time to Repair.

From the Eq. (1), it can be seen that a higher MTTF leads to higher reliability and availability. However, high availability does not always equate to high reliability. If the system is repaired quickly, with a low MTTR, it may maintain availability, but this does not necessarily reflect the system's overall reliability. Reliability can also be measured in different ways depending on the system's recovery mechanism:

- For systems with no recovery mechanism, the system cannot repair itself once a failure occurs, and operation stops until manually restored. In such cases, MTTF is used to measure reliability, as the system's availability and reliability are the same based solely on the time it operates without failure before a breakdown [81], and can be calculated as Eq. (2) illustrated:

  $$\lambda = \frac{1}{MTTF} \tag{2}$$

  where λ represents the failure rate, defined as the expected number of failures per unit time.

- For a system that can be maintained, reliability is measured by the MTBF, calculated as Eq. (3):

  $$\lambda = \frac{1}{MTBF} \tag{3}$$

Finally, to quantitatively system reliability over time, the reliability function R(t) is introduced in Eq. (4):

$$R(t) = e^{-\lambda t} \tag{4}$$

This function provides a formal means to describe the probability that a system or component will continue to perform without failure up to a given time t, following an exponential decay pattern. This formulation is commonly used to represent the reliability of individual components under the assumption of random, time-independent failures. However,

IoT systems typically have multiple interdependent elements, including hardware, software, and human interaction components. Therefore, Eq. (5) extends this concept by aggregating the reliabilities of these distinct elements to estimate the overall system reliability, $R_{\mathrm{S}}(t)$.

$$R_s(t) = R_{HW}(t) + R_{SF}(t) + R_H(t) \tag{5}$$

Each component reliability, $R_{\mathrm{HW}}(t)$ for hardware, $R_{\mathrm{SF}}(t)$ for software, and $R_{\mathrm{H}}(t)$ for human factors, can individually be modeled using the exponential form described in Eq. (4). Thus, Eq. (5) highlights that the system's reliability depends on the combined contribution of its key parts, each following its failure behavior over time [81].

2) Security Dimension Performance Requirement and Metrics: Security has become a significant concern that significantly affects the performance of IoT networks, particularly as the number and sophistication of attacks continue to grow. According to [84], IoT networks are inherently more vulnerable than traditional networks due to the unique attributes of IoT devices and the communication protocols they employ. For instance, IoT devices are often equipped with low-power microcontrollers and limited battery capacities, making them susceptible to resource exhaustion attacks. Moreover, they communicate over protocols such as GSM, Bluetooth, Wi-Fi, and ZigBee, which are more prone to attacks.

Security measures in IoT systems aim to reduce the probability of successful attacks and minimize security risks. A secure system ensures that unauthorized access is prevented, resources are protected, and operational integrity is maintained. By preventing malicious actors from accessing or exploiting system resources, the IoT system can continue to perform its tasks efficiently and reliably. Attacks such as Denial of Service (DoS) or resource exploitation can severely degrade system performance by causing system failures or slowing down operations through the exhaustion of memory, processing power, or storage. Consequently, maintaining security is critical to ensuring IoT systems function perfectly while balancing the trade-off between security and system performance [85].

To foster IoT security, Aman et al. [86] outlined several essential mechanisms that can be applied:

- All IoT devices operating within a network should run authorized and verified software.
- Devices must be authenticated to verify their legitimacy before transmitting or receiving data.
- Packet filtering via firewalls at the device level is recommended to compensate for limited computational and memory capacities.
- Regular updates and security patches must be applied to ensure protection against newly discovered vulnerabilities.

For optimal performance of IoT systems, applications and services must be secured, user privacy must be safeguarded, and threats such as spoofing and data manipulation must be prevented. Furthermore, IoT systems should operate independently without overreliance on external systems to maintain resilience [87].

Several fundamental security measures must be enforced across IoT ecosystems, including integrity, confidentiality, and authentication [82], [86], [87].

Confidentiality is a fundamental security measure that ensures data is accessible only to authorized users [87]. It protects against unauthorized interception or access to sensitive information transmitted between IoT devices [88]. Encryption and access validation mechanisms are essential to enforce confidentiality [89]. For example, sensor nodes must prevent neighboring nodes from accessing collected data, and RFID tags must safeguard sensitive information from unauthorized readers [87].

Integrity ensures that data remains consistent, accurate, and unaltered during transmission or storage, protecting against tampering by malicious users or software [86].

Authenticity ensures the data source is legitimate and trustworthy [87], [90]. Authentication processes must be implemented at every layer of the IoT architecture to prevent unauthorized nodes from injecting false information. For instance, sensor nodes must authenticate themselves at the device layer to avoid DoS attacks caused by rogue devices [91]. Robust authentication mechanisms are critical for maintaining system security across all layers.

IoT systems must carefully balance privacy, confidentiality, integrity, authenticity, and performance trade-offs without introducing unnecessary dependencies or vulnerabilities [86]. Strengthening these security measures is vital to safeguarding IoT ecosystems and ensuring their resilient, efficient, and reliable operation.

3) Scalability Dimension Performance Requirement and Metrics: Due to the rapid expansion of IoT technologies and the enormous volume of data generated by these devices, it has become imperative to develop strategies for accommodating this massive scale without necessitating a complete reengineering of existing systems. **Scalability** is a fundamental characteristic of any system that must manage an increasing workload efficiently; a lack of scalability can lead to degraded performance, increased latency, inefficient resource consumption, and poor utilization of available infrastructure. Achieving scalability presents significant challenges, particularly as a single IoT application often connects to many heterogeneous devices. Thus, extendable and flexible operations are essential to manage the distribution and functionality of these devices effectively [86].

According to study [92], scalability is defined as the ability of a system or device to adapt to environmental changes and meet future demands without compromising performance. Furthermore, scalability is recognized as an integral component of the broader performance requirements for IoT services, which places increased pressure on researchers and developers to devise solutions capable of handling the vast and growing volumes of data [93]. Scalability can manifest at both the hardware and software levels: horizontal scalability involves expanding the network by adding additional hardware devices or software entities, thereby distributing the workload across a broader system, whereas vertical scalability refers to enhancing the capabilities of existing devices or programs by integrating additional resources, such as computational power or storage capacity [94].

For optimal performance, it is essential to implement scalable solutions capable of managing millions of users and service requests simultaneously. Several researchers have explored methods for evaluating and measuring scalability in this context. One commonly used method involves assessing the system's latency and throughput under varying loads. Ideally, in a scalable system, latency remains stable even as the number of servers increases. In contrast, throughput proportionally increases with the addition of servers, meaning the system is able to process more requests concurrently [95]. Another scalability metric discussed in [96] evaluates the system's ability to dynamically increase the number of software instances to meet the rising demand for services. Importantly, scalable systems are expected to maintain the same average response time and consistent QoS regardless of the volume of service requests, ensuring reliability even under heavy loads. Thus, scalability is essential for supporting the expanding IoT ecosystem and a critical determinant of a system's long-term success and performance stability.

4) Service Quality Dimension Performance Requirement and Metrics: The quality of IoT systems plays a pivotal role in ensuring overall system performance and achieving the required QoS levels. However, maintaining high quality across IoT ecosystems presents a significant challenge due to the heterogeneity of devices, networks, and platforms. To address these complexities, it is essential to establish a comprehensive framework capable of evaluating each component individually and verifying whether it meets its expected performance and output standards.

QoS in IoT can be broadly defined as the network's ability to deliver an appropriate level of service to meet the specific needs of applications and users [97]. However, QoS requirements in IoT environments are highly variable and largely depend on the intended use case and system architecture. As outlined in [60], QoS expectations can typically be classified into three categories:

- No QoS: Best-effort service with no formal guarantees on performance or delivery.
- Differentiated Services (Soft QoS): Services that prioritize traffic based on application needs but do not guarantee strict performance standards.
- Guaranteed Services (Hard QoS): Services that provide strict guarantees for performance metrics such as delay, bandwidth, and reliability.

Quality and performance are inherently intertwined in IoT systems. While performance refers to the measurable behavior of the system (e.g., response time, throughput), quality encompasses broader aspects such as reliability, user satisfaction, and adherence to service-level agreements. Therefore, achieving high-quality standards is a prerequisite for attaining optimal system performance. In this research, quality was considered a foundational dimension that directly impacts the ability to optimize the IoT system's overall performance and user experience.

QoS requirements in IoT environments vary significantly depending on the specific needs of the system and the nature of the applications involved. To ensure that appropriate service levels are delivered, it is crucial to implement targeted QoS techniques at each layer of the IoT architecture. Each layer has distinct QoS metrics and parameters that contribute to determining the overall service quality.

According to study [97] [60] [98], the quality parameters in IoT can be classified based on architecture layers:

1) QoS at the Application Layer, this layer focuses on application-specific requirements related to the behavior and context of the devices and users:
   - Location and Mobility
   - Sampling Parameters
   - Time Synchronization
2) QoS at the Support Layer, ensures efficient management of computational and storage resources across distributed infrastructures (cloud, fog, edge):
   - Load Balancing
   - Response Time
   - Resource Orchestration
3) QoS at the Network Layer, addresses the performance of data transmission and communication reliability:
   - Jitter
   - Bandwidth
   - Delay
   - Throughput
   - Packet Delivery Time
   - Packet Loss Rate
4) QoS at the Sensing Layer, the sensing layer evaluates the quality and efficiency of data collection and initial processing:
   - Accuracy of Service and Information
   - Cost of Network Deployment and Service Delivery
   - Service Attributes (Priority, Availability, Response Time, Delay, and Load)

Ensuring high-quality service delivery in IoT systems requires a comprehensive understanding of the QoS requirements at each architectural layer. By systematically addressing quality parameters across the application, support, network, and sensing layers, it becomes possible to optimize performance, enhance user satisfaction, and maintain the resilience of IoT ecosystems. This layered approach is foundational to achieving holistic performance optimization in modern IoT environments.

5) Energy Efficiency Dimension Performance Requirement and Metrics: Energy constraints in the IoT ecosystem, particularly regarding limited battery capacities and energy harvesting capabilities, make energy efficiency a critical requirement for maintaining system performance. Inefficient energy management directly impacts core system attributes such as reliability, security, and scalability. Therefore, optimizing energy efficiency is a major research priority in the development of IoT technologies.

Energy efficiency in IoT systems is commonly defined as the number of bits successfully transmitted per joule of consumed energy [99]. It can be mathematically expressed by Eq. (6):

$$\text{Energy Efficiency (EE)} = \frac{\text{Number of Transmitted Bits}}{\text{Energy Consumption (EC) in Joules}} \quad (6)$$

where Energy Consumption (EC) represents the total amount of energy expended by the device during its operation, typically measured in joules. A higher energy efficiency value indicates more effective use of energy resources.

High energy efficiency is crucial for energy-constrained domains such as smart industrial systems, implantable medical devices, and remote environmental monitoring, where continuous maintenance or battery replacement is impractical. For less critical applications, such as consumer sports wearables, moderate energy efficiency levels may be sufficient. Supplying sufficient energy to operate IoT systems autonomously, without degrading other performance requirements, remains a significant implementation challenge. Given the pivotal role of energy in battery-operated IoT devices, extensive research efforts have focused on developing energy-saving mechanisms at both the hardware and system levels.

Energy management is a primary consideration in IoT device design. Strict control over device power consumption is necessary to achieve energy efficiency and preserve the expected battery lifetime. Three key metrics are typically employed to evaluate energy efficiency:

- Energy Consumption (EC): The total energy consumed by the device over its operating period, measured in joules.
- Power Consumption (PC): The rate at which the device uses energy during operation, typically measured in watts.
- Battery Lifetime: The operational duration of the device before requiring battery replacement or recharging, typically measured in hours, days, or years, depending on the application.

Battery lifetime requirements in IoT systems vary widely depending on the application. For instance, consumer wearables may operate for a few days, whereas sensor nodes deployed in remote or hazardous environments are expected to function autonomously for several years. Although advancements in low-power electronics have contributed to reducing individual component energy usage, a holistic understanding of system-wide energy consumption and power profiles remains essential for optimizing overall energy efficiency and extending device operational lifetimes.

E. Technologies Dimension Performance Requirement and Metrics

IoT is an integration of multiple **technologies** working together. Due to the diverse characteristics of IoT systems and the distinct purposes and functions of each architectural layer, various enabling technologies have been proposed in the literature to meet the specific requirements of each layer. IoT deployment in real-world environments is made possible only through the collaboration of these enabling technologies, which collectively enhance overall system performance. Accordingly, this section is dedicated to discussing the key enabling technologies that support and optimize the functionality of IoT systems.

According to study [100], the techniques utilized in IoT systems are categorized into three phases based on their functional roles:

1) Collection Phase: Involves real-time sensing, data gathering, and constructing a comprehensive view of the physical environment using technologies such as RFID, sensors, and NFC.
2) Transmission Phase: Focuses on delivering the collected data to external applications and servers through communication technologies such as wireless networks, satellite links, and Ethernet.
3) Processing, Management, and Utilization Phase: Responsible for analyzing and processing the incoming data streams, forwarding information to applications and services, and generating feedback to control actuators or services. This phase also encompasses critical tasks such as device discovery and management, data filtering, aggregation, analysis, and intelligent decision-making.

Similarly, [101] classified IoT enabling technologies into three functional categories:

1) Technologies responsible for acquiring information.
2) Technologies responsible for processing and managing relevant information.
3) Technologies aimed at enhancing privacy and security.

The first two categories represent the fundamental building blocks necessary for imparting intelligence to ”things,” distinguishing the IoT from the traditional Internet. In contrast, the third category, privacy and security technologies, is not a functional layer but a critical prerequisite for IoT adoption. Without robust privacy and security mechanisms, IoT systems' widespread deployment and acceptance would be severely constrained [102].

IoT integrates a heterogeneous combination of hardware, software, and communication system technologies. These diverse technologies must be effectively adapted and coordinated to ensure IoT systems' reliability, security, scalability, and energy efficiency. Such adaptation directly enhances the overall performance and resilience of IoT deployments. In this thesis, the enabling technologies are broadly classified into the following categories:

- Hardware and Wireless Technologies
- Software and Algorithmic Solutions
- Machine Intelligence Techniques
- Telecommunication Systems

Table II summarizes the key enabling technologies relevant to the IoT ecosystem, classified based on their technological type, hardware and wireless technologies, software and algorithms, machine intelligence, and telecommunication systems. The table also maps these technologies to their respective contributions across five critical performance dimensions: reliability,

TABLE II. MAPPING OF ENABLING TECHNOLOGIES TO MULTI-DIMENSIONAL IOT PERFORMANCE REQUIREMENTS

	Type	Multi-dimensional requirements for performance optimization				
		Reliability	**Scalability**	**Security**	**Quality**	**Energy**
Enabling Technologies	Hardware and Wireless	RFID, 6LoWPAN	ZigBee, Dash7, 6LoWPAN, RFID	RFID, NFC, 6LoWPAN	Cognitive Radio, Wireless Optics, CDMA / Spread Spectrum	Microcontrollers (UNB), LoRa, LPWAN, Arduino with ZigBee, WiFi, Bluetooth
	Software and Algorithms	SDN	Blockchain, ICN, Virtualization Algorithms	Cipher Algorithms, Blockchain, Steganography	Call Admission Control (CAC)	–
	Machine Intelligence	Anomaly Detection	SDN	SDN	SDN	–
	Telecommunication Systems	–	5G, 6G	5G	5G/6G	5G, 6G

scalability, security, quality assurance, and energy efficiency. This comprehensive classification illustrates how each technology supports multi-dimensional optimization within IoT systems.

F. Novelty and Positioning of the Proposed Framework

While numerous studies have explored IoT performance optimization from isolated perspectives—such as microservice-based reliability, fault-tolerant mechanisms, lightweight security techniques, and device/network-level enhancements—these contributions remain largely fragmented across architectural layers and performance dimensions. Existing works typically address one layer at a time, or optimize a single performance requirement without acknowledging its interaction with other dimensions.

The proposed framework distinguishes itself from prior studies by offering a unified, multi-layer perspective that systematically integrates IoT architectural layers (device, network, support, and application) with multi-dimensional performance attributes (reliability, security, scalability, quality, and energy efficiency). Unlike previous reviews, which categorize solutions based solely on technology type or problem focus, the framework explicitly maps where each performance factor originates, how it propagates across layers, and which components or mechanisms influence it.

This holistic integration represents the primary novelty of the study. It enables a cross-layer understanding of IoT performance—an aspect not collectively addressed in existing literature—and provides a conceptual structure that researchers can use to analyze, compare, and design solutions more systematically. The accompanying taxonomy further reinforces this contribution by revealing performance-impacting components across layers and highlighting interdependencies that were previously treated in isolation.

IV. TAXONOMY OF IOT PERFORMANCE OPTIMIZATION COMPONENTS

Previous framework layers address the IoT multidimensional performance optimization problem and present various dimensions of requirements that are related to the IoT performance. This layer of the framework provides a taxonomy for the classification of various performance-impact components across multi-dimensional requirements and the main architectural layers of IoT systems. Furthermore, each component is analyzed based on the specific performance dimensions it targets, such as reliability, security, scalability, quality, and energy efficiency. The structured taxonomy and mapping of performance-impact components is presented in Table III. This mapping clearly explains how critical performance dimensions, scalability, quality, reliability, energy efficiency, and security are addressed across the IoT network layer architecture. The table taxonomy outlines the essential components within each layer (i.e., application, support, network, and device layers) and identifies the most relevant metrics for evaluating performance within those components. Besides, each architectural layer is decomposed into a key performance service or tool, allowing optimization-related performance components to be mapped with greater granularity.

V. PROMINENT SUGGESTED SOLUTIONS

Given the continuous evolution of IoT systems and their varying levels of complexity, exhaustively capturing and detailing all potential solutions is inherently difficult. However, this section seeks to synthesize the most salient solutions identified by researchers throughout the previously reviewed literature. The Table IV outlines these proposed approaches, categorizing them based on their contribution to critical performance requirements: Reliability, Security, Scalability, Quality, and Energy Efficiency. The following section discusses the key insights derived from these findings and highlights the implications for IoT performance optimization research.

VI. DISCUSSION AND KEY INSIGHTS

The findings of this study indicate that IoT performance research remains highly fragmented across architectural layers and performance dimensions. While numerous studies propose solutions targeting reliability, security, scalability, quality, or energy efficiency, these contributions are often isolated and optimized within a single layer or for a single performance requirement. This fragmentation limits the ability of researchers and practitioners to understand IoT performance holistically and to design solutions that address cross-layer interactions.

The literature review further shows a clear imbalance in research efforts. Most contributions focus on the network and device layers, particularly on routing, fault tolerance, cryptography, and lightweight service mechanisms. In contrast, the support and application layers receive less attention despite their growing role in enabling cloud–fog–edge intelligence, policy enforcement, orchestration, and application-level QoS. This gap highlights the need for more research

TABLE III. A TAXONOMY OF MULTI-DIMENSIONAL PERFORMANCE COMPONENTS ACROSS IOT ARCHITECTURE LAYERS

Layer	Impact Component, Tools, Service	Reliability	Scalability	Security	Quality	Energy Efficiency
Application Layer	Software Design and Engineering	Availability, Fault Tolerance, MTTR, MTTF	Response Time, Elasticity, Modularity, Throughput under Load	Integrity, Confidentiality, Authenticity, Privacy	Code Quality, Test Coverage, Reusability, Design Flexibility	Battery Life, Power Consumption
	Policies	Availability, Fault Tolerance	Policy Mgmt., Scalability, Elastic Demand Handling	Integrity, Confidentiality	Policy Completeness, Policy Failure Rate, Policy Rollback Time	Power Consumption per Operation
	Application Protocols	Availability, Fault Tolerance	Low Protocol Overhead, Latency Stability, Concurrent Support	Integrity, Confidentiality, Authenticity	Error Resilience, Latency for Data Delivery, Data Synchronization Quality	Energy Consumption during Idle and Active States
Support Layer	Resource Orchestrator	Fault-Tolerant, Redundancy	Resource Allocation, Task Scheduling, Concurrent Tasks Supported	Integrity, Confidentiality, Authentication	Resource Utilization Accuracy, Orchestration Decision Accuracy, SLA Compliance	Power Utilization Efficiency, Energy Management
	Cloud/Fog/Edge Integration	Availability, Fault Tolerance	Load Balancing, Elastic Resource Scaling	Integrity, Privacy	Interoperability, Data Consistency	Power Consumption for Data Processing
	Data (stored)	Availability, Fault Tolerance	Storage Access Scalability, Query Response Time	Integrity, Privacy, Confidentiality	Data Integrity, Latency of Data Access	Data Storage Power Efficiency
	Software/Hardware Components	Availability, Fault Tolerance	Component Modularity and Upgrade Flexibility, Resource Adaptability	Integrity, Authentication	Compatibility, Maintainability	Battery Efficiency
Network Layer	Routing Protocol	Availability, Fault Tolerance	Network Overhead, Convergence Time	Integrity, Confidentiality, Authentication	Packet Delivery Ratio (PDR), Latency, Stability	Energy Battery Life, Energy Consumption
	Internetworking Protocols	Availability, Fault Tolerance	Network Topology Scalability, Overhead, Interoperability	Integrity, Privacy, Authentication	Latency, Jitter, Channel Load, Packet Loss Rate	Transmission Energy Efficiency, Energy per Bit
	Flow Control	Availability, Fault-Tolerant, Error-Free Transmission	Load Handling Capacity	Integrity, Confidentiality	Buffer Size, Flow Stability, Admission Delay	Packet Processing Energy, Network Energy Efficiency
	Admission and Congestion Control Protocols	Availability, Fault Tolerance	Scalability with Flows, Queue Efficiency	Confidentiality, Authenticity	Queue Delay, QoS Maintenance, Rate of Packet Loss, Congestion Avoidance Efficiency	Power Consumption
	Addressing Protocols	Availability, Fault Tolerance	Address Allocation Efficiency, Address Space Utilization	Integrity, Confidentiality, Authentication	Resolution Delay, Address Uniqueness, Throughput	Power Consumption for Address Assignment
Device Layer	Communication and Signaling Protocols	Availability, Fault Tolerant	Protocol Overhead, Concurrent Device Support, Signal Range Expansion	Authentication, Confidentiality	Signal Strength Stability, Message Delivery Success Rate	Power Consumption for Transmission
	MAC and Access Control Protocol	Availability, Fault Tolerance	Access Contention Handling, Dynamic Node Joining Support	Integrity, Confidentiality, Authentication	MAC Delay, Packet Collision Rate	Energy Use for Access Control, Power Efficiency
	Error Correction and Detection	Availability, Fault Tolerance	Error Handling Scalability	Integrity, Privacy	Error Detection Rate, Detection Latency, Recovery Time from Errors	Power Consumption for Error Handling
	Data Collection and Buffering	Availability, Fault Tolerance	Buffer Scalability, Data Throughput under Load	Integrity, Privacy	Data Aggregation Efficiency, Collection Delay, Buffer Overflow Rate	Energy per Byte, Power during Data Collection
	Sensor Hardware and Software	Availability, Fault Tolerance	Device Resource Scalability, Firmware Update Flexibility	Authentication, Identification	Sensor Accuracy, Signal Quality	Energy Consumption per Sensor, Sleep Mode Power, Battery Life

into performance-aware service orchestration, data lifecycle management, and application-level adaptability.

The proposed multi-dimensional performance framework addresses these gaps by providing a unified structure that links IoT architectural layers with key performance dimensions and measurable metrics. Unlike existing studies that treat performance dimensions independently, the framework emphasizes their interdependence, illustrating how improvements at one layer (e.g., routing efficiency) may impact performance attributes at other layers (e.g., energy efficiency or QoS). The framework also clarifies the role of enabling technologies—such as virtualization, 5G/6G, blockchain, and IoT-specific protocols—in optimizing performance across the entire IoT ecosystem.

The taxonomy further contributes to the field by classifying performance-impact components across layers, revealing patterns and research priorities. For example, reliability-related components are heavily explored at the device and network layers, while quality-oriented solutions appear mostly at the application layer. Energy efficiency spans multiple layers, but most optimizations remain hardware-centric rather than system-wide. These patterns underscore the need for integrated, cross-layer optimization strategies.

Overall, the combined framework and taxonomy provide

TABLE IV. SUGGESTED SOLUTION APPROACHES

Solution approaches			Design requirements				
Techniques	**Class**	**Samples**	**Reliability**	**Security**	**Scalability**	**Quality**	**Energy efficiency**
Redundant design	Hardware redundancy	Triple modular redundancy	**X**	**X**		**X**	**X**
	Software redundancy	Multiversion programming					
	Information redundancy	Correction methods					
	Time redundancy	Same operation multiple times					
	Data redundancy	Keeping data in multiple locations					
ML tools	Classification	Naive Bayes	**X**	**X**		**X**	**X**
	Clustering	K-means					
	Regression	Linear regression					
Mathematical-based model	Deterministic	–	**X**	**X**	**X**	**X**	**X**
	Stochastic	–					
Numerical and computational method	Newton method	–	**X**	**X**	**X**	**X**	**X**
	Simpson rule	–					
	Euler method	–					
	Trapezoidal rule	–					
Statistical-based model	Parametric techniques	Gaussian, Non-Gaussian	**X**	**X**	**X**	**X**	**X**
	Non-parametric techniques	Kernel, Histogram					
Trust-based methods	Policy-based	–	**X**	**X**			**X**
	Recommendation-based	–					
	Reputation and feedback-based	–					
Data analysis	Descriptive	–			**X**	**X**	**X**
	Predictive	–					
	Prescriptive	–					
	Diagnostic	–					
Context-aware systems	Hardware context-awareness	–	**X**	**X**	**X**	**X**	**X**
	Software context-awareness	–					
Microservice architecture	Decomposition patterns	Sidecar	**X**	**X**	**X**	**X**	**X**
	Integration patterns	Aggregator					
	Observability patterns	Log aggregation					
	Cross-cutting concern patterns	Circuit breaker					
	Database patterns	Saga					
Optimization model	Linear optimization techniques	Integer, continuous, mixed-integer	**X**	**X**	**X**	**X**	**X**
	Nonlinear optimization techniques	–					
AI	Neural networks (NN)	–	**X**	**X**		**X**	**X**
	Fuzzy logic	–					
Swarm intelligence algorithms	Genetic algorithms (GA)	–	**X**				**X**
	Ant colony optimization (ACO)						
	Particle swarm optimization (PSO)						
	Differential evolution (DE)						
	Artificial bee colony (ABC)						
	Glowworm swarm optimization (GSO)						
	Cuckoo search algorithm (CSA)						
Ontology-based technique	Objective	–	**X**		**X**		**X**
	Subjective	–					

a foundation for future IoT performance research by 1) offering a structured view of performance-related components, 2) enabling systematic comparison of existing solutions, and 3) identifying gaps and opportunities for multi-layer optimization. This structured analytical view represents the primary contribution of this study and serves as a roadmap for designing next-generation IoT systems that balance reliability, security, energy, scalability, and quality in a unified manner.

VII. CONCLUSION

This paper successfully presented a comprehensive performance optimization framework designed for application across all layers of the IoT architecture. The framework serves as a critical foundation for identifying performance-related challenges and systematically guiding the development of tailored optimization solutions. While the overall design is holistic, a detailed taxonomy of existing optimization components was also introduced, synthesized from an extensive literature review. These components were classified according to five critical performance dimensions: reliability, security, scalability, quality assurance, and energy efficiency. Each dimension was analyzed by detailing its unique challenges and the specific metrics required for practical evaluation.

Additionally, the paper highlighted the vital role of enabling technologies—spanning hardware, software, machine intelligence, and telecommunication systems—in supporting multi-dimensional performance optimization. The integration of these technologies is essential for realizing scalable, secure, and efficient IoT environments. The conceptual model, perfor-

mance taxonomy, and technological mapping developed in this paper collectively lay the groundwork for future research and methodical system design.

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REFERENCES

[1] F. Zantalis, G. Koulouras, S. Karabetsos, and D. Kandris, "A review of machine learning and iot in smart transportation," *Future Internet*, vol. 11, no. 4, p. 94, 2019.

[2] M. Swan, "Sensor mania! the internet of things, wearable computing, objective metrics, and the quantified self 2.0," *Journal of Sensor and Actuator networks*, vol. 1, no. 3, pp. 217–253, 2012.

[3] D. Evans, "The internet of things how the next evolution of the internet is changing everything," *CISCO white paper*, vol. 1, pp. 1–11, 2011.

[4] S. Rudrakar and P. Rughani, "Iot based agriculture (ag-iot): A detailed study on architecture, security and forensics," *Information Processing in Agriculture*, 2023.

[5] A. Rayes and S. Salam, "The things in iot: Sensors and actuators," in *Internet of Things From Hype to Reality*. Springer, 2022, pp. 63–82.

[6] N. K. Saini, "Trust factor and reliability-over-a-period-of-time as key differentiators in iot enabled services," in *2016 International Conference on Internet of Things and Applications (IOTA)*. IEEE, 2016, pp. 411–414.

[7] A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, "Internet of things: A survey on enabling technologies, protocols, and applications," *IEEE communications surveys & tutorials*, vol. 17, no. 4, pp. 2347–2376, 2015.

[8] S. J. Moore, C. D. Nugent, S. Zhang, and I. Cleland, "Iot reliability: a review leading to 5 key research directions," *CCF Transactions on Pervasive Computing and Interaction*, vol. 2, no. 3, pp. 147–163, 2020.

[9] M. A. da Cruz, J. J. Rodrigues, A. K. Sangaiah, J. Al-Muhtadi, and V. Korotaev, "Performance evaluation of iot middleware," *Journal of Network and Computer Applications*, vol. 109, pp. 53–65, 2018.

[10] Z. Menter, W. Z. Tee, and R. Dave, "Application of machine learning-based pattern recognition in iot devices," in *Proceedings of International Conference on Communication and Computational Technologies*. Springer, 2021, pp. 669–689.

[11] C. Santana, L. Andrade, F. C. Delicato, and C. Prazeres, "Increasing the availability of iot applications with reactive microservices," *Service Oriented Computing and Applications*, vol. 15, no. 2, pp. 109–126, 2021.

[12] L. M. e. Martins, F. L. d. C. Filho, R. T. d. S. Júnior, W. F. Giozza, and J. P. C. da Costa, "Increasing the dependability of iot middleware with cloud computing and microservices," in *Companion Proceedings of the10th International Conference on Utility and Cloud Computing*, 2017, pp. 203–208.

[13] G. Aquino, R. Queiroz, G. Merrett, and B. Al-Hashimi, "The circuit breaker pattern targeted to future iot applications," in *International Conference on Service-Oriented Computing*. Springer, 2019, pp. 390–396.

[14] N. Mohamed, J. Al-Jaroodi, and I. Jawhar, "Towards fault tolerant fog computing for iot-based smart city applications," in *2019 IEEE 9th Annual Computing and Communication Workshop and Conference (CCWC)*. IEEE, 2019, pp. 0752–0757.

[15] R. K. Behera, K. H. K. Reddy, and D. S. Roy, "Reliability modelling of service oriented internet of things," in *2015 4th International Conference on Reliability, Infocom Technologies and Optimization (ICRITO)(Trends and Future Directions)*. IEEE, 2015, pp. 1–6.

[16] T. N. Gia, A.-M. Rahmani, T. Westerlund, P. Liljeberg, and H. Tenhunen, "Fault tolerant and scalable iot-based architecture for health monitoring," in *2015 IEEE Sensors Applications Symposium (SAS)*. IEEE, 2015, pp. 1–6.

[17] M. Z. Hasan and F. Al-Turjman, "Optimizing multipath routing with guaranteed fault tolerance in internet of things," *IEEE Sensors Journal*, vol. 17, no. 19, pp. 6463–6473, 2017.

[18] A. Mavrogiorgou, A. Kiourtis, C. Symvoulidis, and D. Kyriazis, "Capturing the reliability of unknown devices in the iot world," in *2018 Fifth International Conference on Internet of Things: Systems, Management and Security*. IEEE, 2018, pp. 62–69.

[19] T. T. Zin, P. Tin, and H. Hama, "Reliability and availability measures for internet of things consumer world perspectives," in *2016 IEEE 5th Global Conference on Consumer Electronics*. IEEE, 2016, pp. 1–2.

[20] K. Periyasamy, V. Alagar, and K. Wan, "Dependable design for elderly health care," in *2017 Federated Conference on Computer Science and Information Systems (FedCSIS)*. IEEE, 2017, pp. 803–806.

[21] A. Celesti, L. Carnevale, A. Galletta, M. Fazio, and M. Villari, "A watchdog service making container-based micro-services reliable in iot clouds," in *2017 IEEE 5th International Conference on Future Internet of Things and Cloud (FiCloud)*. IEEE, 2017, pp. 372–378.

[22] A. Power and G. Kotonya, "A microservices architecture for reactive and proactive fault tolerance in iot systems," in *2018 IEEE 19th International Symposium on" A World of Wireless, Mobile and Multimedia Networks"(WoWMoM)*. IEEE, 2018, pp. 588–599.

[23] I. Kopestenski and P. Van Roy, "Erlang as an enabling technology for resilient general-purpose applications on edge iot networks," in *Proceedings of the 18th ACM SIGPLAN International Workshop on Erlang*, 2019, pp. 1–12.

[24] P. Vedavalli and C. Deepak, "Enhancing reliability and fault tolerance in iot," in *2020 International Conference on Artificial Intelligence and Signal Processing (AISP)*. IEEE, 2020, pp. 1–6.

[25] W.-T. Lee and P.-J. Law, "A case study in applying security design patterns for iot software system," in *2017 international conference on applied system innovation (ICASI)*. IEEE, 2017, pp. 1162–1165.

[26] E. B. Fernandez, H. Washizaki, N. Yoshioka, and T. Okubo, "The design of secure iot applications using patterns: State of the art and directions for research," *Internet of Things*, vol. 15, p. 100408, 2021.

[27] I. Ali and M. Asif, "Applying security patterns for authorization of users in iot based applications," in *2018 International Conference on Engineering and Emerging Technologies (ICEET)*. IEEE, 2018, pp. 1–5.

[28] Z. B. Celik, G. Tan, and P. D. McDaniel, "Iotguard: Dynamic enforcement of security and safety policy in commodity iot." in *NDSS*, 2019.

[29] I. Cvitić, D. Peraković, M. Periša, and B. Gupta, "Ensemble machine learning approach for classification of iot devices in smart home," *International Journal of Machine Learning and Cybernetics*, vol. 12, no. 11, pp. 3179–3202, 2021.

[30] N. Paul, W. B. Tesfay, D.-K. Kipker, M. Stelter, and S. Pape, "Assessing privacy policies of internet of things services," in *IFIP International Conference on ICT Systems Security and Privacy Protection*. Springer, 2018, pp. 156–169.

[31] S. A. Chaudhry, K. Yahya, F. Al-Turjman, and M.-H. Yang, "A secure and reliable device access control scheme for iot based sensor cloud systems," *IEEE Access*, vol. 8, pp. 139 244–139 254, 2020.

[32] M. Singh, M. Rajan, V. Shivraj, and P. Balamuralidhar, "Secure mqtt for internet of things (iot)," in *2015 fifth international conference on communication systems and network technologies*. IEEE, 2015, pp. 746–751.

[33] D. Nagothu, R. Xu, S. Y. Nikouei, and Y. Chen, "A microservice-enabled architecture for smart surveillance using blockchain technology," in *2018 IEEE international smart cities conference (ISC2)*. IEEE, 2018, pp. 1–4.

[34] A. A. Omala, A. S. Mbandu, K. D. Mutiria, C. Jin, and F. Li, "Provably secure heterogeneous access control scheme for wireless body area network," *Journal of Medical Systems*, vol. 42, no. 6, pp. 1–14, 2018.

[35] A. Strielkina, V. Kharchenko, and D. Uzun, "Availability models for healthcare iot systems: Classification and research considering attacks on vulnerabilities," in *2018 IEEE 9th international conference on dependable systems, services and technologies (DESSERT)*. IEEE, 2018, pp. 58–62.

[36] C. L. Stergiou, K. E. Psannis, and B. B. Gupta, "Iot-based big data secure management in the fog over a 6g wireless network," *IEEE Internet of Things Journal*, vol. 8, no. 7, pp. 5164–5171, 2021.

[37] C. Zhang, Y. Miao, Q. Xie, Y. Guo, H. Du, and X. Jia, "Privacy-preserving deduplication of sensor compressed data in distributed fog computing," *IEEE Transactions on Parallel and Distributed Systems*, vol. 33, no. 12, pp. 4176–4191, 2022.

[38] W. Jerbi, A. Guermazi, and H. Trabelsi, "A secure routing protocol in heterogeneous networks for internet of things," in *2020 International Wireless Communications and Mobile Computing (IWCMC)*. IEEE, 2020, pp. 571–576.

[39] ——, "Design and deployment of a security protocol to provide authentication services for connected objects," in *Proceedings of the 10th Euro-American Conference on Telematics and Information Systems*, 2020, pp. 1–6.

[40] M. Conti, P. Kaliyar, M. M. Rabbani, and S. Ranise, "Split: A secure and scalable rpl routing protocol for internet of things," in *2018 14th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*. IEEE, 2018, pp. 1–8.

[41] ——, "Attestation-enabled secure and scalable routing protocol for iot networks," *Ad Hoc Networks*, vol. 98, p. 102054, 2020.

[42] K. Haseeb, A. Almogren, N. Islam, I. Ud Din, and Z. Jan, "An energy-efficient and secure routing protocol for intrusion avoidance in iot-based wsn," *Energies*, vol. 12, no. 21, p. 4174, 2019.

[43] Y. He, G. Han, H. Wang, J. A. Ansere, and W. Zhang, "A sector-based random routing scheme for protecting the source location privacy in wsns for the internet of things," *Future Generation Computer Systems*, vol. 96, pp. 438–448, 2019.

[44] K. Quist-Aphetsi and M. C. Xenya, "Node to node secure data communication for iot devices using diffie-hellman, aes, and md5 cryptographic schemes," in *2019 International Conference on Cyber Security and Internet of Things (ICSIoT)*. IEEE, 2019, pp. 88–92.

[45] D. Dinculeană and X. Cheng, "Vulnerabilities and limitations of mqtt protocol used between iot devices," *Applied Sciences*, vol. 9, no. 5, p. 848, 2019.

[46] A. Cohen, A. Cohen, and O. Gurewitz, "Secured data gathering protocol for iot networks," in *International Symposium on Cyber Security Cryptography and Machine Learning*. Springer, 2018, pp. 129–143.

[47] H. Tao, M. Z. A. Bhuiyan, A. N. Abdalla, M. M. Hassan, J. M. Zain, and T. Hayajneh, "Secured data collection with hardware-based ciphers for iot-based healthcare," *IEEE Internet of Things Journal*, vol. 6, no. 1, pp. 410–420, 2018.

[48] M. S. Yousefpoor, E. Yousefpoor, H. Barati, A. Barati, A. Movaghar, and M. Hosseinzadeh, "Secure data aggregation methods and countermeasures against various attacks in wireless sensor networks: A comprehensive review," *Journal of Network and Computer Applications*, vol. 190, p. 103118, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1084804521001375

[49] A. Razzaq, "A systematic review on software architectures for iot systems and future direction to the adoption of microservices architecture," *SN Computer Science*, vol. 1, no. 6, pp. 1–30, 2020.

[50] A. El-Mougy, I. Al-Shiab, and M. Ibnkahla, "Scalable personalized iot networks," *Proceedings of the IEEE*, vol. 107, no. 4, pp. 695–710, 2019.

[51] I. Zyrianoff, F. Borelli, G. Biondi, A. Heideker, and C. Kamienski, "Scalability of real-time iot-based applications for smart cities," in *2018 IEEE Symposium on Computers and Communications (ISCC)*. IEEE, 2018, pp. 00 688–00 693.

[52] S. Busanelli, S. Cirani, L. Melegari, M. Picone, M. Rosa, and L. Veltri, "A sidecar object for the optimized communication between edge and cloud in internet of things applications," *Future Internet*, vol. 11, no. 7, p. 145, 2019.

[53] S. K. Mishra and A. Sarkar, "Service-oriented architecture for internet of things: a semantic approach," *Journal of King Saud University-Computer and Information Sciences*, 2021.

[54] H. Guo, J. Ren, D. Zhang, Y. Zhang, and J. Hu, "A scalable and manageable iot architecture based on transparent computing," *Journal of Parallel and Distributed Computing*, vol. 118, pp. 5–13, 2018.

[55] S. Verma and A. Bala, "Auto-scaling techniques for iot-based cloud applications: a review," *Cluster Computing*, vol. 24, no. 3, pp. 2425–2459, 2021.

[56] B. Sonkoly, D. Haja, B. Németh, M. Szalay, J. Czentye, R. Szabó, R. Ullah, B.-S. Kim, and L. Toka, "Scalable edge cloud platforms for iot services," *Journal of Network and Computer Applications*, vol. 170, p. 102785, 2020.

[57] E. Rojas, H. Hosseini, C. Gomez, D. Carrascal, and J. R. Cotrim, "Outperforming rpl with scalable routing based on meaningful mac addressing," *Ad Hoc Networks*, vol. 114, p. 102433, 2021.

[58] F. Li, S. Nastic, and S. Dustdar, "Data quality observation in pervasive environments," in *2012 IEEE 15th International Conference on Computational Science and Engineering*. IEEE, 2012, pp. 602–609.

[59] E. Al-Masri, "Qos-aware iiot microservices architecture," in *2018 IEEE International Conference on Industrial Internet (ICII)*. IEEE, 2018, pp. 171–172.

[60] G. White, V. Nallur, and S. Clarke, "Quality of service approaches in iot: A systematic mapping," *Journal of Systems and Software*, vol. 132, pp. 186–203, 2017.

[61] M. Singh and G. Baranwal, "Quality of service (qos) in internet of things," in *2018 3rd International Conference On Internet of Things: Smart Innovation and Usages (IoT-SIU)*. IEEE, 2018, pp. 1–6.

[62] M. Taneja, N. Jalodia, J. Byabazaire, A. Davy, and C. Olariu, "Smartherd management: A microservices-based fog computing–assisted iot platform towards data-driven smart dairy farming," *Software: practice and experience*, vol. 49, no. 7, pp. 1055–1078, 2019.

[63] M. Quwaider and Y. Shatnawi, "Congestion control model for securing internet of things data flow," *Ad Hoc Networks*, vol. 106, p. 102160, 2020.

[64] L. Yao, J.-Y. Shen, and W. H. Lim, "Real-time energy management optimization for smart household," in *2016 IEEE International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData)*. IEEE, 2016, pp. 20–26.

[65] S. Kim, C. Kim, and J. Kim, "Reliable smart energy iot-cloud service operation with container orchestration," in *2017 19th Asia-Pacific Network Operations and Management Symposium (APNOMS)*. IEEE, 2017, pp. 378–381.

[66] N.-T. Dinh and Y. Kim, "An efficient on-demand latency guaranteed interactive model for sensor-cloud," *IEEE Access*, vol. 6, pp. 68 596–68 611, 2018.

[67] Z. T. Al-Azez, A. Q. Lawey, T. E. El-Gorashi, and J. M. Elmirghani, "Energy efficient iot virtualization framework with passive optical access networks," in *2016 18th International Conference on Transparent Optical Networks (ICTON)*. IEEE, 2016, pp. 1–4.

[68] I. S. M. Isa, M. O. Musa, T. E. El-Gorashi, A. Q. Lawey, and J. M. Elmirghani, "Energy efficiency of fog computing health monitoring applications," in *2018 20th International Conference on Transparent Optical Networks (ICTON)*. IEEE, 2018, pp. 1–5.

[69] H. Q. Al-Shammari, A. Lawey, T. El-Gorashi, and J. M. Elmirghani, "Energy efficient service embedding in iot networks," in *2018 27th Wireless and Optical Communication Conference (WOCC)*. IEEE, 2018, pp. 1–5.

[70] N. Kaur and S. K. Sood, "An energy-efficient architecture for the internet of things (iot)," *IEEE Systems Journal*, vol. 11, no. 2, pp. 796–805, 2015.

[71] H. M. Al-Kadhim and H. S. Al-Raweshidy, "Energy efficient and reliable transport of data in cloud-based iot," *IEEE Access*, vol. 7, pp. 64 641–64 650, 2019.

[72] L. Lyu, C. Chen, S. Zhu, and X. Guan, "5g enabled codesign of energy-efficient transmission and estimation for industrial iot systems," *IEEE Transactions on Industrial Informatics*, vol. 14, no. 6, pp. 2690–2704, 2018.

[73] Y. Wang, W. Yang, X. Shang, J. Hu, Y. Huang, and Y. Cai, "Energy-efficient secure transmission for wireless powered internet of things with multiple power beacons," *IEEE Access*, vol. 6, pp. 75 086–75 098, 2018.

[74] A. Slalmi, H. Kharraz, R. Saadane, C. Hasna, A. Chehri, and G. Jeon, "Energy efficiency proposal for iot call admission control in 5g network," in *2019 15th International Conference on Signal-Image Technology & Internet-Based Systems (SITIS)*. IEEE, 2019, pp. 396–403.

[75] D. Purkovic, M. Hönsch, and T. R. M. K. Meyer, "An energy efficient communication protocol for low power, energy harvesting sensor modules," *IEEE Sensors Journal*, vol. 19, no. 2, pp. 701–714, 2018.

[76] S. Abbasian Dehkordi, K. Farajzadeh, J. Rezazadeh, R. Farahbakhsh, K. Sandrasegaran, and M. Abbasian Dehkordi, "A survey on data aggregation techniques in iot sensor networks," *Wireless Networks*, vol. 26, no. 2, pp. 1243–1263, February 2020. [Online]. Available: https://doi.org/10.1007/s11276-019-02142-z

[77] E. Bradley, *Reliability engineering: a life cycle approach*. Crc Press, 2016.

[78] S. J. Pokorni, "Reliability and availability of the internet of things," *Vojnotehnički glasnik*, vol. 67, no. 3, pp. 588–600, 2019.

[79] R. C. Fries, *Reliable design of medical devices*. CRC Press, 2005.

[80] S. J. Moore, C. D. Nugent, S. Zhang, and I. Cleland, "Iot reliability: a review leading to 5 key research directions," *CCF Transactions on Pervasive Computing and Interaction*, vol. 2, no. 3, pp. 147–163, 2020.

[81] S. J. Pokorni, "Reliability and availability of the internet of things," *Vojnotehnički glasnik*, vol. 67, no. 3, pp. 588–600, 2019.

[82] F. M. R. Junior and C. A. Kamienski, "A survey on trustworthiness for the internet of things," *IEEE Access*, vol. 9, pp. 42 493–42 514, 2021.

[83] S. Sarkar, "Internet of things—robustness and reliability," in *Internet of Things*. Elsevier, 2016, pp. 201–218.

[84] S. V. Kolla, "Machine learning and its application in iot," 2021.

[85] L. E. Kane, J. J. Chen, R. Thomas, V. Liu, and M. Mckague, "Security and performance in iot: A balancing act," *IEEE access*, vol. 8, pp. 121 969–121 986, 2020.

[86] A. H. M. Aman, E. Yadegaridehkordi, Z. S. Attarbashi, R. Hassan, and Y.-J. Park, "A survey on trend and classification of internet of things reviews," *Ieee Access*, vol. 8, pp. 111 763–111 782, 2020.

[87] S. Vashi, J. Ram, J. Modi, S. Verma, and C. Prakash, "Internet of things (iot): A vision, architectural elements, and security issues," in *2017 international conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC)*. IEEE, 2017, pp. 492–496.

[88] R. Hu, Z. Yan, W. Ding, and L. T. Yang, "A survey on data provenance in iot," *World Wide Web*, vol. 23, no. 2, pp. 1441–1463, 2020.

[89] F. Zafar, A. Khan, S. Suhail, I. Ahmed, K. Hameed, H. M. Khan, F. Jabeen, and A. Anjum, "Trustworthy data: A survey, taxonomy and future trends of secure provenance schemes," *Journal of network and computer applications*, vol. 94, pp. 50–68, 2017.

[90] T. Ulz, T. Pieber, C. Steger, R. Matischek, and H. Bock, "Towards trustworthy data in networked control systems: A hardware-based approach," in *2017 22nd IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*. IEEE, 2017, pp. 1–8.

[91] I. Belkacem, S. Nait-Bahloul, and D. Sauveron, "Enhancing dependability through profiling in the collaborative internet of things," *Multimedia Tools and Applications*, vol. 78, no. 3, pp. 2983–3007, 2019.

[92] A. B. Bondi, "Characteristics of scalability and their impact on performance," in *Proceedings of the 2nd international workshop on Software and performance*, 2000, pp. 195–203.

[93] I. Zyrianoff, F. Borelli, G. Biondi, A. Heideker, and C. Kamienski, "Scalability of real-time iot-based applications for smart cities," in *2018 IEEE Symposium on Computers and Communications (ISCC)*. IEEE, 2018, pp. 00 688–00 693.

[94] A. Gupta, R. Christie, and R. Manjula, "Scalability in internet of things: features, techniques and research challenges," *Int. J. Comput. Intell. Res*, vol. 13, no. 7, pp. 1617–1627, 2017.

[95] A. Javed, A. Malhi, T. Kinnunen, and K. Främling, "Scalable iot platform for heterogeneous devices in smart environments," *IEEE Access*, vol. 8, pp. 211 973–211 985, 2020.

[96] A. Al-Said Ahmad and P. Andras, "Scalability analysis comparisons of cloud-based software services," *Journal of Cloud Computing*, vol. 8, no. 1, pp. 1–17, 2019.

[97] K. Subash, D. J. Ramya, and L. Arockiam, "Quality of service in the internet of things (iot)–a survey," *TIRUCHIRAPPALLI-620 002, TAMIL NADU, INDIA*, 2019.

[98] B. S. Ahmed, M. Bures, K. Frajtak, and T. Cerny, "Aspects of quality in internet of things (iot) solutions: A systematic mapping study," *IEEE Access*, vol. 7, pp. 13 758–13 780, 2019.

[99] E. Cero, J. Baraković Husić, and S. Baraković, "Iot's tiny steps towards 5g: Telco's perspective," *Symmetry*, vol. 9, no. 10, p. 213, 2017.

[100] E. Borgia, "The internet of things vision: Key features, applications and open issues," *Computer Communications*, vol. 54, pp. 1–31, 2014.

[101] O. Vermesan and P. Friess, *Internet of things: converging technologies for smart environments and integrated ecosystems*. River publishers, 2013.

[102] O. Vermesan, P. Friess *et al.*, *Internet of things-from research and innovation to market deployment*. River publishers Aalborg, 2014, vol. 29.

Q-Learning Guided Local Search for the Traveling Salesman Problem

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***Abstract*—The Traveling Salesman Problem (TSP) remains a fundamental challenge in combinatorial optimization with applications in logistics, routing, and network design. Classical local search methods face a trade-off between solution quality and computational efficiency: while 3-opt delivers better solutions than 2-opt, its $O(n^3)$ complexity renders it impractical for large instances. This paper presents a reinforcement learning (RL) approach that addresses this challenge through intelligent guidance of local search operators. Our method employs a simple one-dimensional Q-table that learns to identify poorly positioned cities and directs 2-opt and 3-opt operations toward the most promising tour segments. We evaluate the approach on 55 TSPLIB benchmark instances ranging from 51 to 18,512 cities. For instances up to 1,000 cities, RL-guided 3-opt (RL-3opt) achieves optimality gaps of 0.9–2.2% compared to 3.8–4.3% for classical 3-opt, with execution times reduced from hours to under one second and speedups reaching 32,323×. For instances between 1,000–5,000 cities, RL-3opt maintains computational efficiency (100–30,000× speedups) while achieving competitive 6.3% gaps. Both RL-2opt and RL-3opt execute in sub-second to a few seconds even on problems with over 18,000 cities. All experiments run on standard CPU hardware without GPU acceleration, demonstrating that effective TSP optimization remains accessible without specialized resources.**

***Keywords*—Traveling salesman problem; reinforcement learning; Q-Learning; local search; 2-opt; 3-opt**

I. Introduction

The Traveling Salesman Problem (TSP) asks for the shortest route visiting each city exactly once before returning to the origin [1]. Given n cities with distances d_{ij} between pairs, the objective is to find a permutation $\pi = \{s_1, s_2, \ldots, s_n\}$ minimizing:

$$\sum_{k=1}^{n-1} d_{s_k s_{k+1}} + d_{s_n s_1}. \quad (1)$$

Despite this simple formulation, the TSP is NP-hard [2], with $(n-1)!/2$ possible tours for symmetric instances where $d_{ij} = d_{ji}$. This computational difficulty has motivated decades of research, with applications spanning logistics, manufacturing, circuit design, and delivery routing [3]. TSP solution methods have evolved through several generations. Classical heuristics combine construction methods with local search operators and remain widely used for their simplicity and reliability. Metaheuristic algorithms offer more sophisticated search strategies that balance exploration and exploitation through mechanisms such as population evolution, adaptive search, and strategic diversification. More recently, machine learning techniques, particularly deep neural networks and RL, have shown they can learn solution strategies directly from data [4], [5]. Researchers have also developed hybrid methods that combine classical algorithms with learning components [6], [7].

Despite these advances, two fundamental challenges persist. Most learning-based approaches require substantial computational resources [8], [9]. Deep learning methods typically need GPU acceleration and extensive training on large datasets [10]. Even simpler learning frameworks often employ multi-dimensional state representations that scale poorly with problem size. This limits their accessibility for users without high-performance computing infrastructure, including small businesses, educational institutions, and organizations in developing regions. At the same time, classical local search methods face an inherent trade-off between speed and solution quality. The 2-opt operator runs quickly but often settles at poor local minima because it only examines a limited neighborhood around the current solution. The 3-opt operator explores substantially larger neighborhoods and typically finds better solutions, but at much higher computational cost. On large instances, 3-opt can require hours or even days to complete. This creates a practical dilemma: users must choose between fast but suboptimal solutions, or high-quality solutions that may be computationally prohibitive.

We address both challenges through a simple RL framework designed for efficiency. Our method uses a one-dimensional Q-table indexed by cities rather than state-action pairs, reducing memory complexity from $O(n^2)$ to $O(n)$. During tour improvement, the table learns which cities are poorly positioned based on their involvement in successful optimization moves. These learned priorities then guide both 2-opt and 3-opt operators to focus on tour segments most likely to benefit from modification. This design combines the simplicity and accessibility of classical methods with the adaptive intelligence of learning-based approaches. Three principles shape our work: prioritize algorithmic simplicity, learn during optimization rather than through offline training, and execute on standard CPU hardware without GPU acceleration.

We validate the approach on 55 TSPLIB benchmark instances [11] ranging from 51 to 18,512 cities. To directly measure the contribution of RL, we include systematic comparisons against classical baselines: nearest neighbor construction, classical 2-opt, and classical 3-opt. Results demonstrate that RL-guided methods outperform their classical counterparts in solution quality for instances up to 1,000 cities. For larger instances (1,000-5,000 cities), RL-3opt achieves competitive quality (6.3% gap) compared to classical 3-opt (5.5% gap) while running 100 to over 30,000 times faster, effectively

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transforming hours or days into seconds on large instances. Both RL-2opt and RL-3opt complete in a few seconds even on problems with over 18,000 cities, where classical 3-opt becomes entirely impractical. All experiments run on standard CPU hardware, confirming that the approach requires no specialized computing resources.

This research aims to: 1) develop an efficient RL-guided framework reducing $O(n^3)$ complexity while maintaining solution quality, 2) ensure accessibility through a minimalist one-dimensional Q-table operating on standard CPU hardware, 3) demonstrate scalability across 51 to 18,512-city instances, 4) achieve sub-second to few-second execution times for real-time applications, and 5) quantify quality-time trade-offs compared to classical methods.

The paper proceeds as follows. Section II reviews related work on TSP solution methods and learning-based optimization. Section III describes our approach in detail, including RL fundamentals, classical local search methods, and our RL-guided framework. Section IV presents experimental methodology and comprehensive results on 55 TSPLIB benchmarks. Section V concludes the paper.

II. Related Work

The TSP has been extensively studied through classical heuristics, metaheuristics, and modern learning-based approaches. This section reviews key methodologies relevant to our hybrid framework.

A. Classical Heuristics and Local Search

Classical heuristics provide rapid initial solutions. The nearest neighbor heuristic [12] constructs tours by iteratively selecting the closest unvisited city. Zuhanda et al. [13] demonstrated that hybrid methods consistently outperform pure heuristics on TSPLIB benchmarks. Alkafaween et al. [14] proposed an iterative approximate method achieving polynomial-time solutions with competitive quality.

Local search operators refine initial tours through edge exchanges. The k-opt family [15], [16], particularly 2-opt and 3-opt, systematically improves tours by removing and reconnecting edges. The Lin-Kernighan-Helsgaun algorithm [17], [18] represents the state-of-the-art, employing variable k-opt moves with intelligent candidate selection to achieve near-optimal solutions on large instances.

B. Metaheuristic Approaches

Metaheuristic algorithms escape local optima through diversified search mechanisms. Genetic algorithms [19] employ evolutionary principles, with Al-Ibrahim [20] demonstrating near-optimal solutions through specialized crossover operators. Bio-inspired methods have shown promise: Abd Algani [21] applied African Buffalo Optimization to TSP, while Ant Colony Optimization [22] uses pheromone-based search strategies.

Swarm intelligence techniques offer efficient optimization across domains. Kou and Wei [23] combined particle swarm optimization with grey wolf algorithm for improved convergence. Wu et al. [24] developed dynamic multi-population PSO for complex trajectory planning. Recent applications by Zhou [25] and Bai [26] to resource allocation problems demonstrate the versatility of these approaches.

C. Learning-Based Approaches

Deep learning has introduced end-to-end TSP solving. Kafakthong and Sinapiromsaran [27] proposed deep attention mechanisms predicting near-optimal tours directly from distance matrices. Pointer Networks [28] and actor-critic architectures [29] generate tours without supervised training. Graph Neural Networks [30] and Transformers [31] capture complex inter-node relationships. However, these approaches typically require substantial GPU resources and extensive training, limiting their accessibility for resource-constrained environments.

RL addresses sequential decision-making in combinatorial optimization. Wang et al. [32] showed Double Q-Learning outperforms traditional Q-Learning and SARSA for TSP. Pan et al. [33] proposed hierarchical RL scaling to instances with thousands of nodes, though computational requirements remain significant.

D. Hybrid Methods

Hybrid approaches combine classical and learning-based techniques. d'O Costa et al. [34] trained policy models to guide 2-opt operations. Zheng et al. [35] integrated Q-learning into LKH, forming Reinforced LKH with strong TSPLIB performance. NeuroLKH [7] uses neural networks to predict edge candidates without modifying LKH's core structure.

El Jaghaoui et al. [36], [37] explored adaptive exploration-exploitation strategies and combined Q-learning with ACO, demonstrating improved convergence on benchmarks. Ruan et al. [38] merged RL with genetic algorithms for enhanced solution discovery.

E. Positioning of this Work

Existing hybrid methods often rely on complex architectures or multi-dimensional Q-tables that scale poorly. Deep learning approaches typically demand GPU acceleration and extensive computational resources, limiting their accessibility for resource-constrained environments. Our approach addresses these limitations through a minimalist one-dimensional Q-table indexed by cities, drastically reducing memory and computational requirements. The method operates efficiently on standard CPU-only hardware without requiring GPUs or specialized equipment. Unlike methods requiring extensive offline training, our framework learns dynamically during optimization. By combining nearest neighbor initialization with RL-guided 2-opt and 3-opt operators, we demonstrate that effective TSP optimization is achievable on commodity hardware across 55 TSPLIB instances.

III. Methodology

We propose a hybrid framework that combines Q-learning with local search methods for solving the TSP. The key contribution is the use of RL to intelligently guide edge selection in 2-opt and 3-opt operators. This section presents the RL fundamentals (Section III-A), classical local search methods (Section III-B), and our proposed RL-2opt and RL-3opt algorithms (Section III-C).

A. Reinforcement Learning Fundamentals

RL [39] is a machine learning paradigm in which an agent learns to make optimal decisions through interaction with an environment. This process is formalized as a Markov Decision Process (MDP), defined by the tuple $\langle S, A, P, R\rangle$, where S is the state space, A the action space, P the transition probabilities, and R the reward function. The agent seeks to maximize cumulative reward by learning an optimal policy $\pi : S \to A$. Q-learning is a model-free RL algorithm that learns the Q-function, representing the expected return of taking action a in state s. The Q-values are updated using the Bellman equation:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[r + \gamma \max_{a'} Q(s',a') - Q(s,a) \right], \quad (2)$$

where $\alpha \in (0,1]$ is the learning rate, $\gamma \in [0,1]$ the discount factor, r the immediate reward, and s' the resulting state.

B. Local Search Methods

Local search methods iteratively improve solutions by exploring neighborhoods through local modifications. For the TSP, *k*-opt operators [16] represent the most prominent local search techniques, where *k* denotes the number of edges removed and reconnected.

The 2-opt operator removes two non-adjacent edges and reconnects the path segments in an alternative configuration. With $O(n^2)$ complexity per iteration, 2-opt quickly improves solutions but often converges to mediocre local optima [15].

The 3-opt operator extends this by removing three edges and evaluating multiple reconnection patterns [16]. While producing superior solutions, its $O(n^3)$ complexity becomes prohibitive for large instances. Section III-C presents our RL-guided approach that addresses this computational bottleneck.

C. RL-Guided Local Search Framework

Given an initial TSP tour, we apply a Q-learning-guided local search procedure to iteratively refine the solution. This framework integrates RL with classical k-opt operators to intelligently guide edge selection. The following sections present two algorithms: RL-2opt (Section III-C1), which combines Q-learning with 2-opt, and RL-3opt (Section III-C2), which extends the approach to 3-opt operators.

1) RL-2opt algorithm: We propose an RL-guided variant of the 2-opt algorithm in which a Q-learning agent learns to identify promising city pairs for edge swaps. Unlike classical 2-opt, which exhaustively examines all possible swaps, our approach prioritizes cities that are more likely to yield improvements based on accumulated experience.

a) Q-Learning Components: The RL framework is defined as follows:

- State: The current tour T, represented as an ordered sequence of cities.
- Action: Select two non-adjacent cities (i, j) and perform a 2-opt swap by reversing the tour segment between them.
- Reward: $r = \text{len}_{\text{current}} - \text{len}_{\text{new}}$, where $\text{len}_{\text{current}}$ and len_{new} are the tour lengths before and after the swap. The reward is positive if the swap shortens the tour; otherwise, $r = 0$ and the swap is rejected.
- Q-Table: A one-dimensional array $Q \in \mathbb{R}^n$, where each entry $Q[i]$ estimates the expected benefit when city i participates in a swap. This compact representation avoids the computational overhead of a full state-action Q-table.

b) Action Selection Strategy: City selection follows an ε-greedy policy that balances exploration and exploitation:

- Exploration (probability ε): Select two distinct cities (i, j) uniformly at random.
- Exploitation (probability $1 - \varepsilon$): Choose the city with the highest Q-value, $i = \arg\max_k Q[k]$, then select a second city $j \neq i$ randomly.

The underlying intuition is that well-positioned cities yield minimal improvement when swapped, maintaining low Q-values. Conversely, poorly positioned cities produce significant gains when swapped, accumulating higher Q-values over time. This mechanism naturally directs the search toward unstable tour regions where improvements are most likely.

c) Efficient Tour Update: The 2-opt swap removes edges $(i, \text{succ}(i))$ and $(j, \text{succ}(j))$ and adds edges (i, j) and $(\text{succ}(i), \text{succ}(j))$, where $\text{succ}(i)$ denotes the successor of city i in tour T. The tour length change can be computed locally without recalculating the entire tour:

$$\text{dist}_{\text{removed}} = d(i, \text{succ}(i)) + d(j, \text{succ}(j)), \quad (3)$$

$$\text{dist}_{\text{added}} = d(i, j) + d(\text{succ}(i), \text{succ}(j)), \quad (4)$$

$$\text{len}_{\text{new}} = \text{len}_{\text{current}} - \text{dist}_{\text{removed}} + \text{dist}_{\text{added}}. \quad (5)$$

This localized computation ensures $O(1)$ update complexity per swap, critical for scalability to large instances.

d) Q-Value Update: After each swap attempt, the Q-values of the involved cities are updated using a simplified temporal difference rule:

$$Q[i] \leftarrow Q[i] + \alpha(r - Q[i]), \quad Q[j] \leftarrow Q[j] + \alpha(r - Q[j]), \quad (6)$$

where $\alpha \in (0,1]$ is the learning rate. No discount factor γ is used since each iteration involves a single immediate decision with no delayed consequences, eliminating the need for multi-step credit assignment. The complete procedures are formalized in Algorithms 1 and 2.

Algorithm 1 2-opt Swap Operation

Input: T: current tour, d: distance matrix, $\text{len}_{\text{current}}$: tour length, i, j: cities to swap
Output: T_{new}: updated tour, len_{new}: new tour length

function SWAP-2OPT($T, d, \text{len}_{\text{current}}, i, j$)
  $\text{dist}_{\text{removed}} \leftarrow d(i, \text{succ}(i)) + d(j, \text{succ}(j))$
  $\text{dist}_{\text{added}} \leftarrow d(i, j) + d(\text{succ}(i), \text{succ}(j))$
  if $\text{dist}_{\text{added}} \geq \text{dist}_{\text{removed}}$ **then**
    return $T, \text{len}_{\text{current}}$ ▷ No improvement
  else
    $\text{len}_{\text{new}} \leftarrow \text{len}_{\text{current}} - \text{dist}_{\text{removed}} + \text{dist}_{\text{added}}$
    Reverse tour segment between $\text{succ}(i)$ and j to obtain T_{new}
    return $T_{\text{new}}, \text{len}_{\text{new}}$
  end if
end function

Algorithm 2 RL-2opt Algorithm

Input: n: number of cities, d: distance matrix, T_{init}: initial tour, len_{init}: initial length, α: learning rate, ε: exploration rate, n_{episodes}: number of episodes
Output: T_{best}: best tour found, len_{best}: best length

function RL-2OPT($n, d, T_{\text{init}}, \text{len}_{\text{init}}, \alpha, \varepsilon, n_{\text{episodes}}$)
  $T_{\text{best}} \leftarrow T_{\text{init}}, \text{len}_{\text{best}} \leftarrow \text{len}_{\text{init}}$
  $Q \leftarrow \mathbf{0}_n$ ▷ Initialize Q-table
  for episode $= 1$ to n_{episodes} **do**
    Select cities (i, j) **using** ε**-greedy:**
    if random() $< \varepsilon$ **then** ▷ Exploration
      $i, j \leftarrow$ two random distinct cities
    else ▷ Exploitation
      $i \leftarrow \arg\max_k Q[k]$
      $j \leftarrow$ random city with $j \neq i$
    end if
    $T_{\text{new}}, \text{len}_{\text{new}} \leftarrow \text{Swap-2opt}(T_{\text{best}}, d, \text{len}_{\text{best}}, i, j)$
    $r \leftarrow \text{len}_{\text{best}} - \text{len}_{\text{new}}$
    Update Q-values:
    $Q[i] \leftarrow Q[i] + \alpha(r - Q[i])$
    $Q[j] \leftarrow Q[j] + \alpha(r - Q[j])$
    if $r > 0$ **then** ▷ Accept improvement
      $T_{\text{best}} \leftarrow T_{\text{new}}, \text{len}_{\text{best}} \leftarrow \text{len}_{\text{new}}$
    end if
  end for
  return $T_{\text{best}}, \text{len}_{\text{best}}$
end function

2) RL-3opt algorithm: We extend the RL-guided approach to the more powerful 3-opt operator, which explores a significantly larger neighborhood than 2-opt. While 2-opt removes two edges and performs a single reconnection, 3-opt removes three edges and evaluates multiple reconnection patterns, potentially yielding higher-quality solutions at the cost of increased computational complexity.

a) Q-Learning Components: The RL framework for 3-opt follows the same structure as RL-2opt, with the key difference being the action space:

- State: The current tour T.
- Action: Select three cities $i < j < k$ in tour T, remove the edges $(i, \text{succ}(i))$, $(j, \text{succ}(j))$, and $(k, \text{succ}(k))$, and evaluate all valid reconnection patterns to find the best configuration.
- Reward: $r = \text{dist}_{\text{removed}} - \text{dist}_{\text{added}}(m^*)$, where m^* is the best reconnection pattern among the seven non-trivial configurations.
- Q-Table: The same one-dimensional array $Q \in \mathbb{R}^n$ as in RL-2opt, where $Q[i]$ estimates the expected benefit when city i is involved in a 3-opt move.

b) 3-opt Reconnection Patterns: Removing three edges $(i, \text{succ}(i))$, $(j, \text{succ}(j))$, and $(k, \text{succ}(k))$ partitions the tour into three segments:

- S_1: from $\text{succ}(i)$ to j,
- S_2: from $\text{succ}(j)$ to k,
- S_3: from $\text{succ}(k)$ to i.

Each segment can be traversed forward or reversed, yielding $2^3 = 8$ total combinations. The first configuration (all segments in original orientation) is trivial and yields no change. The remaining seven configurations are evaluated. Table I lists all eight cases and their corresponding edge insertions.

TABLE I. THE 8 RECONNECTION PATTERNS IN 3-OPT AND THEIR INSERTED EDGES. CONFIGURATION 1 IS THE IDENTITY AND IS IGNORED. NOTATION: $^\circlearrowleft$ INDICATES SEGMENT REVERSAL

Case	Segment orientation	Inserted edges
1	$S_1 \to S_2 \to S_3$	Identity (ignored)
2	$S_1^\circlearrowleft \to S_2 \to S_3$	$(i, j), (\text{succ}(i), \text{succ}(j)), (k, \text{succ}(k))$
3	$S_1 \to S_2^\circlearrowleft \to S_3$	$(i, \text{succ}(i)), (j, k), (\text{succ}(j), \text{succ}(k))$
4	$S_1 \to S_2 \to S_3^\circlearrowleft$	$(i, \text{succ}(i)), (j, \text{succ}(j)), (k, i)$
5	$S_1^\circlearrowleft \to S_2^\circlearrowleft \to S_3$	$(i, j), (\text{succ}(i), k), (\text{succ}(j), \text{succ}(k))$
6	$S_1^\circlearrowleft \to S_2 \to S_3^\circlearrowleft$	$(i, k), (\text{succ}(i), \text{succ}(j)), (j, \text{succ}(k))$
7	$S_1 \to S_2^\circlearrowleft \to S_3^\circlearrowleft$	$(i, \text{succ}(i)), (j, k), (\text{succ}(j), i)$
8	$S_1^\circlearrowleft \to S_2^\circlearrowleft \to S_3^\circlearrowleft$	$(i, k), (\text{succ}(i), j), (\text{succ}(j), \text{succ}(k))$

c) Efficient Configuration Evaluation: To avoid recomputing the full tour length for each configuration, we use local distance calculations:

$$\text{dist}_{\text{removed}} = d(i, \text{succ}(i)) + d(j, \text{succ}(j)) + d(k, \text{succ}(k)), \quad (7)$$

$$\text{dist}_{\text{added}}(m) = d(y_1) + d(y_2) + d(y_3), \quad (8)$$

where (y_1, y_2, y_3) are the three edges inserted in configuration $m \in \{2, \ldots, 8\}$. The best configuration m^* is:

$$m^* = \arg \min_{m \in \{2,\ldots,8\}} \text{dist}_{\text{added}}(m). \quad (9)$$

If $\text{dist}_{\text{added}}(m^*) < \text{dist}_{\text{removed}}$, the move improves the tour and is accepted:

$$\text{len}_{\text{new}} = \text{len}_{\text{current}} - \text{dist}_{\text{removed}} + \text{dist}_{\text{added}}(m^*), \quad (10)$$

$$r = \text{dist}_{\text{removed}} - \text{dist}_{\text{added}}(m^*). \quad (11)$$

Otherwise, the tour remains unchanged and $r = 0$.

d) Q-Value Update: After each move attempt, the Q-values of all three involved cities are updated:

$$Q[c] \leftarrow Q[c] + \alpha(r - Q[c]), \quad \forall c \in \{i, j, k\}. \quad (12)$$

e) Action Selection Strategy: City selection follows the same ε-greedy policy as RL-2opt: with probability ε (exploration), we select three distinct cities i, j, k uniformly at random; with probability $1 - \varepsilon$ (exploitation), we choose $i = \arg\max_c Q[c]$, then randomly select two additional distinct cities $j \neq i$ and $k \neq i, j$. The complete procedures are formalized in Algorithms 3 and 4.

Algorithm 3 3-opt Swap Operation

Input: T: current tour, d: distance matrix, $\text{len}_{\text{current}}$: tour length, i, j, k: cities with $i < j < k$
Output: T_{new}: updated tour, len_{new}: new tour length

function SWAP-3OPT($T, d, \text{len}_{\text{current}}, i, j, k$)
  $\text{dist}_{\text{removed}} \leftarrow d(i, \text{succ}(i)) + d(j, \text{succ}(j)) + d(k, \text{succ}(k))$
  $r_{\text{best}} \leftarrow 0$
  $T_{\text{new}} \leftarrow T, \text{len}_{\text{new}} \leftarrow \text{len}_{\text{current}}$
  for each configuration $m \in \{2, \ldots, 8\}$ **do**
    $(y_1, y_2, y_3) \leftarrow$ edges inserted in configuration m (from Table I)
    $\text{dist}_{\text{added}} \leftarrow d(y_1) + d(y_2) + d(y_3)$
    $r \leftarrow \text{dist}_{\text{removed}} - \text{dist}_{\text{added}}$
    if $r > r_{\text{best}}$ **then**
      $r_{\text{best}} \leftarrow r$
      $\text{len}_{\text{new}} \leftarrow \text{len}_{\text{current}} - \text{dist}_{\text{removed}} + \text{dist}_{\text{added}}$
      $T_{\text{new}} \leftarrow$ tour reassembled according to configuration m
    end if
  end for
  return $T_{\text{new}}, \text{len}_{\text{new}}$
end function

Having presented the detailed mechanisms of both RL-2opt and RL-3opt algorithms, Fig. 1 provides a unified visual representation of the complete framework.

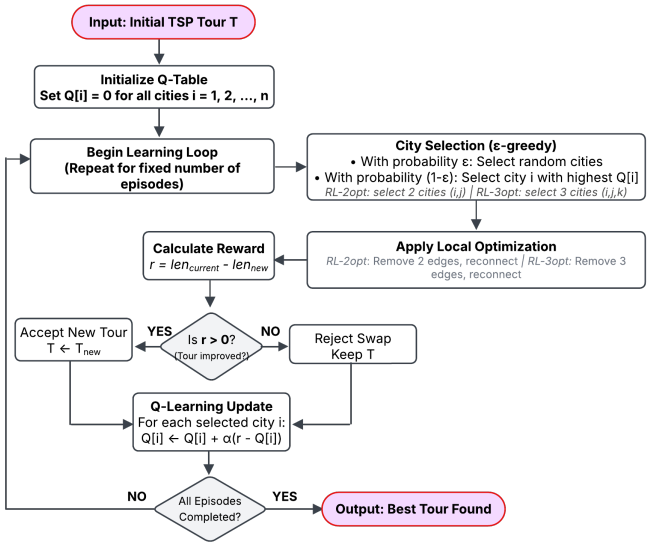


Fig. 1. Flowchart of the Q-learning guided local search framework.

Algorithm 4 RL-3opt Algorithm

Input: n: number of cities, d: distance matrix, T_{init}: initial tour, len_{init}: initial length, α: learning rate, ε: exploration rate, n_{episodes}: number of episodes
Output: T_{best}: best tour found, len_{best}: best length

function RL-3OPT($n, d, T_{\text{init}}, \text{len}_{\text{init}}, \alpha, \varepsilon, n_{\text{episodes}}$)
  $T_{\text{best}} \leftarrow T_{\text{init}}, \text{len}_{\text{best}} \leftarrow \text{len}_{\text{init}}$
  $Q \leftarrow \mathbf{0}_n$ ▷ Initialize Q-table
  for episode $= 1$ to n_{episodes} **do**
    Select cities (i, j, k) **using** ε**-greedy:**
    if random() $< \varepsilon$ **then** ▷ Exploration
      $i, j, k \leftarrow$ three random distinct cities
    else ▷ Exploitation
      $i \leftarrow \arg\max_c Q[c]$
      $j, k \leftarrow$ two random distinct cities with $j \neq i, k \neq i, j \neq k$
    end if
    $T_{\text{new}}, \text{len}_{\text{new}} \leftarrow$ Swap-3opt($T_{\text{best}}, d, \text{len}_{\text{best}}, i, j, k$)
    $r \leftarrow \text{len}_{\text{best}} - \text{len}_{\text{new}}$
    Update Q-values:
    for $c \in \{i, j, k\}$ **do**
      $Q[c] \leftarrow Q[c] + \alpha(r - Q[c])$
    end for
    if $r > 0$ **then** ▷ Accept improvement
      $T_{\text{best}} \leftarrow T_{\text{new}}, \text{len}_{\text{best}} \leftarrow \text{len}_{\text{new}}$
    end if
  end for
  return $T_{\text{best}}, \text{len}_{\text{best}}$
end function

IV. EXPERIMENTAL EVALUATION

This section presents the experimental protocol, parameter configuration, and comprehensive performance analysis of the proposed RL-guided local search framework.

A. Experimental Setup

a) Implementation and Hardware: All algorithms were implemented in C and executed on an HP laptop equipped with an Intel® Core™ i5-8265U CPU (1.6 GHz base frequency) and 16 GB of RAM. No parallelization or GPU acceleration was used, ensuring a fair comparison based on single-threaded performance.

b) Benchmark Instances: We evaluate our approach on 55 symmetric instances from the TSPLIB repository [11], ranging from 51 to 18,512 cities. All instances use the Euclidean distance metric (`EUC_2D`), ensuring consistency in distance calculations across experiments. Table II lists all tested instances with their optimal solutions.

c) Experimental Protocol: For each instance, the following three-stage workflow is applied:

1) Initialization: Generate an initial tour using the Nearest Neighbor (NN) heuristic starting from a randomly selected city.
2) Refinement: Apply RL-2opt or RL-3opt independently to improve the initial tour. Each RL algorithm is executed for 10,000 episodes.

3) Baseline Comparison: Evaluate against classical 2-opt and 3-opt local search using the same initial tour to ensure fair comparison.

To ensure statistical reliability, each RL algorithm is executed 20 independent runs per instance with different random seeds. We report the best solution across these runs, along with a variability metric (GAP%) defined as:

$$\text{GAP}\% = 100 \times \frac{\sqrt{\frac{1}{20}\sum_{i=1}^{20}(\text{len}_i - \overline{\text{len}})^2}}{\text{len}_{\min}}, \tag{13}$$

where len_i is the tour length in run i, $\overline{\text{len}}$ is the average length, and $\text{len}_{\min}$ is the best length observed. Lower GAP% values indicate more consistent performance across runs.

d) Hyperparameters: All RL experiments use fixed hyperparameters to ensure reproducibility: number of episodes $n_{\text{episodes}} = 10{,}000$, learning rate $\alpha = 0.1$, discount factor $\gamma = 0$ (immediate rewards only), and exploration rate $\varepsilon = 0.1$. These values remain constant across all instances.

e) Performance Metrics: We evaluate algorithms using three metrics:

- Solution Quality: Gap percentage from known optimal or best-known solutions:

$$\text{Gap}(\%) = \frac{\text{Solution} - \text{Optimal}}{\text{Optimal}} \times 100. \tag{14}$$

- Computational Time: Wall-clock execution time in seconds, excluding I/O operations.
- Stability: Variability across runs measured by GAP% as shown in Equation (13).

B. Results and Analysis

Table II presents comprehensive results for all 55 instances, including optimal values, tour lengths, computation times, and variability metrics for each method. Classical 3-opt becomes computationally impractical for the largest instances (indicated by —), requiring estimated days of computation time.

Before analyzing these results in detail, we contextualize our approach relative to existing TSP methods. Specialized solvers like LKH [17], [18] represent the state of the art for solution quality. We compared our approach with LKH version 3.0.6 (default parameters, run until convergence), which systematically produces the highest-quality solutions across all instances. However, execution time differences are particularly pronounced on large instances: while LKH systematically achieves the highest quality solutions through extensive computation (hours), our framework provides near-optimal results orders of magnitude faster (seconds). This confirms our positioning: our framework is not designed to replace specialized solvers like LKH, but rather to provide a practical, resource-efficient alternative under constrained computational conditions—suitable for real-time applications, standard hardware deployment, or batch processing of thousands of instances.

Other Q-learning approaches for TSP focus on tour construction by learning city selection policies, while our method addresses a fundamentally different problem: *improving* existing tours rather than *generating* tours from scratch. Classical Q-learning tour construction methods typically achieve gaps of 5–15%, while our improvement-focused approach delivers sub-1% gaps on small instances (≤ 100 cities). Direct experimental comparison is not included because these approaches operate in fundamentally different settings: construction methods learn sequential decisions from an empty tour, while our improvement approach starts from an existing solution and learns neighborhood restriction. Comparing final tour quality would conflate these distinct problem formulations (generation vs. refinement) and initial conditions rather than isolating the contribution of RL guidance itself.

We compare four local search improvement methods across all instances: classical 2-opt, classical 3-opt, RL-guided 2-opt (RL-2opt), and RL-guided 3-opt (RL-3opt). Classical 2-opt achieves an average optimality gap of 8.95% across all problem sizes, while classical 3-opt reduces this to 5.31% on instances where it is computationally feasible. RL-guided methods demonstrate size-dependent performance: For instances up to 1,000 cities, RL-3opt achieves exceptional quality with gaps of 0.9–2.2%, including near-optimal solutions on several instances (`rd100`: 0.00%, `kroA100`: 0.01%, `berlin52`: 0.03%), while RL-2opt maintains competitive gaps of 1.6–2.6%. For instances between 1,000–5,000 cities, performance degrades: RL-3opt achieves 6.3% gaps compared to 5.5% for classical 3-opt, while RL-2opt reaches 9.1% gaps comparable to classical 2-opt's 9.0%. Despite this quality trade-off in the 1,000–5,000 range, RL methods maintain substantial computational advantages with speedups exceeding 100× to 30,000×. For very large instances exceeding 5,000 cities, RL-3opt achieves 9.8% gaps while RL-2opt reaches 12.2%. In this range, RL-3opt matches classical 2-opt quality (both 9.8%) while executing orders of magnitude faster, though RL-2opt shows some quality degradation compared to classical methods.

Table III reveals systematic performance differences across improvement methods.For instances up to 1,000 cities, RL-3opt achieves 2-4× better gaps than classical 3-opt. However, for instances between 1,000-5,000 cities, classical 3-opt achieves slightly better quality (5.5% vs 6.3%) while RL-3opt maintains substantial computational advantages.

Fig. 2 illustrates these quality differences on five representative instances spanning different problem sizes. RL-3opt (dark blue) achieves near-optimal solutions, including exact optimality on `rd100`, while classical 2-opt (dark red) and classical 3-opt (light red) consistently show higher approximation ratios. RL-2opt (light blue) provides intermediate quality between classical and RL-3opt approaches.

Beyond quality, computational efficiency differs dramatically across methods. Classical 3-opt exhibits cubic scaling, becoming impractical beyond 1000 cities (requiring 16 minutes to over six hours for instances with 2,000–6,000 cities) and entirely infeasible for problems exceeding 10,000 cities. Classical 2-opt executes faster but still requires seconds for large instances. In contrast, RL-guided methods maintain near-linear scalability: instances up to 2,400 cities complete in under 0.25 seconds, up to 6,000 cities finish in under 1 second, and 18,512-city problems solve in under 4 seconds—yielding speedups over classical 3-opt ranging from 4,334× to 32,323×.

TABLE II. COMPREHENSIVE COMPARISON ON 55 TSPLIB INSTANCES. FOR EACH METHOD: BEST TOUR LENGTH AND RUNTIME (SECONDS). FOR RL METHODS: GAP% STABILITY METRIC OVER 20 RUNS. CLASSICAL 3-OPT BECOMES IMPRACTICAL (—) FOR THE LARGEST INSTANCES

Problem	Optimal	NN	NN+2opt		NN+3opt		NN+RL2opt			NN+RL3opt		
			Dist	Time (s)	Dist	Time (s)	Best	GAP%	Time (s)	Best	GAP%	Time (s)
kroA100	21282	26856	23228	0.001	21864	0.033	21371	0.50	0.015	21285	0.26	0.021
kroB100	22141	29155	22907	0.002	22886	0.0130	22295	0.45	0.014	22243	0.22	0.022
kroC100	20749	26327	22943	0.001	22176	0.009	20947	0.42	0.016	20852	0.29	0.021
kroD100	21294	26950	23422	0.002	21826	0.015	21845	0.49	0.015	21485	0.33	0.021
kroE100	22068	27587	24475	0.001	23490	0.014	22403	0.40	0.014	22141	0.40	0.023
kroA200	29368	35798	31735	0.002	29823	0.260	29953	0.26	0.022	29963	0.27	0.025
kroB200	29437	36982	32539	0.003	31124	0.232	30205	0.51	0.021	30154	0.38	0.028
rd100	7910	9941	8731	< 0.001	8207	0.025	7975	0.34	0.016	7910	0.12	0.021
rd400	15281	19168	16847	0.004	15870	3.212	15745	0.30	0.037	15676	0.19	0.045
ch130	6110	7575	6848	0.001	6459	0.054	6284	0.31	0.017	6239	0.23	0.023
ch150	6528	8195	6727	0.001	6812	0.060	6597	0.39	0.017	6580	0.11	0.024
berlin52	7542	8981	8287	< 0.001	7801	0.002	7544	0.11	0.012	7544	0.10	0.019
eil51	426	514	449	< 0.001	437	0.002	432	0.09	0.011	430	0.09	0.018
eil76	538	712	572	< 0.001	552	0.010	549	0.11	0.012	545	0.13	0.019
st70	675	806	727	< 0.001	689	0.009	696	0.18	0.012	687	0.07	0.022
eil101	629	825	707	0.001	669	0.025	657	0.19	0.017	656	0.15	0.020
pr76	108159	153462	119489	< 0.001	109170	0.015	109210	0.33	0.014	109120	0.25	0.020
pr107	44303	46678	46194	0.001	44728	0.021	44768	0.41	0.017	44724	0.28	0.020
pr124	59030	69299	64335	0.002	60484	0.032	59685	0.39	0.016	59551	0.31	0.022
pr152	73682	85703	77351	0.002	77536	0.035	74004	0.20	0.018	73877	0.17	0.027
pr226	80369	94685	85113	0.002	81594	0.217	80914	0.27	0.023	80769	0.24	0.029
pr264	49135	58023	55188	0.003	50279	0.643	50803	0.57	0.024	50679	0.43	0.033
pr299	48191	59899	51414	0.003	49467	0.74	49955	0.60	0.029	49653	0.52	0.036
pr439	107217	131282	117331	0.003	113722	2.409	110231	0.87	0.039	109928	0.61	0.043
pr1002	259045	315597	284317	0.028	272929	36.104	275363	0.64	0.081	272280	0.34	0.090
pr2392	378032	461207	417036	0.456	401880	957.91	417473	0.37	0.206	406317	0.42	0.221
rat99	1211	1565	1331	< 0.001	1306	0.024	1272	0.17	0.015	1260	0.10	0.025
rat195	2323	2762	2511	0.001	2419	0.296	2387	0.28	0.020	2386	0.18	0.027
rat575	6773	8449	7342	0.011	7231	11.596	7085	0.57	0.045	7042	0.47	0.052
rat783	8806	11255	9816	0.014	9308	16.505	9296	0.27	0.067	9219	0.31	0.087
u159	42080	54669	47578	0.001	44916	0.076	43583	0.41	0.018	42900	0.39	0.024
u1060	224094	281636	247562	0.062	237724	63.38	241904	0.89	0.085	233538	0.80	0.111
u1432	152970	188815	168415	0.099	163043	120.598	167796	0.52	0.110	164102	0.36	0.132
u1817	57201	71103	62867	0.147	61265	437.57	63969	0.44	0.145	61995	0.34	0.178
u2152	64253	80180	70741	0.287	68741	681.072	71870	0.33	0.168	70187	0.27	0.191
u2319	234256	278783	246510	0.257	243418	702.340	254347	0.34	0.178	243379	0.24	0.203
lin105	14379	20363	16400	0.001	15394	0.040	14630	0.47	0.016	14529	0.20	0.019
rl1304	252948	339797	284062	0.140	273043	179.664	274694	0.85	0.136	269556	0.89	0.138
rl1323	270199	332095	298286	0.075	286679	182.035	284152	0.54	0.101	280689	0.48	0.122
rl1889	316536	400685	343363	0.144	332865	507.93	344585	0.42	0.151	334100	0.50	0.175
rl5915	565530	707499	622550	2.501	588813	22625.876	619163	0.25	0.669	606306	0.23	0.700
rl5934	556045	683806	614093	3.122	597867	18309.009	623758	0.22	0.667	606867	0.35	0.705
rl11849	923288	1139496	1014854	21.466	—	—	1025936	0.30	1.888	1006586	0.17	2.00
bier127	118282	135752	123768	0.001	120764	0.099	120462	0.56	0.016	119852	0.91	0.023
vm1084	239297	301469	258092	0.074	250083	129.744	258659	0.79	0.085	254407	0.55	0.109
vm1748	336556	408089	365952	0.273	353458	473.991	363160	0.86	0.133	355258	0.46	0.163
pcb3038	137694	175573	152112	0.544	147145	2107.079	151471	0.27	0.263	147235	0.26	0.280
fl3795	28772	34226	30401	1.399	29713	3784.776	32669	0.46	0.371	31037	0.92	0.397
fnl4461	182566	227157	200121	1.522	192642	8661.879	201355	0.20	0.451	195775	0.22	0.475
usa13509	19982859	25047673	21984724	28.548	—	—	22777155	0.15	2.31	22181451	0.14	2.73
brd14051	469385	577037	514523	22.656	—	—	535127	0.18	2.50	522622	0.11	2.90
d493	35002	43646	37848	0.0160	36373	6.386	36337	0.43	0.044	36112	0.28	0.052
d2103	80450	87469	83437	0.208	81771	371.815	85468	1.01	0.187	84925	0.61	0.207
d15112	1573084	1948433	1719624	26.630	—	—	1760464	1.39	3.66	1731045	0.65	3.84
d18512	645238	797562	703839	45.482	—	—	730690	0.24	3.82	716002	0.13	3.94

TABLE III. AVERAGE OPTIMALITY GAPS (%) BY INSTANCE SIZE, COMPUTED AS GAP(%) = (SOLUTION - OPTIMAL) / OPTIMAL × 100

Size (cities)	N	2-opt	3-opt	RL-2opt	RL-3opt
≤ 100	(12)	8.7	3.8	1.6	**0.9**
100–1,000	(20)	9.0	4.3	2.6	**2.2**
1,000–5,000	(16)	9.0	5.5	9.1	**6.3**
$> 5{,}000$	(7)	9.8	—	12.2	**9.8**

The combined quality-time advantage varies by problem size: small instances ($\leq$100 cities) see RL-3opt achieving 4× better quality than 3-opt with comparable execution times, medium instances (100–1,000 cities) combine millisecond execution with 3× better quality than 3-opt, and large instances (1,000–5,000 cities) demonstrate RL-3opt transforming hours-long searches into sub-second optimizations with 2× quality improvement over 3-opt and 4× over 2-opt. Very large instances (>5,000 cities) remain infeasible for classical 3-opt while RL methods scale gracefully: RL-3opt matches classical 2-opt quality but executes orders of magnitude faster.

Fig. 3 visualizes these advantages. Panel (a) demonstrates RL methods scaling to 18,000+ cities in under 4 seconds, while classical 3-opt exhibits cubic growth. Panel (b) confirms Pareto dominance: classical 2-opt offers speed without quality (ratios 1.08–1.11), classical 3-opt offers better quality at prohibitive cost, while RL methods provide the fastest solution for any

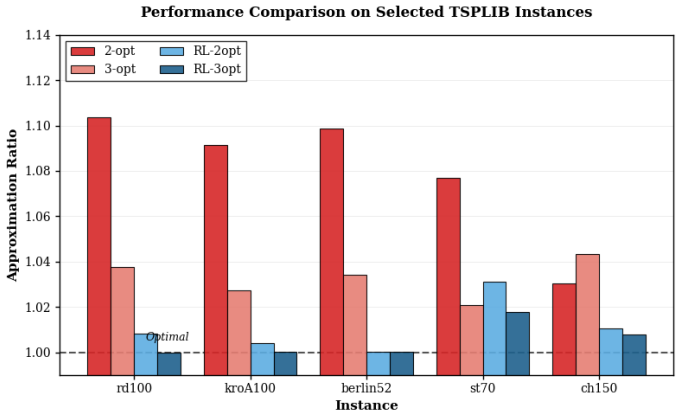


Fig. 2. Performance comparison on five representative instances. RL-3opt (dark blue) achieves near-optimal solutions including exact optimality on `rd100`. RL-2opt (light blue) provides intermediate quality. Classical methods (red) show significantly higher approximation ratios.

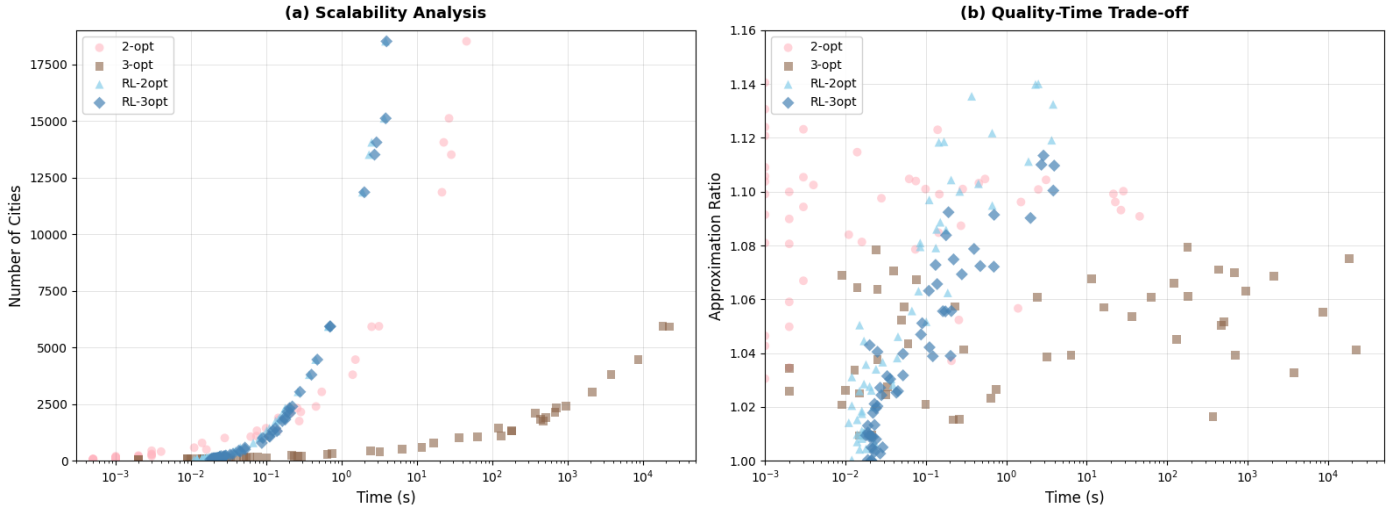


Fig. 3. Computational performance on 55 TSPLIB instances. (a) RL methods maintain near-linear scaling while classical 3-opt exhibits cubic explosion. (b) RL methods dominate the Pareto frontier with approximation ratios of 1.01–1.12 and execution times under 5 seconds.

desired quality level.

To assess robustness, we measured variability across 20 independent runs using the GAP% stability metric (Equation 13). Both RL methods demonstrate excellent stability with GAP% values of 0.1–1.0%. Best cases include `eil51` (0.09%), `usa13509` (0.14–0.15%), and `brd14051` (0.11–0.18%), confirming reliable Q-learning convergence suitable for production deployment.

C. Discussion

Our results demonstrate that a simple one-dimensional Q-table can effectively guide local search for TSP, but with clear limitations tied to problem size. The approach works well because it learns which cities are poorly positioned during optimization and focuses computational effort there. On instances up to 1,000 cities, this adaptive strategy produces solutions 2–4× better than classical 3-opt while running much faster. The Q-values act as a priority signal, directing the algorithm toward tour segments most likely to benefit from modification.

Performance declines on larger instances because the learning signal becomes weaker. With 10,000 fixed episodes, each city receives less attention as n grows, making it harder to identify and fix problematic regions. This reveals the core trade-off of our design: we sacrificed representational power (one-dimensional Q-table instead of multi-dimensional) to gain computational efficiency and simplicity. Methods like Reinforced LKH [35] maintain quality on large problems through richer state representations, while neural approaches [31], [10] learn powerful policies but require extensive training on GPUs. Our framework sits between these extremes—it learns during optimization rather than through offline training, making it accessible but limiting its ability to handle very large instances.

The dramatic speedups (401–32,323×) come from a fundamental algorithmic change: sampling a constant number of moves instead of exhaustively examining all $O(n^3)$ possibilities. This matters practically. A logistics company optimizing 500 delivery routes can complete the task in seconds rather than minutes, enabling real-time adjustments as conditions change. For applications where speed and accessibility matter

more than guaranteed optimality, this framework offers a compelling option. However, the 6.3% gap on medium instances (1,000–5,000 cities) versus 5.5% for classical 3-opt shows there are situations where the extra computation time is worth it.

The broader contribution is accessibility. Running on standard CPUs without hyperparameter tuning makes high-quality TSP optimization available to organizations without specialized computing infrastructure. This democratization matters for small businesses, educational institutions, and resource-constrained environments.

V. Conclusion

This paper introduced a Q-learning-guided local search framework that addresses neighborhood explosion in classical TSP methods by learning city-specific Q-values to guide exploration toward promising moves. The approach transforms $O(n^3)$ 3-opt complexity into practical sub-second optimization.

Experimental evaluation on 55 TSPLIB instances demonstrates size-dependent performance characteristics. For instances up to 1,000 cities, RL-3opt achieves 0.9–2.2% optimality gaps compared to 3.8–4.3% for classical 3-opt, with speedups exceeding 1,000×. For instances between 1,000–5,000 cities, classical 3-opt achieves better quality (5.5% vs 6.3%), but RL-3opt maintains practical efficiency with speedups reaching 32,323× and sub-second execution. For instances exceeding 5,000 cities, RL-3opt achieves 9.8% gaps matching classical 2-opt quality while executing orders of magnitude faster. Classical 3-opt becomes computationally infeasible beyond 1,000 cities.

By delivering near-optimal solutions on small instances and competitive solutions on large instances using standard CPU hardware without GPU acceleration, this framework democratizes access to effective TSP optimization. The combination of sub-second to few-second execution across all problem sizes, minimal configuration requirements, and favorable quality-time trade-offs makes RL-guided local search a practical alternative for real-world logistics, manufacturing, and routing applications where both solution quality and computational efficiency matter.

Future work will focus on implementing dynamic episode scaling and adaptive learning rates to improve performance on large instances, and extending the framework to related combinatorial problems including Vehicle Routing and Job Shop Scheduling.

References

[1] G. Laporte, "The traveling salesman problem: An overview of exact and approximate algorithms," *European Journal of Operational Research*, vol. 59, no. 2, pp. 231–247, 1992.

[2] M. R. Garey and D. S. Johnson, *Computers and Intractability: A Guide to the Theory of NP-Completeness*, W. H. Freeman, New York, 1979.

[3] D. L. Applegate, R. E. Bixby, V. Chvátal, and W. J. Cook, *The Traveling Salesman Problem: A Computational Study*, Princeton, NJ: Princeton University Press, 2011.

[4] Y. Bengio, A. Lodi, and A. Prouvost, "Machine learning for combinatorial optimization: A methodological tour d'horizon," *European Journal of Operational Research*, vol. 290, no. 2, pp. 405–421, 2021.

[5] N. Mazyavkina, S. Sviridov, S. Ivanov, and E. Burnaev, "Reinforcement learning for combinatorial optimization: A survey," *Computers & Operations Research*, vol. 134, p. 105400, 2021.

[6] B. Hudson, Q. Li, M. Malencia, and A. Prorok, "Graph neural network guided local search for the traveling salesperson problem," *arXiv preprint arXiv:2110.05291*, 2021.

[7] L. Xin, W. Song, Z. Cao, and J. Zhang, "NeuroLKH: Combining deep learning model with Lin–Kernighan–Helsgaun heuristic for solving the traveling salesman problem," *Advances in Neural Information Processing Systems*, vol. 34, pp. 7472–7483, 2021.

[8] Y.-D. Kwon, J. Choo, B. Kim, I. Yoon, Y. Gwon, and S. Min, "POMO: Policy optimization with multiple optima for reinforcement learning," in *Advances in Neural Information Processing Systems*, vol. 33, pp. 21188–21198, 2020.

[9] M. Kim, J. Park, and J. Park, "Sym-NCO: Leveraging symmetricity for neural combinatorial optimization," *Advances in Neural Information Processing Systems*, vol. 35, pp. 1936–1949, 2022.

[10] C. K. Joshi, T. Laurent, and X. Bresson, "An efficient graph convolutional network technique for the travelling salesman problem," *arXiv preprint arXiv:1906.01227*, 2019.

[11] G. Reinelt, "TSPLIB—A traveling salesman problem library," *ORSA Journal on Computing*, vol. 3, no. 4, pp. 376–384, 1991.

[12] G. Kizilateş and F. Nuriyeva, "On the nearest neighbor algorithms for the traveling salesman problem," in *Advances in Computational Science, Engineering and Information Technology*, Proc. 3rd Int. Conf. on Computational Science, Engineering and Information Technology (CCSEIT-2013), Konya, Turkey, vol. 1, pp. 111–118, Springer, 2013.

[13] M. Zuhanda, H. Mawengkang, S. Efendi, and M. Zarlis, "Hybrid local search algorithm for optimization route of travelling salesman problem," *International Journal of Advanced Computer Science and Applications (IJACSA)*, vol. 14, no. 9, 2023.

[14] E. Alkafaween, S. Elmougy, E. Essa, S. Mnasri, A. S. Tarawneh, and A. Hassanat, "IAM-TSP: Iterative approximate methods for solving the travelling salesman problem," *International Journal of Advanced Computer Science and Applications (IJACSA)*, vol. 14, no. 11, 2023.

[15] B. Chandra, H. Karloff, and C. Tovey, "New results on the old k-opt algorithm for the traveling salesman problem," *SIAM Journal on Computing*, vol. 28, no. 6, pp. 1998–2029, 1999.

[16] A. Blazinskas and A. Misevicius, "Combining 2-opt, 3-opt and 4-opt with k-swap-kick perturbations for the traveling salesman problem," Technical Report, Department of Multimedia Engineering, Kaunas University of Technology, 2011.

[17] K. Helsgaun, "An effective implementation of the Lin–Kernighan traveling salesman heuristic," *European Journal of Operational Research*, vol. 126, no. 1, pp. 106–130, 2000.

[18] K. Helsgaun, "An extension of the Lin–Kernighan–Helsgaun TSP solver for constrained traveling salesman and vehicle routing problems," *Roskilde University*, vol. 12, pp. 966–980, 2017.

[19] N. M. Razali and J. Geraghty, "Genetic algorithm performance with different selection strategies in solving TSP," in *Proceedings of the World Congress on Engineering*, vol. 2, no. 1, pp. 1–6, International Association of Engineers, Hong Kong, China, July 2011.

[20] Z. H. Ahmed, "Optimization of the travelling salesman problem using a new hybrid genetic algorithm," *International Journal of Computer Science and Network Security*, vol. 23, no. 10, pp. 189–198, 2020.

[21] Y. M. Abd Algani, "Optimization solutions for solving travelling salesman problem in graph theory using African buffalo mechanism," *International Journal of Advanced Computer Science and Applications (IJACSA)*, vol. 14, no. 7, pp. 273–282, 2023.

[22] J. Yang, X. Shi, M. Marchese, and Y. Liang, "An ant colony optimization method for generalized TSP problem," *Progress in Natural Science*, vol. 18, no. 11, pp. 1417–1422, 2008.

[23] G. Kou and G. Wei, "Hybrid particle swarm optimization-based modeling of wireless sensor network coverage optimization," *International Journal of Advanced Computer Science and Applications (IJACSA)*, vol. 14, no. 5, 2023.

[24] R. Wu, Y. Yang, X. Yao, and N. Lu, "Optimal trajectory planning for robotic arm based on improved dynamic multi-population particle swarm optimization algorithm," *International Journal of Advanced Computer Science and Applications (IJACSA)*, vol. 15, no. 5, 2024.

[25] C. Zhou, "Black widow optimization algorithm for virtual machines migration in the cloud environments," *International Journal of Advanced Computer Science and Applications (IJACSA)*, vol. 14, no. 8, 2023.

[26] G. Bai, "Enhancing Harris hawks optimization algorithm for resource allocation in cloud computing environments," *International Journal of Advanced Computer Science and Applications (IJACSA)*, vol. 15, no. 3, 2024.

[27] N. Kafakthong and K. Sinapiromsaran, "Near-optimal traveling salesman solution with deep attention," *International Journal of Advanced Computer Science and Applications (IJACSA)*, vol. 15, no. 12, pp. 918–928, 2024.

[28] O. Vinyals, M. Fortunato, and N. Jaitly, "Pointer networks," in *Advances in Neural Information Processing Systems*, vol. 28, 2015.

[29] I. Bello, H. Pham, Q. V. Le, M. Norouzi, and S. Bengio, "Neural combinatorial optimization with reinforcement learning," *arXiv preprint arXiv:1611.09940*, 2016.

[30] E. Khalil, H. Dai, Y. Zhang, B. Dilkina, and L. Song, "Learning combinatorial optimization algorithms over graphs," *Advances in Neural Information Processing Systems*, vol. 30, 2017.

[31] W. Kool, H. van Hoof, and M. Welling, "Attention, learn to solve routing problems!," *arXiv preprint arXiv:1803.08475*, 2018.

[32] Y. Wang, Z. Zhang, and L. Chen, "Performance comparison of Q-learning, SARSA, and double Q-learning for the traveling salesman problem," *Expert Systems with Applications*, vol. 213, p. 118865, 2023.

[33] X. Pan, Y. Jin, Y. Ding, M. Feng, L. Zhao, L. Song, and J. Bian, "H-TSP: Hierarchically solving the large-scale traveling salesman problem," in *Proc. 37th AAAI Conf. on Artificial Intelligence*, vol. 37, no. 8, pp. 9345–9353, June 2023.

[34] P. R. d'O Costa, J. Rhuggenaath, Y. Zhang, and A. Akcay, "Learning 2-opt heuristics for the traveling salesman problem via deep reinforcement learning," in *Proceedings of the Asian Conference on Machine Learning*, PMLR, pp. 465–480, Sept. 2020.

[35] J. Zheng, K. He, J. Zhou, Y. Jin, and C. M. Li, "Reinforced Lin–Kernighan–Helsgaun algorithms for the traveling salesman problems," *Knowledge-Based Systems*, vol. 260, p. 110144, 2023.

[36] S. El Jaghaoui, A. K. Elmiad, and A. B. Lmah, "Enhancing the traveling salesman problem solutions with reinforcement learning: A variant exploration-exploitation approach beyond ε-greedy," in *Proc. 14th Int. Conf. on Intelligent Systems: Theories and Applications (SITA)*, IEEE, pp. 1–6, Nov. 2023.

[37] S. El Jaghaoui, A. Benaini, and A. K. Elmiad, "An innovative Q-learning and ACO approaches for the traveling salesman problem," in *International Conference on Logistics Operations Management*, Cham: Springer Nature Switzerland, pp. 166–176, May 2024.

[38] Y. Ruan, Z. Li, and X. Wang, "Combining reinforcement learning and genetic algorithms for the traveling salesman problem," *Applied Intelligence*, vol. 54, pp. 3421–3436, 2024.

[39] P. R. Montague, "Reinforcement learning: an introduction, by Sutton, R. S., & Barto, A. G.," *Trends in Cognitive Sciences*, vol. 3, no. 9, p. 360, 1999.

A Two-Step Real-Time Complex Environmental Vehicle Detection Model

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***Abstract*—In recent years, as a critical pillar supporting the national economy and daily life, the safe and efficient operation of road traffic has highly relied on precise environmental perception capabilities. To address this, this study proposes a two-stage "denoising-detection" framework: the first stage restores clear images using an improved Uformer algorithm, which fundamentally merges a probabilistic sparse self-attention mechanism. In contrast, the second stage leverages YOLOv11 for real-time object detection. This framework is introduced in the field for the first time and enhances the accuracy and robustness of vehicle detection in traffic images under complex weather scenarios, providing technical support for intelligent driving systems and traffic monitoring applications. Our experimental validation on our own flexible weather car detection database demonstrated the superior performance of the proposed model: CM-YOLO achieved 0.95 precision and 0.91 mAP50, which promoted 0.2 than the YOLOv11.**

***Keywords*—Object detection; vehicle detection; image denoising**

I. Introduction

In recent years, highway transportation has become an important support for the national economy and daily life, and its safe and efficient operation highly relies on accurate environmental perception capabilities. However, severe weather can significantly reduce the quality of traffic images, seriously affecting the performance of object detection algorithms and increasing the risk of traffic accidents. According to statistics, the incidence of traffic accidents under complex weather conditions is 3-5 times higher than that under normal weather conditions[1]. Traditional object detection algorithms face two core problems in foggy scenes. On the one hand, complex weather scenes lead to blurry image features and reduced contrast between the target and background. On the other hand, the integration between existing denoising algorithms and detection models is insufficient, making it difficult to balance denoising effectiveness and detection efficiency. However, in recent years, transformer-based computer vision algorithms have provided new directions for image denoising and object detection by leveraging the advantages of the self-attention mechanism in global information capture. Therefore, this study proposes a two-stage framework of "denoising detection", in which the first stage restores clear images through an improved Uformer algorithm, and the second stage uses YOLOv11 to achieve real-time object detection, aiming to improve the accuracy and robustness of traffic vehicle detection in complex weather scenes and provide technical support for traffic monitoring systems.

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Image denoising algorithms can be divided into traditional methods and deep learning methods. Traditional methods, represented by dark channel prior (DCP) [2], estimate transmittance and atmospheric light through physical models, but edge distortion is prone to occur in complex scenes. In deep learning based methods, convolutional neural network (CNN) models such as AOD Net [3] and DehazeNet [4] achieve denoising through end-to-end learning, but are limited by local receptive fields and difficult to capture global complex noise distribution patterns. In recent years, transformer-based denoising algorithms have become a research hotspot. The Uformer model[5] integrates Transformer and U-Net structures, captures long-range dependencies through self self-attention mechanism, and performs well in denoising and other tasks. However, the traditional Uformer's window self-attention mechanism has the problem of high computational complexity, which limits its application in real-time scenes.

Object detection algorithms can be divided into two stages such as Faster R-CNN and single-stage, such as YOLO method [6]. YOLOv11, as the latest single-stage algorithm, achieves high-precision detection while maintaining real-time performance through anchor-free design and a feature fusion mechanism. However, YOLOv8 lacks the ability to recognize blurry targets in low-quality images and needs to be combined with dehazing preprocessing to improve performance. Moreover, existing joint frameworks often adopt a "denoising+detection" serial structure, and there are still shortcomings in the collaborative optimization of dehazing and detection modules. Based on this, this study improves the attention mechanism of Uformer and deeply combines it with YOLOv11 to achieve efficient object detection in complex sky scenes.

In addition, in the field of image restoration, many related studies have provided ideas for enhancing complex weather scene images, such as the application of enhanced deep residual networks in super-resolution tasks [7], the hierarchical visual Transformer design of Swin Transformer [8], and the exploration of spatial attention mechanisms [9] and model-driven deep neural networks [10] in complex weather denoising tasks. At the same time, the solution to specific image restoration tasks, such as removing patterns [11], also provides a reference for processing complex foggy scenes. In terms of model optimization, techniques such as decoupling weight decay regularization [12] and dual residual networks [13] provide effective means to improve the performance and stability of denoising and detection models.

To address vehicle detection in complex traffic scene images, this paper proposes a system framework named CM-YOLO, which autonomously denoises and analyzes complex

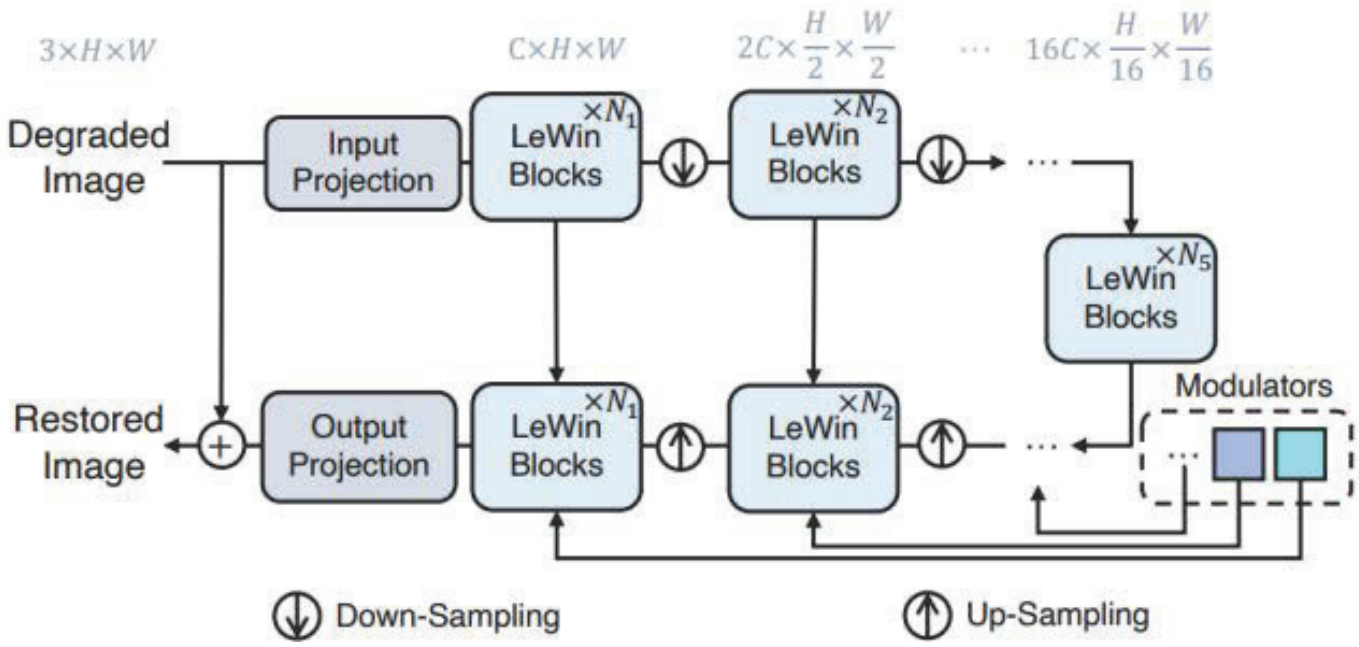


Fig. 1. Schematic of the Uformer.

scene information within images. Owing to the dual requirements of accuracy and real-time performance imposed by dispatch centers for traffic flow regulation, the target detection algorithm must maintain high detection accuracy while completing tasks with high efficiency. In this framework, all module is trained separately. The image will first be denoised by the improved Uformer algorithm to simplify image scenes, and then use the YOLOv11 algorithm as the recognition module to perform target detection on the simplified images. This cascaded architecture effectively achieves target detection in complex traffic scene images.

A. Denoising Module

To address the challenges of vehicle detection in complex traffic image scenarios with variable weather conditions on highways, this paper employs the Uformer model as the denoising module of CM-YOLO. This algorithm, as shown in Fig. 1, rooted in a Transformer-based architecture, integrates the classic U-Net structure, enabling high-quality execution of diverse image denoising tasks such as noise reduction, deblurring, and defogging. Notably, Uformer excels at capturing long-range dependencies within images, making it particularly well-suited for processing high-resolution images. By balancing restoration quality with computational efficiency, it effectively reduces computational complexity while maintaining high-quality image recovery, thus addressing the dual requirements of accuracy and real-time performance in traffic flow regulation scenarios.

Meanwhile, given the characteristics of terminal devices with limited memory and slow computing speeds, it is imperative to reduce the complexity of Uformer. To address this, this paper replaces the window-based multi-head self-attention mechanism used in traditional Uformer with a probabilistic sparse self-attention mechanism.

In the probabilistic sparse self-attention mechanism, each self-attention operation defines attention through a query sparsity measurement based on

$$q_i(K,V) = \sum_{j=1} \frac{k(q_i,k_j)}{\sum_{l=1} k(q_i,k_l)} v_j = E_p(k_j|q_i)[V_j] \quad (1)$$

In the probabilistic sparse self-attention mechanism[14], the attention of the i-th feature over all values is defined as a probability $p(k_j|q_i)$, and the output is generated by k combining this probability with the corresponding value v. If $p(k_j|q_i)$ approaches a uniform distribution

$$q(k_j,q_i) = \frac{1}{L_K} \quad (2)$$

Self-attention then degenerates into the summation of value V, becoming repetitive with other fixed inputs. Therefore, the similarity between two distributions p and q can be used to distinguish the importance of queries. The probabilistic sparse self-attention mechanism measures the similarity between these two distributions using the Kullback-Leibler divergence.

$$KL(q||p) = ln \sum_{l=1}^{L_K} e^{\frac{q_i k_l^t}{\sqrt{d}}} - \frac{1}{L_K} \sum_{j=1}^{L_K} \frac{q_i k_l^t}{\sqrt{d}} \quad (3)$$

Here, the first term represents the average of the log-sum-exp over all features, and the second term denotes their arithmetic mean. If the i-th query obtains a larger $M(q_i,K)$ its attention probability becomes more diverse, increasing the likelihood of including key head-field pairs in the head-tail self-attention distribution that determines the output.

Based on the proposed measurement method, the probabilistic sparse self-attention mechanism ensures each feature

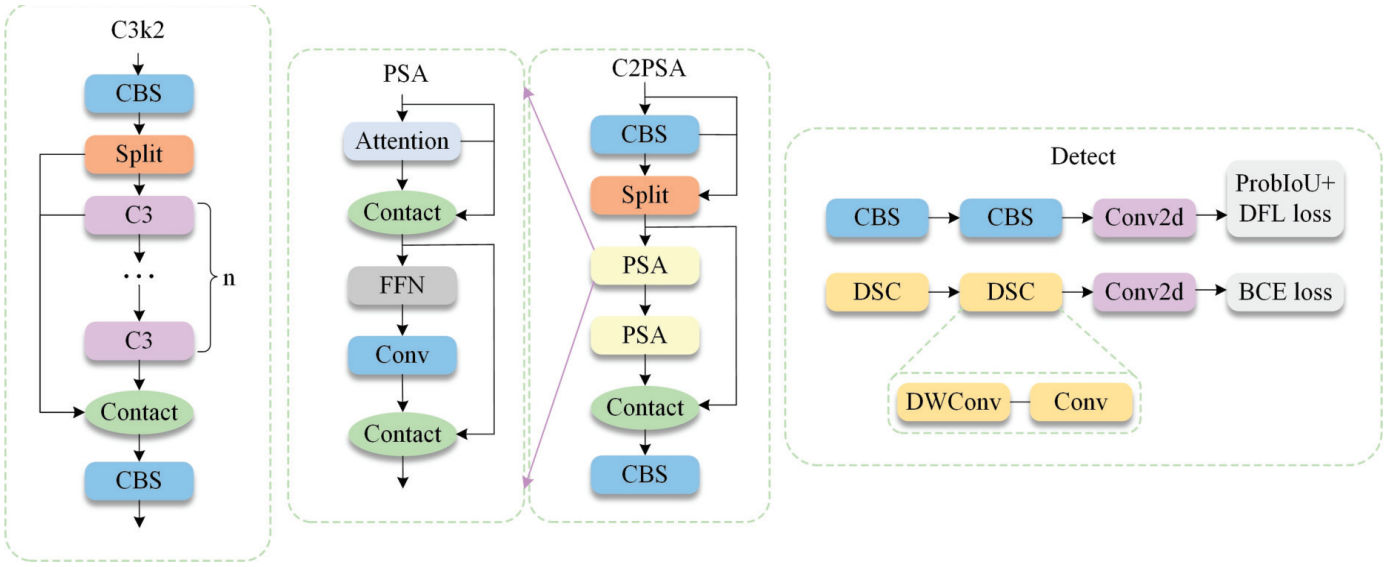


Fig. 2. The detection module structure.

only attends to u key queries:

$$A(Q,K,V) = Softmax(\frac{\overline{Q}K^T}{\sqrt{d}})V \tag{4}$$

Here, Q denotes a sparse matrix of the same size as q, containing only the $M(q,K)$ most critical queries under the sparsity measure u.

By utilizing this strategy, the space and time complexity ultimately approximates to $O(LlnL)$. and the Table I shows the superiority of this self-attention mechanism.

TABLE I. COMPARISON OF ROAD DAMAGE DETECTION RESULTS FOR VARIOUS MODEL SETS

method	time complexity	space complexity	runtime	memory
window-based self-attention	$O(L_K L_Q)$	$O(L_K L_Q)$	3.01ms	15.60GB
probabilistic sparse self-attention	$O(L_K lnL_Q)$	$O(L_K lnL_Q)$	2.57ms	11.35GB

B. Detection Module

To ensure efficient processing of simplified images, the model proposed in this paper employs the YOLOv11 algorithm as shown in Fig. 2 for vehicle recognition. Compared to traditional object detection algorithms such as R-CNN and its variants (e.g., Fast R-CNN, Faster R-CNN), the most significant advantage of YOLOv11 lies in its processing speed. The R-CNN series first generates region proposals and then classifies each region individually. Although this two-stage process achieves superior accuracy, its slower speed renders it unsuitable for real-time applications. In contrast, the holistic architectural design of YOLOv11 enables it to execute detection tasks at extremely high speeds, thereby meeting the rapid detection requirements of dispatch centers in this vehicle recognition task.

II. RESULTS

A. Datasets

In this study, the I-HAZE[15] and NH-Haze[16][17] were used to train the Denoising module and test on SPAD[18] for denoising. The train image samples were shown as Fig. 3. The BITVehicle dataset cite dongVehicleTypeClassification2015 was used to train the detection module. For efficient validation of our model, we built our own flexible weather car detection database, which has 6789 pictures with 17355 annotations. The Denoising module and the Detection module were trained separately, but detected sequentially; the undetected image will first utilize the improved Uformer module to denoise and use YOLOv11 to detect.

B. Evaluation Metrics

To rigorously validate the performance of CM-YOLO in multi-scale pavement crack detection, we adopted the following metrics aligned with real-time detection challenges:

The peak signal-to-noise ratio (PSNR) is an objective metric that quantifies the quality of a reconstructed image by measuring the ratio of the maximum possible pixel intensity to the noise power. It is widely used in image processing and compression tasks.

$$MSE = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}[I(i,j) - K(i,j)]^2 \tag{5}$$

where I represents the original image, K represents the processed image, M and N are the dimensions of the image.

$$PSNR = 10log_{10}\frac{MAX_I^2}{MSE} \tag{6}$$



Fig. 3. Samples of I-HAZE and NH-Haze database.



Fig. 4. Samples of BITVehicle database.

where MAX is the maximum pixel value.

SSIM evaluates the similarity between two images by analyzing structural, luminance, and contrast information, mimicking human visual perception.

Precision (P) measures the proportion of correct crack predictions among all detected regions and is critical for reducing false alarms in crack detection.

$$Precision = \frac{TP}{TP + FP} \tag{7}$$

where TP (true positive) denotes predicted boxes with $IoU \geq 0.5$ and correct class labels, and FP (false positive) indicates spurious detection.

Recall(R) evaluates the model's ability to capture all genuine cracks, which is essential for avoiding missed defects in safety-critical scenarios.

$$Recall = \frac{TP}{TP + FP} \tag{8}$$

where FN (false negatives) represent undetected ground-truth cracks ($IoU \leq 0.5$)

The average precision (AP) quantifies the model's category-specific detection consistency by computing the mean of the maximum precision values achieved across varying recall rates. The mean average precision (mAP) extends this evaluation by averaging AP scores across all object classes, thereby serving as a comprehensive metric for the model's cross-category detection performance. The mathematical formulation is

$$AP = \int_0^1 P(r)\, dr \tag{9}$$

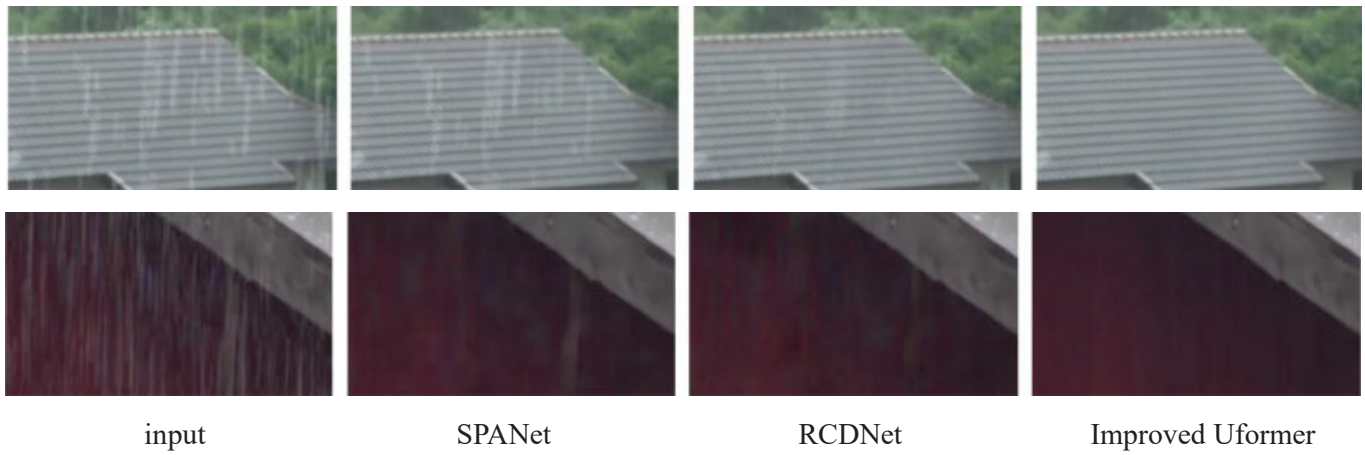


Fig. 5. Comparison of denoising results in SPAD database.

$$mAP = \frac{\sum_{i=1}^{C} AP\,(i)}{C} \tag{10}$$

Here, C is the number of crack subtypes.

C. Experimental Environment

The experimental framework in this study was implemented on a high-performance computing system running Ubuntu 11.04 as the operating system. The hardware setup included an Intel® Xeon® Platinum 8474C processor and an NVIDIA RTX 4090D graphics card with 24 GB of video memory, ensuring efficient computation for deep-learning tasks. The software environment was built using PyTorch 2.0.1, Python 3.10.8, and CUDA 11.8, which provided a robust foundation for model training and evaluation. The key hyperparameters were carefully tuned to optimize performance: The input images were resized to a resolution of 640 × 640 pixels, the initial learning rate was set to 0.0001, and the momentum for the learning rate was configured at 0.9. This combination of hardware, software, and Adaptive Moments with Weight Decay (AdamW) optimizer was used for training. These parameter settings ensured a stable and efficient training process for the proposed model.

D. Experimental Implementation and Results

1) Comparison of denosing results: This paper employs the improved Uformer algorithm for training on the I-HAZE data set and testing on the SPAD dataset. By analysing the PSNR and SSIM metrics of the improved Uformer algorithm, SPANet and RCDNet models, as Table II, which were tested by SPAD, and Fig. 5 shows that the improved Uformer algorithm can effectively restore images while retaining image features, with less noise, good denoising performance and small memory usage.

2) Ablation experiment results: To comprehensively assess the superiority of the denoising module, we primarily use three evaluation metrics: mAP50, recall, and precision. These metrics are compared against the baseline to validate the performance of the denoising module.

TABLE II. COMPARISON OF DENOSING RESULTS IN SPAD DATABASE

method	PSNR	SSIM	runtime(per image)	memory
SPANet	40.24	0.9811	-	-
RCDNet	41.47	0.9834	-	-
Uformer	47.92	0.9928	3.01ms	15.60GB
Ours	47.84	0.9925	2.57ms	11.35GB

TABLE III. COMPARISON OF DETECTION RESULTS FOR VARIOUS MODEL SETS IN OUR DATABASE

method	Denoising Model	P	R	mPA50
YOLOv11		0.93	0.86	0.89
	✓	0.95	0.88	0.91

As Table III , the results demonstrate that the introduced denoising model has positively affected model performance.

3) Comparison of results: To comprehensively assess the performance of the CM-YOLO model, we primarily use three evaluation metrics: mAP50, recall, and precision. These metrics are compared against YOLOv11 and YOLOv8 models to validate the effectiveness of our multi-modal fusion approach.

TABLE IV. COMPARISON OF DETECTION RESULTS IN OUR DATABASE

method	P	R	mAP50
YOLOv8n	0.90	0.84	0.88
RT-DETR(resnet18)	0.92	0.88	0.86
YOLOv11n	0.93	0.86	0.89
Ours	0.95	0.88	0.91

As the Table IV and Fig. 6 show that the proposed CM-YOLO algorithm demonstrates superior detection performance, achieving $P = 0.95$ and $mAP50 = 0.91$, outperforming YOLOv8n, RT-DETR(resnet18), and YOLOv11n. This advancement enables precise detection of vehicle models in complex weather scenarios, including rain, snow, and fog, where traditional models struggle due to noise interference and reduced visibility.



Fig. 6. Comparison of detection figures in our database.

III. Conclusion

CM-YOLO demonstrates strong adaptability to the complex scenario requirements of real-world traffic conditions, enabling effective image object detection tasks in challenging weather-related traffic environments. By fully leveraging the respective strengths of the Transformer model and the YOLOv11n model, it enhances the performance and efficacy of vehicle model detection in complex scenarios. However, practical applications of this algorithm still face certain limitations. Specifically, its object detection workflow requires parallel execution of two algorithms, imposing higher computational performance demands compared to standalone algorithms. In real-world deployments, its performance is constrained by the processing capabilities of vehicle systems.

For future research on such vehicle detection algorithms, the following directions warrant further exploration:

(1) Model optimization to accelerate detection speed: Current Uformer algorithms-even the version used in this study with probabilistic sparse self-attention mechanisms-exhibit larger parameter counts compared to previous de-fogging models, despite superior de-fogging performance. Continued optimization of model parameters is necessary.

(2) Algorithm/training strategy refinement for stability and accuracy: While the algorithm achieves competitive accuracy on normal scene images, there remains room for improvement. Iterative upgrades to the algorithm are needed. Additionally, scenario-specific data and training strategies should be prioritized. For example, pre-training the model on a dedicated dataset, adjusting pre-trained weights, and fine-tuning on downstream tasks could further enhance performance.

(3) Joint training of detection and de-noising algorithms: Collecting paired normal and complex weather traffic images under the same scenarios, followed by annotation, would enable pre-trained detection and de-noising models to be fine-tuned on this dataset.

In summary, the Transformer-based foggy weather traffic video object detection algorithm still has significant room for development. Ongoing research is essential to continuously improve detection speed, accuracy, and robustness in real-world applications.

Declarations

- Competing interests
  The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
- Ethics approval and consent to participate
  We promise that this manuscript will not be submitted to multiple journals or conferences simultaneously. We promise to abide by ethical standards, respect the autonomy of participants in the use of data, and ensure the legal, transparent, and secure use of data.
- Data availability
  Data will be made available on request.
- Author contribution
  Xingju Wang and Yiqian Liang designed the new method, Yiqian Liang and Zhihui Huo provided suggestions and analyzed the results. Yiqian Liang and Zhihui Huo wrote the manuscript.Yiqian Liang and Xingju Wang reviewed and edited this manuscript. All authors contributed to this work and approved the submitted version.

References

[1] M. Won, T. Park, and S. H. Son, "Toward Mitigating Phantom Jam Using Vehicle-to-Vehicle Communication," *IEEE TRANSACTIONS ON*

INTELLIGENT TRANSPORTATION SYSTEMS, vol. 18, no. 5, pp. 1313–1324, May 2017.

[2] A. Willig, "A Sensitivity Analysis of the DCP/Vardis Protocol for Coordinating Drone Swarms," in *2025 IEEE Vehicular Networking Conference (VNC)*.

[3] B. Li, X. Peng, Z. Wang, J. Xu, and D. Feng, "An All-in-One Network for Dehazing and Beyond," Jul. 2017.

[4] B. Cai, X. Xu, K. Jia, C. Qing, and D. Tao, "DehazeNet: An End-to-End System for Single Image Haze Removal," *IEEE TRANSACTIONS ON IMAGE PROCESSING*, vol. 25, no. 11, pp. 5187–5198, Nov. 2016.

[5] Z. Wang, X. Cun, J. Bao, W. Zhou, J. Liu, and H. Li, "Uformer: A General U-Shaped Transformer for Image Restoration," in *2022 IEEE/CVF CONFERENCE ON COMPUTER VISION AND PATTERN RECOGNITION (CVPR 2022)*. Los Alamitos: IEEE Computer Soc, 2022, pp. 17 662–17 672.

[6] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," May 2016.

[7] B. Lim, S. Son, H. Kim, S. Nah, and K. M. Lee, "Enhanced Deep Residual Networks for Single Image Super-Resolution," *IEEE*, 2017.

[8] Z. Liu, Y. Lin, Y. Cao, H. Hu, Y. Wei, Z. Zhang, S. Lin, and B. Guo, "Swin Transformer: Hierarchical Vision Transformer using Shifted Windows," in *2021 IEEE/CVF INTERNATIONAL CONFERENCE ON COMPUTER VISION (ICCV 2021)*. New York: IEEE, 2021, pp. 9992–10 002.

[9] T. Wang, X. Yang, K. Xu, S. Chen, Q. Zhang, and R. W. H. Lau, "Spatial Attentive Single-Image Deraining with a High Quality Real Rain Dataset," in *2019 IEEE/CVF CONFERENCE ON COMPUTER VISION AND PATTERN RECOGNITION (CVPR 2019)*. New York: IEEE, 2019, pp. 12 262–12 271.

[10] H. Wang, Q. Xie, Q. Zhao, and D. Meng, "A Model-driven Deep Neural Network for Single Image Rain Removal," *IEEE*, 2020.

[11] Y. Sun, Y. Yu, and W. Wang, "Moire Photo Restoration Using Multiresolution Convolutional Neural Networks," *IEEE TRANSACTIONS ON IMAGE PROCESSING*, vol. 27, no. 8, pp. 4160–4172, Aug. 2018.

[12] I. Loshchilov and F. Hutter, "Decoupled Weight Decay Regularization," 2017.

[13] X. Liu, M. Suganuma, Z. Sun, and T. Okatani, "Dual Residual Networks Leveraging the Potential of Paired Operations for Image Restoration," in *2019 IEEE/CVF CONFERENCE ON COMPUTER VISION AND PATTERN RECOGNITION (CVPR 2019)*. New York: IEEE, 2019, pp. 7000–7009.

[14] H. Zhou, S. Zhang, J. Peng, S. Zhang, J. Li, H. Xiong, and W. Zhang, "Informer: Beyond Efficient Transformer for Long Sequence Time-Series Forecasting," Mar. 2021.

[15] C. O. Ancuti, C. Ancuti, R. Timofte, and C. De Vleeschouwer, "I-HAZE: A dehazing benchmark with real hazy and haze-free indoor images," 2018.

[16] C. O. Ancuti, C. Ancuti, and R. Timofte, "NH-HAZE: an image dehazing benchmark with non-homogeneous hazy and haze-free images," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, ser. IEEE CVPR 2020, 2020.

[17] C. O. Ancuti, C. Ancuti, F.-A. Vasluianu, R. Timofte *et al.*, "NTIRE 2020 challenge on nonhomogeneous dehazing," 2020.

[18] K. He, J. Sun, and X. Tang, "Single Image Haze Removal Using Dark Channel Prior," *IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE*, vol. 33, no. 12, pp. 2341–2353, Dec. 2011.

HCC: A Hierarchical Chart Captioning Model for Enhanced Accessibility of Chart Data for Visually Impaired Users

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***Abstract*—In educational settings, charts and graphs are commonly used to convey complex information in a simple and understandable manner. However, these visual representations often present accessibility challenges regarding Accessibility for Visually Impaired users, as they cannot be directly interpreted by screen readers without proper alternative text. This paper proposes a novel hierarchical captioning model (HCC: Hierarchical Chart Captioning) designed to facilitate effective Chart Interpretation. The model utilizes spatial token features to generate captions at multiple levels, each offering varying degrees of detail and abstraction, mimicking human cognitive processing. Three hierarchical levels are developed: *Level 1* offers basic and factual descriptions, *Level 2* presents more detailed information, and *Level 3* provides intuitive interpretations and inferences. By integrating a fine-tuned Transformer Models, this approach ensures efficient caption generation and supports user-selectable caption lengths. The model's effectiveness is evaluated through user surveys involving 20 instructors, confirming that Level 2 captions provide the most comprehensible descriptions. Experimental results demonstrate that the proposed method outperforms existing captioning approaches, improving both the efficiency and accessibility of educational materials for visually impaired students. These findings highlight the potential of hierarchical learning models to create more inclusive and accessible educational experiences.**

***Keywords*—Hierarchical captioning; accessibility for visually impaired; chart interpretation; transformer models**

I. Introduction

Various chart materials, including graphs, are used in educational curricula. These charts and graphs are presented in a visual format and are an effective means of conveying complex information in a simple and understandable way. However, materials presented in visual form cannot be directly conveyed to individuals with visual impairments, as they are transmitted in text form through services such as screen readers [1], [2]. For visually impaired learners, the inability to directly perceive these visual materials not only limits their comprehension during lessons but also creates a persistent accessibility gap in real-world educational settings, reducing their opportunities for equal participation and achievement.

First, screen readers deliver content composed of text and images to people with visual impairments in an audio form. For graphs and charts, typically provided as images, instructors or content creators must manually input alternative text. Without it, visually impaired users cannot access the image content [3], [4].

Second, in most classes, when graphs or charts appear in lecture materials, instructors often assume that students have already perceived the visual information from the chart and focus on explaining its features. As a result, visually impaired students, lacking basic information about the chart, must rely solely on the instructor's spoken explanation, which limits the completeness of information they receive.

Third, this situation creates additional challenges for instructors when preparing lecture materials, as they must manually provide explanations for every graph and chart. The laborious task of setting alternative text often leads to omissions, resulting in images with insufficient descriptions.

The visually impaired learners, thus, struggle to access information through visual materials, and lack equal educational opportunities compared to other learners. The need to interpret images such as charts used in educational materials is critical to improving the quality of education for people with disabilities. While charts and graphs help to deliver and understand information quickly, for individuals with disabilities, accessing data in this visual form may be restricted. Therefore, research that helps individuals with disabilities easily access and interpret chart and graph information carries significant social value and meaning. To achieve this, this paper proposes a new methodology for generating image descriptions for individuals with disabilities. The approach leverages the spatial features of tokens—small image patches extracted from the chart that preserve both their content and position within the overall layout. By analyzing these tokens not only for their visual appearance but also for their location and relative arrangement, our method captures the structural context of the chart, which is essential for generating accurate and context-aware descriptions across multiple layers. This approach leverages hierarchical structures divided into four layers based on principles of human cognitive processing—progressing from basic visual perception to higher-level abstraction. Each layer corresponds to a distinct stage in how humans interpret visual information: 1) recognizing simple visual elements, 2) identifying relationships between elements, 3) summarizing overall patterns or trends, and 4) inferring contextual or conceptual meaning. Captions at each level vary in length and detail to align with different user needs and preferences. This method is referred to as

HCC: Hierarchical **C**hart **C**aptioning, highlighting its focus on providing multi-level descriptions that enhance accessibility for visually impaired users.

For individuals with visual impairments who receive all information through auditory means, only intuitive and concise information will be provided to facilitate their understanding of sound-based data [22]. Existing research on caption generation for charts and graphs primarily focuses on the accuracy of the generated captions, typically evaluated by measuring the similarity between human-generated and machine-generated captions. For instance, models such as PReFIL [12] and MATCHA [18] emphasize improving caption accuracy ... without explicitly addressing varying user needs or accessibility for visually impaired users. **The main contributions of this work are as follows:** 1) This study proposes a hierarchical captioning framework that generates captions at multiple levels of detail, enabling user-selectable descriptions tailored for accessibility needs. 2) Principles of hierarchical human cognition are integrated into caption generation, producing captions that balance factual accuracy and interpretability. 3) A user-centered evaluation is conducted to determine the most effective caption level for visually impaired users. Unlike prior works that produce a single, static caption optimized for text-similarity metrics, the proposed method introduces a multi-level captioning framework designed specifically for accessibility. This approach enables users—especially those with visual impairments—to select captions that balance factual accuracy and interpretability according to their needs, an aspect largely overlooked in existing chart captioning research. The novelty lies in integrating hierarchical human cognition principles into caption generation, coupled with a user-centered evaluation to determine the most effective caption level. The primary goal of this study is to develop a hierarchical chart captioning model (HCC) that enhances accessibility for visually impaired users by providing multi-level, user-selectable captions that balance factual accuracy with interpretability. This approach allows for the exploration of the optimal level and length for caption generation for chart images.

Unlike prior works that produce a single, static caption optimized for text-similarity metrics, our method introduces a multi-level captioning framework designed specifically for accessibility. This framework enables users—especially those with visual impairments—to select captions that balance factual accuracy and interpretability according to their needs, an aspect largely overlooked in existing chart captioning research. The novelty lies in integrating hierarchical human cognition principles into caption generation, coupled with a user-centered evaluation to determine the most effective caption level. The primary goal of this study is to develop a hierarchical chart captioning model (HCC) that enhances accessibility for visually impaired users by providing multi-level, user-selectable captions that balance factual accuracy with interpretability.

II. Related Research

A. Image Captioning Datasets

Datasets related to chart image interpretation and captioning have expanded from Question-Answering datasets [5], [6] to Image-caption pair datasets [7], [8]. Compared to large-scale natural language processing datasets [9], [10], the number of image captioning-related datasets is relatively small, limiting the use of large datasets like Transformer models [11]. PReFIL [12] has been proposed as a solution for Question-Answering data and has become a mainstream model for chart explanations. However, issues such as the complexity of Question-Answering data remain unresolved. Most natural language processing models primarily utilize the powerful capabilities of Transformers. These efforts have led to the successful integration with Large Language Models (LLMs) [13], [14], but practical applications of chart explanation models still focus mainly on their relation to labels. To build an effective caption generation model for charts, an approach based on human cognition is needed to facilitate smooth information delivery. Additionally, while image-based data should be factually accurate, overly narrow information delivery should be avoided.

B. Attention Mechanism for Natural Language Process

The attention mechanism primarily works through three components: K (key), V (value), and Q (query). Its main goal is to recognize information related to the input data and understand dependencies within sequences. This attention mechanism is used in various artificial intelligence (AI) models, primarily in encoder-decoder architectures. For example, GPT (Generative Pre-trained Transformer) [15], which is based on a decoder structure, utilizes attention mechanisms to perform unidirectional learning. This model calculates attention for input sequences and generates subsequent words. In contrast, BERT (Bidirectional Encoder Representations from Transformers) [16], based on an encoder structure, performs bidirectional learning by applying attention to both directions of the input sequence to understand context and learn effective representations. These models use the attention mechanism to dynamically detect and process relevant information in its input data, demonstrating excellent performance in natural language processing and other AI tasks.

C. Deep Learning-based Image Captioning Models

Image captioning has drawn significant attention with the advancement of deep learning techniques. Models that generate captions for images combine visual feature extraction and natural language processing. The most commonly used deep learning-based image captioning models are those that combine Convolutional Neural Network (CNN) and Recurrent Neural Network (RNN) architectures. CNN models such as VGG [26] and ResNet [27] extract visual features from images, which are then used as input for natural language generation models. After obtaining the visual features of the image, an RNN-based model generates sentences, and model performance is evaluated using automatic metrics (such as BLEU [24], METEOR [25]) and human evaluation. Deep learning-based image captioning models learn meaningful relationships between images and text and are utilized to generate descriptions for images. However, most existing caption generation models focus on creating captions at a single level by considering the overall context of the image. However, people's perception and information processing involve multiple stages of abstraction, gradually moving from detailed information to higher-level concepts [19].

Recent large-scale vision-language models, such as BLIP [29] and DePlot [30], have achieved state-of-the-art performance in general image captioning and chart-to-table translation. These models primarily focus on maximizing data extraction accuracy and reasoning capabilities, often treating chart captioning as a "one-shot" generation task optimized for text-similarity metrics (e.g., BLEU, CIDEr). However, from an accessibility perspective, these approaches exhibit a critical limitation: they produce a single, static output that fails to account for the cognitive constraints of visually impaired users receiving information via audio.

In an auditory environment, presenting a lengthy, unstructured description generated by these models can induce cognitive overload, making it difficult for users to grasp the overall context before diving into details. Unlike these general-purpose models, the HCC model is fundamentally distinct in its architectural assumption and task formulation. Chart captioning redefined not as a static translation task but as a user-centric, hierarchical scaffolding process. By explicitly modeling human cognitive stages—from fragmented perception to concrete interpretation—HCC offers variable-level captions that allow users to control the granularity of information. This "accessibility-first" design ensures that the generated captions are not just factually accurate, but also cognitively digestible for screen reader users, addressing a dimension of usability that standard vision-language models overlook.

III. Hierarchical Chart Caption Generation Model

A. Model Design for Hierarchical Chart Extraction

The goal of this section is to present the design and methodology of our proposed Hierarchical Chart Captioning (HCC) model, which generates multi-level captions for chart images to enhance accessibility for visually impaired users.In this work, the term hierarchical captions refers to a structured set of captions describing the same chart image at multiple levels of detail and abstraction, where lower levels focus on basic, factual elements and higher levels provide progressively richer, more interpretive information. The dataset and model architecture used for hierarchical caption extraction are first outlined, followed by the strategy for generating captions at varying levels of detail. This study is guided by the following research question: *"Can a transformer-based captioning model, when fine-tuned to generate descriptions at multiple hierarchical levels, improve the comprehensibility and accessibility of chart data for visually impaired users compared to single-level captioning approaches?"* The working hypothesis is that generating captions across multiple levels—aligned with human cognitive processing—will provide flexibility for different user needs while preserving factual accuracy and enhancing interpretability.

This study develops a model that generates hierarchical captions for chart images based on the LineCAP dataset [28]. The dataset is a comprehensive collection of annotated line chart images designed to enhance automatic chart analysis and processing in the fields of computer vision and machine learning. It includes various types of line charts with annotations for chart type, labels, axes, and data points, which can be used to extract hierarchical captions. For training the proposed model, pre-existing multi-level captions in the dataset were not relied upon; instead, three separate training subsets—one for each hierarchical level—were constructed by programmatically transforming the original LineCAP annotations. Specifically, Level 1 captions were generated by extracting only the most basic factual elements from the annotations (e.g., axis labels, line identifiers), Level 2 captions incorporated more detailed relationships and trends between elements, and Level 3 captions added shallow inferential statements derived from the annotated data. These level-specific subsets were then used to fine-tune the model in a multi-task learning setup, where each input chart image was paired with three corresponding captions, one per level. Fig. 1 shows the structure of the hierarchical caption generation model based on the Transformer architecture.

This model uses the attention mechanism to focus on the features of the chart image and generate captions focused on three different types, allowing for hierarchical caption generation. The hierarchical generation of captions in this study was achieved by fine-tuning the T5 model [17], a large-scale, multi-purpose pre-trained text-to-text Transformer, with sequence lengths limited to 16, 32, and 64 tokens. These lengths were chosen to balance accessibility for visually impaired users—avoiding overly long captions that hinder auditory processing and overly short captions that omit key details—with empirical stability observed during preliminary experiments. The T5-base configuration was utilized, which contains 12 layers in the encoder and 12 layers in the decoder, each with a hidden size of 768 and 12 attention heads. The base architecture was preserved, but the input embedding layer was modified to accept spatial token features from the chart image encoder instead of standard text embeddings, and the output projection layer was adjusted to generate captions at three predefined sequence lengths corresponding to the hierarchical levels. No other structural changes were made to the Transformer blocks.

Other lengths such as 24 and 48 tokens were also tested, but they provided no significant improvement in comprehension or training stability, leading to the adoption of the 16–32–64 configuration. Multiple experiments were conducted to explore the optimal setup, starting with an initial learning rate of 3e-5, weight decay of 0.01, batch size of 32, and gradient clipping at a maximum norm of 1.0. Hyperparameters were tuned through an iterative manual adjustment process guided by validation loss trends. Common defaults from prior Transformer-based captioning studies were initially employed, after which each parameter—learning rate, weight decay, and batch size—was adjusted individually while monitoring validation loss and caption quality on a held-out set. Configurations yielding the lowest validation loss without overfitting signs were selected as the final values. When validation loss plateaued for three consecutive epochs or increased by more than 10.

Despite the powerful tokenizer and architecture of the original model, instability during training led to adjustments to the learning rate and repeated implementations. If divergence was observed, training parameters were adjusted to prevent information loss due to sequence length limitations. T5, a text-to-text model, uses both the original image caption data and the input sequences limited in length during training. As a

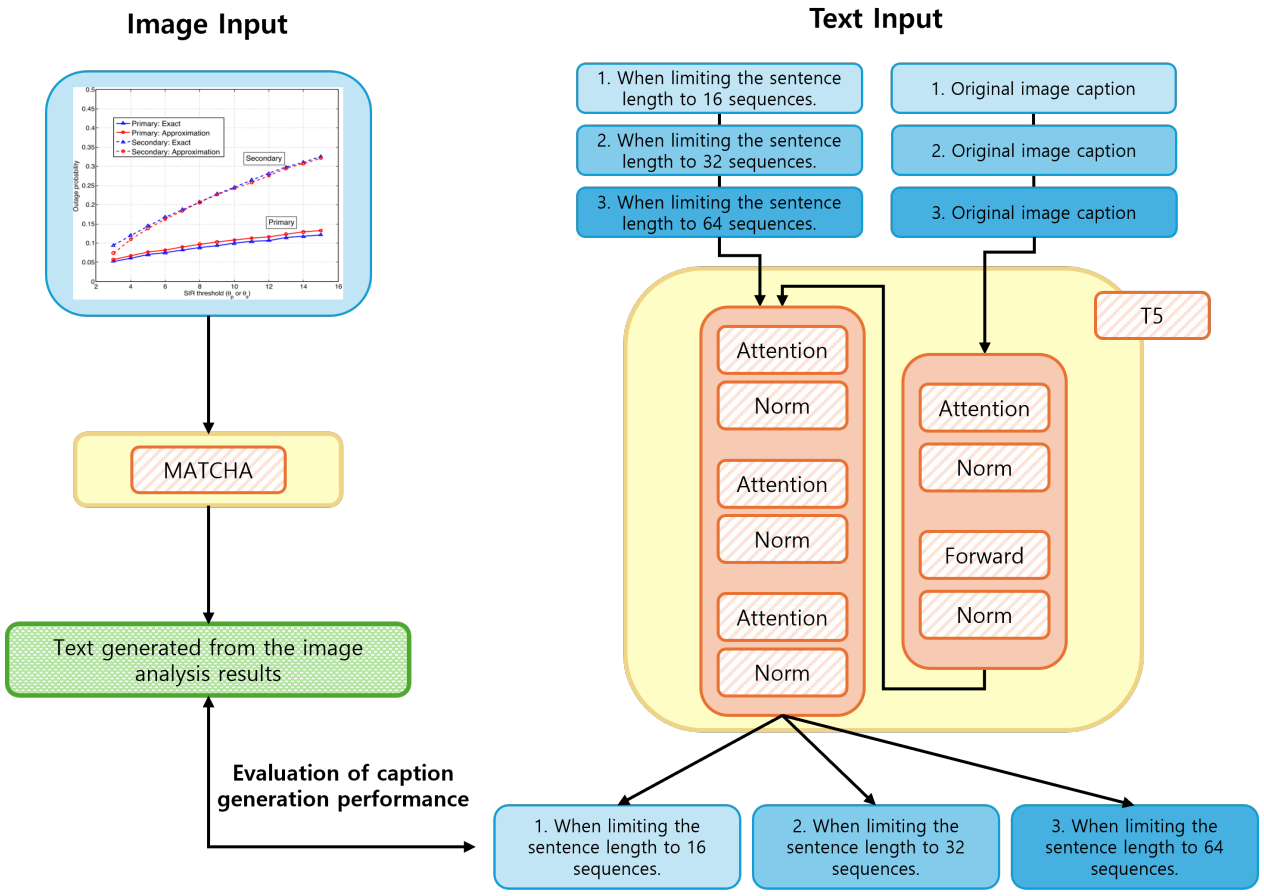


Fig. 1. Overall architecture of the proposed Hierarchical Chart Captioning (HCC) model. The visual encoder (left) processes spatial token features extracted from the input chart image, capturing both visual content and positional structure. These features are fed into the hierarchical caption generator (center, based on the T5 Transformer), where the encoder stack refines the representations and the decoder stack produces captions at three target sequence lengths (16, 32, 64 tokens) corresponding to different abstraction levels (Level 1–3). The encoder and decoder interact via cross-attention, allowing the decoder to selectively attend to relevant encoded features while generating the caption. MATCHA is used as a baseline comparison model, and the generated captions are evaluated for accessibility and comprehension.

result, captions of lengths 16, 32, and 64 are generated as outputs. These outputs are compared with MATCHA's image feature description text for performance evaluation. In this study, MATCHA is used solely as a benchmarking baseline to evaluate the quality of generated captions. It is not involved in the training process of our model. Specifically, after generating hierarchical captions with our fine-tuned T5-based model, The descriptive quality of the generated captions is compared against captions produced by MATCHA, following the same chart image inputs, to provide a consistent reference for performance assessment. MATCHA adopts the same structure as Pix2Struct [18], where the image encoder processes the input image through a series of Transformer layers to extract features, while the text decoder generates token sequences representing the structural layout of the image.

B. Hierarchical Caption Extraction Method

The hierarchical structure of the caption generation model proposed in this study consists of three levels: *Level 1, Level 2,* and *Level 3*, as shown in Fig. 2. This figure illustrates the link between these caption levels and information granularity. Specifically, the graph on the left (PDR% vs. percentage of source nodes) demonstrates how selecting different caption levels allows for balancing interpretability, detail, and performance under varying data conditions. The reason for dividing the caption into three levels is that human information recognition is performed in four stages, and Layers 1–4 correspond to fragmented information, refined information, specific information, and abstract information [19]. Therefore, captions were initially derived in four types to align with these cognitive stages. However, Level 4 captions were excluded from the final analysis because, despite being intended to represent the "abstract" stage of cognition, they exhibited substantial textual redundancy with the human-written reference captions. This meant that Level 4 did not introduce a genuinely new cognitive layer but instead reproduced the reference captions with minimal lexical changes, thereby failing to capture an additional abstraction process beyond Level 3. Quantitative evidence supports this decision: the average BLEU-4 score between Level 4 captions and the references was 0.92, and over 85% of sentences matched almost verbatim. For instance, in many samples, Level 4 captions duplicated entire reference sentences except for minor punctuation differences. Given this lack of conceptual distinction, retaining Level 4 would confound the analysis of hierarchical abstraction. Consequently, the focus

remained exclusively on Levels 1–3, which demonstrated clearer, progressive gradations in detail and interpretability. The captions of Level 1 explain the basic and factual elements of the chart in simple and intuitive language, focusing only on the basic expression of the data. The Level 2 captions provide more detailed expressions than the Level 1, offering information that can be directly extracted from the chart. Lastly, the captions of the Level 3 add interpretations to the chart by providing shallow inferences based on intuitive facts. This hierarchical expression structure expands the model's

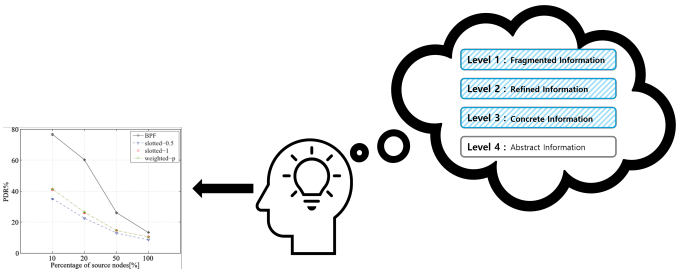


Fig. 2. Hierarchical caption levels in the proposed HCC model and their link to information granularity.

practical application in chart explanation, reflecting an attempt to reflect subjective human interpretation. This is a strategic approach to appropriately interpret the complexity of data visualization and offers deeper insights. In this study, the sequence length was limited to 16, 32, and 64 during training to maintain model learning efficiency while considering the necessary information to generate appropriate captions related to the input image.

In the context of the attention mechanism in neural networks, computational complexity is closely related to the number of tokens (n). In our model, controlling n is directly tied to the sequence length settings (16, 32, 64 tokens) used for different hierarchical caption levels. This allows us to balance descriptive detail with computational feasibility for accessibility-focused caption generation. Despite not performing computations for all token pairs, the computational burden increases proportionally to the square of n, as described in Eq. (1).

$$T(n) = O(n^2 \cdot d) \tag{1}$$

Moreover, the model's processing capacity in the input space increases linearly with n, as outlined in Eq. (2), where c represents a model-dependent constant. In practical terms, this reflects how increasing caption length expands the model's ability to capture detailed chart features, but at the cost of higher processing demands.

$$T(n) = c \cdot n \tag{2}$$

Considering inductive bias within the framework of Ridge Regression [23], the cost function (J) can be formulated by setting the attention mechanism as the hypothesis function.Here, inductive bias is interpreted as a form of regularization that constrains the model's attention weights when generating captions of varying lengths. When computing dependencies between text sequences x and y, the parameters (θ) and the regularization parameter (λ) can be derived from the number of training samples (m) and the number of features (n). By controlling n through sequence length limits, consequently, the inductive bias is implicitly regulated, which helps maintain stable learning across hierarchical levels without overfitting to any single caption length. This suggests that by controlling the number of tokens (n) within a constrained space of m, x, and y, the inductive bias can be effectively regulated [Eq. (3)].

$$J(\theta) = \sum_{i=1}^{m} \left(h_\theta(x^{(i)}) - y^{(i)} \right)^2 + \lambda \sum_{j=1}^{n} \theta_j^2 \tag{3}$$

IV. Experiment and Evaluation

A. Experiment and Results

The primary objective of our experiments is to comprehensively evaluate the proposed HCC model in terms of four key aspects: 1) its ability to control the input space while preserving the intrinsic properties of the attention mechanism, 2) its usability for visually impaired users through clarity-focused caption generation, and 3) the validity and effectiveness of the newly introduced performance metric M.

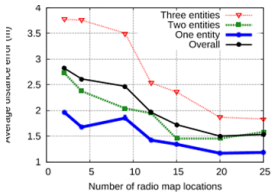
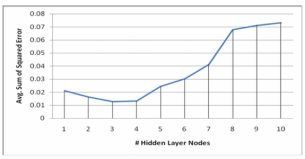
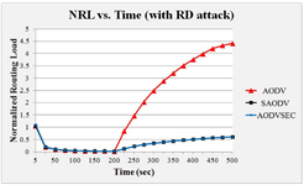
This paper proposes a model that can effectively control the input space while preserving the intrinsic properties of the attention mechanism. To develop this model, a pre-trained T5-base Transformer model [17] is utilized, originally trained on the Colossal Clean Crawled Corpus (C4) dataset [20] containing 60,000 tokens.

All encoder and decoder layers were fine-tuned, while only the input embedding layer was modified to accept spatial token features from the chart image encoder and the output projection layer was adjusted to support multiple sequence length targets (16, 32, 64 tokens) corresponding to the proposed hierarchical captioning levels. This fine-tuning was necessary to adapt the model from its original text-to-text objective to the chart captioning task, ensuring it could effectively map spatial visual features to multi-level textual descriptions.

For fine-tuning, the learning rate was set to 3e-5, the batch size to 32, and the model was trained for 20 epochs using the AdamW optimizer with a weight decay of 0.01. These parameters were selected based on preliminary experiments to ensure stable convergence and reproducibility. Cross-entropy loss was utilized as the objective function. Prior to training, all chart images were resized to 512×512 pixels, normalized to the range [0, 1], and converted into spatial tokens via patch embedding. The LineCAP dataset was split into 80% training, 10% validation, and 10% testing sets, ensuring that charts from the same source did not appear in multiple splits to prevent data leakage. All experiments were implemented in Python 3.10 using PyTorch 2.1.0 and HuggingFace Transformers 4.36.2, with supporting libraries including NumPy 1.26.4, OpenCV 4.8.1, and scikit-learn 1.3.2. Training was performed on Ubuntu 22.04 with an NVIDIA RTX 3090 GPU (24 GB VRAM) and CUDA 12.1.

This extensive dataset ensures that the model can recognize and represent complex patterns and relationships in the data. As shown in Table I, hleach hierarchical level offers

TABLE I. COMPARISON OF HIERARCHICAL CAPTIONS GENERATED BY HCC MODEL AND ORIGINAL CAPTIONS

Chart ID	Chart Image	Captions
1	 Original Caption: Lines 2 and 4 intersect a total of three times. They first intersect at xlabel 12, then at xlabel 20, and lastly at xlabel 25.	**Layer 1**: Lines 2 and 4 intersect at xlabel 12, then at xlabel 20, and lastly at x. **Layer 2**: Lines 2 and 4 intersect at xlabel 12, then at xlabel 20, and lastly at x. **Layer 3**: Lines 2 and 4 intersect three times at xlabel 12, then at xlabel 20, and lastly at x.
2	 Original Caption: ylabel at first decreases at a decreasing rate, then increases roughly at an increasing rate, and then increases at a decreasing rate.	**Layer 1**: The line at first decreases, then increases. **Layer 2**: The line at first decreases at a decreasing rate, then increases at an increasing rate. **Layer 3**: The line at first decreases at a decreasing rate, then increases roughly at an increasing rate.
3	 Original Caption: All lines share the same trend from xlabel 5 to 200. Lines 2 and 3 even share the same trend for all values of xlabel.	**Layer 1**: All lines have the same trend from xlabel 5 to 200. **Layer 2**: All lines have the same trend from xlabel 5 to 200. **Layer 3**: All lines have the same trend from xlabel 5 to 200. Lines 2 and 3 share the same trend for all xlabel values.

a distinct balance between brevity and detail. Specifically, Layer 1 captions provide concise factual descriptions, Layer 2 adds moderate detail for improved clarity, and Layer 3 incorporates the most comprehensive explanation, sometimes adding interpretive insights. Layer 2 captions, for example, provide sufficient context without excessive complexity, which aligns with our usability study finding that Layer 2 is the most comprehensible for visually impaired users. This supports our claim that an intermediate level of abstraction maximizes accessibility. It is noteworthy that the captions at each layer convey the same information from diverse perspectives, and all of the explanations highlight the tendency of the third and fourth lines to be similar. Overall, in Layer 1, it is challenging to discern the extent of data representation in the chart due to the uniformity of the lines in their description of the trend. Layer 2 offers slightly more descriptive capabilities than Layer 1. Layer 3 augments the information in Layer 2, incorporating an explanation of the data represented by the chart.

To apply the generated captions as descriptions for chart materials provided to individuals with visual impairments, usability evaluation is crucial. To evaluate the proposed hierarchical chart caption generation model, a within-subjects survey was conducted with 20 actual instructors. The participants rated three caption layers for five samples, including those shown in Table I, using a 5-point Likert scale. The remaining samples were randomly selected from the LINECAP dataset. Each respondent was tasked with selecting the most comprehensible caption from the provided options for each layer, with a 5-point Likert scale utilized to assess the perceived clarity of each caption. The 5-point Likert scale was composed of 1 = Very Dissatisfied and 5 = Very Satisfied. The results of this survey indicated that the captions generated by Layer 2 seem to be the most comprehensible, as shown in Fig. 3. Fig. 3 presents a graph showing the average understanding score for each caption layer, evaluated on a 5-point Likert scale.

According to Fig. 3, the captions generated by the Layer 3 were also rated as highly relevant, while Layer 1 had the lowest score (Layer 2=3.35, Layer 3 = 2.88, Layer 1 =2.75). In addition, an analysis of variance (ANOVA) was performed to determine if the mean comprehension scores between each layer were statistically significant. The P value of 0.019 confirmed that the mean comprehension scores between the groups were different and statistically significant. In fact, the Diagram Center Image Description [21], which is used by the U.S. Department of Education as a guideline for writing descriptions to make visuals accessible and usable by students with disabilities, suggests that when writing descriptions for diagrams, the captions should be minimal and informative such as the captions in the layer 2. The hierarchical captions generated by this model not only automatically generates

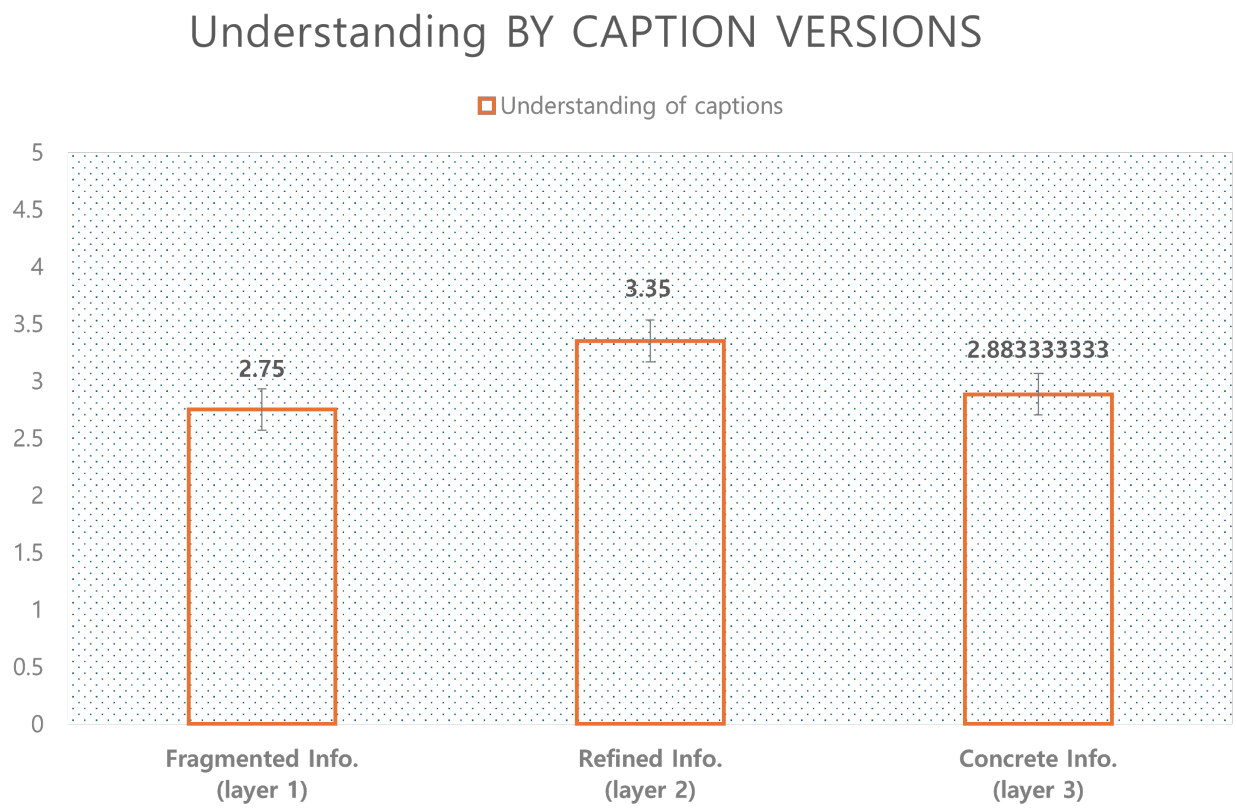


Fig. 3. Graph showing the average understanding score for each caption layer, evaluated on a 5-point Likert scale.

captions when an image is entered, but also automatically assigns the layer 2 captions selected by the usability evaluation so that it can be entered.

B. Caption Generation Performance Evaluation

Before introducing the new metric M, the data preparation process used for this evaluation is first described. The datasets LineCAP, DVQA, and FigureQA were selected because they provide diverse chart types and high-quality annotations necessary for training a robust chart captioning model, covering both low-level data extraction and high-level reasoning tasks. For each of these datasets, the same preprocessing pipeline was applied as in model training: all chart images were resized to 512×512 pixels, normalized to the range [0,1], and converted into spatial tokens via patch embedding. For each test set, hierarchical captions (Levels 1–3) were generated using the fine-tuned HCC model. The corresponding attention masks from the decoder cross-attention layers were stored to enable the computation of SV_{am} in the metric formula. No training or validation samples were included, ensuring that all metric computations were performed on unseen data to maintain evaluation integrity.

Traditional captioning metrics such as BLEU or CIDEr are designed to reward lexical overlap between a generated caption and a single reference caption. In our hierarchical setting, captions at different levels (e.g., Level 1 vs. Level 3) are intentionally diverse in length, detail, and abstraction, meaning that a low lexical match does not imply poor quality. For example, a concise Level 1 caption can be perfectly accurate yet achieve a low BLEU score simply due to its brevity. Similarly, CIDEr's term-frequency weighting favors n-gram overlap, which biases against higher-level captions that incorporate interpretive language absent from the reference. These metrics are therefore discarded because they conflate intended stylistic variation with error, and metric M is adopted instead to directly assess feature preservation and attention distribution properties that remain meaningful across levels

Therefore, the objective of this research is not to ensure high performance on the correct answer labels generated by the model, but rather to prioritize stable learning through caption generation to enhance the practical utility of the model. To this end, the following metric was established, given in Eq. (4).

$$M = \cos(f_\theta(x), y) \cdot k + \sigma(SV_{am}) \tag{4}$$

This metric comprises two terms. The first utilizes cosine similarity to ensure that the model's output preserves the features of the input tokens without compromising their characteristics. Here, "input" refers to the vectorized embedding representation of the spatial tokens extracted from the chart image encoder, and "output" refers to the embedding representation of the generated caption tokens produced by the decoder. Both are mapped into the same latent space using the final projection layer before similarity computation. This ensures that cosine similarity measures alignment between semantic feature vectors rather than raw token IDs or unprocessed

TABLE II. EVALUATION OF CAPTION GENERATION PERFORMANCE ACROSS THREE DATASETS (LINECAP, DVQA, FIGUREQA) USING THE PROPOSED METRIC M. HIGHER SCORES INDICATE BETTER SEMANTIC FEATURE PRESERVATION AND BALANCED ATTENTION FOCUS. 'M(OURS)' REPRESENTS THE PROPOSED HCC MODEL, WHILE 'M(NEW BASELINE)' DENOTES A STANDARD FINE-TUNED T5 MODEL

M/dataset	**LineCAP**	**DVQA**	**FigureQA**
Existing performance evaluation metrics	**BLEU-4/CIDEr**	Structure/Data/Reasoning	Accuracy
Existing evaluation metrics results	0.418/1.096	94.47/65.40/44.03	72.54

TABLE III. COMPARE THE NEW "M (BASELINE)" RESULTS WITH OUR "M (OURS)" RESULTS

M/dataset	**LineCAP**	**DVQA**	**FigureQA**
M(New baseline)	15.98	13.24	16.98
M(Ours)	10.92	9.84	7.34

sequences, avoiding ambiguity between "input tokens" and "output tokens."

The second term examines the standard deviation of the singular values (SV_{am}) of the attention mask. SV_{am} denotes the set of singular values obtained by applying Singular Value Decomposition (SVD) to the attention mask matrices extracted from the decoder's cross-attention layers. For each generated caption, the attention mask $A \in \mathbb{R}^{n \times n}$ is collected, where n is the sequence length, and SVD is performed: $A = U\Sigma V^\top$. The diagonal entries of Σ represent the singular values, which capture the distribution of energy across attention components. Singular values are aggregated across all heads and layers for each caption, and the standard deviation is computed to quantify the variability in attention focus. This process is repeated for all samples in the test set to produce the final SV_{am} value used in the metric M. Rather than implying that lower variance always equates to better expressiveness, a moderate reduction is interpreted as desirable because it suggests a balanced allocation of attention that preserves relevant structural information while avoiding noise-induced dispersion.

The earlier discussion of attention complexity in Eq. (1) and (2) directly informs the interpretation of metric M. Controlling the sequence length n in the hierarchical captions not only constrains the $O(n^2 \cdot d)$ computational cost but also influences the structure of the attention masks from which SV_{am} is computed. Shorter sequences reduce potential attention dispersion, leading to a more concentrated singular value spectrum, whereas longer sequences increase complexity and variability in attention focus. By incorporating SV_{am} into M, this trade-off between descriptive richness and computational efficiency is captured.

This value $k = 10$ was selected through preliminary sensitivity analysis, where k was varied across 1, 5, 10, 20 and the resulting metric distributions were inspected. It was observed that $k = 10$ provided a balanced scaling between the cosine similarity term and the singular value variability term.

Table II and III demonstrate that our model consistently achieves lower M scores across all datasets compared to the baseline, with reductions of up to 56.8% (FigureQA). Since a lower M indicates better semantic alignment and more balanced attention distribution, these results provide quantitative evidence that the proposed HCC model more effectively preserves key features of the input space while controlling complexity.

Focusing on the results of the newly proposed 'M(baseline)' and our 'M(Ours)', the following observations can be made. In the LineCAP dataset, the baseline achieved 15.98, while our model achieved 10.92. Similarly, for DVQA, the baseline scored 13.24, and our model scored 9.84, while in FigureQA, the baseline result was 16.98, and our model scored 7.34. In all datasets, our model outperformed the baseline. Notably, in FigureQA, the M value decreased by almost half, indicating an improvement in performance.

V. DISCUSSION : ENHANCING ACCESSIBILITY THROUGH USER-COGNIZANT HIERARCHICAL CAPTIONING

The Hierarchical Chart Captioning (HCC) model is fundamentally distinguished from prior works, which primarily focused on maximizing lexical similarity metrics, by aiming to resolve the practical accessibility gap through a user-centered approach. This section discusses the behavioral and cognitive implications of our hierarchical framework.

A. The Mechanism of Hierarchical Captioning in Mitigating Cognitive Load

HCC's effectiveness is rooted in its ability to translate the complex stages of human visual information processing—which progresses from visual perception to higher-level abstraction—into a manageable auditory information delivery structure. This mechanism directly addresses the significant cognitive load associated with processing lengthy, undifferentiated auditory descriptions in non-visual environments.

The multi-level structure segments chart information into ascending cognitive levels: Level 1 (basic facts), Level 2 (relationships and trends), and Level 3 (shallow inferences). This managed segmentation allows users to assimilate the chart data incrementally, supporting a fundamental principle of Universal Access by providing flexible information delivery based on individual processing needs. Furthermore, the approach of offering user-selectable sequence lengths (16, 32, 64 tokens) introduces a critical HCI benefit, empowering the visually impaired user to tailor the information depth to their immediate needs, thereby overcoming the inefficiency of auditory searching through overly long, static narratives.

B. Level 2 as the Optimal Threshold for Information Comprehension

The user evaluation, which involved a survey with 20 instructors, empirically confirmed that the Layer 2 caption

achieved the highest comprehensibility score (3.35), positioning it as the optimal level for driving positive information comprehension behavior. This finding is central to our work, highlighting a critical trade-off between descriptive detail and cognitive feasibility. The inadequacy of extremes was clearly demonstrated, as Level 1 captions, due to their limited and fragmented information, scored the lowest (2.75) because they failed to establish the necessary overall context or data relationships. Conversely, Level 3 captions, while relevant due to the inclusion of inferences, imposed a higher cognitive burden due to their increased length and complexity, resulting in a comprehension score (2.88) lower than Level 2. Level 2 is thus identified as the optimal point of cognitive equilibrium. By detailing the relationships and trends directly extractable from the chart, Level 2 provides sufficient context while judiciously avoiding the excessive complexity and subjective interpretation of Level 3. This balanced delivery strategy aligns precisely with accessibility best practices, such as those recommended by the U.S. Department of Education's Diagram Center, which advocates for minimal yet informative descriptions. The superior performance of Level 2 captions provides strong empirical evidence that effective accessibility solutions must be driven not merely by technological performance metrics, but by an HCI design balance that explicitly accounts for user-specific cognitive capacities to yield successful behavioral outcomes.

Consequently, this finding challenges the prevailing assumption in captioning research that higher text similarity scores (e.g., BLEU) automatically equate to better utility. By confirming that instructors—the domain experts in education—prioritize the 'refined' information of Level 2 over the more exhaustive Level 3, this study provides a concrete HCI design guideline: accessibility tools should prioritize cognitive load management over mere data exhaustion. This shift from technical optimization to human-centered validation is the core contribution of our work, demonstrating that the 'best' model is not the one with the most detailed output, but the one that aligns with the pedagogical needs of the users.

VI. Conclusion

Visually impaired individuals, particularly those who are completely blind, face significant challenges in accessing and understanding descriptive information about graph or chart images. If an image lacks recorded descriptions, screen readers are unable to convey its content; therefore, when a graph or chart image is provided, an accompanying explanation is essential to enhance accessibility for visually impaired users. However, conventional graph captions are often overly detailed, deviating from their original intent and hindering practical usability and scalability. This highlights a critical need to re-examine the purpose of such descriptions by refining the levels of human cognitive processing and applying this to chart explanation methodologies.

This study proposed the HCC (Hierarchical Chart Captioning) model to address this accessibility gap by generating multi-level, user-selectable captions. Unlike traditional captioning methods that provide information at a single layer, the HCC model utilizes spatial token features to generate three hierarchical levels of captions that mimic human cognitive processing. This design ensures that the model provides varying degrees of detail and abstraction, allowing users to select the description length that best suits their needs.The model's effectiveness was rigorously evaluated through user surveys involving 20 instructors, which revealed a critical insight: Layer 2 captions were the easiest to understand, scoring 3.353. This result confirms that the most effective solution lies in achieving an optimal balance between factual detail and cognitive load, aligning with the "minimal yet informative" approach advocated by guidelines like the Diagram Center Image Description4444. Consequently, this finding underscores that technical complexity does not guarantee practical utility. Future accessibility metrics must therefore evolve beyond statistical correlation to prioritize human-centric clarity. By identifying Level 2 as the optimal granularity, this study establishes a practical standard that bridges AI capabilities with real-world educational needs.

Furthermore, the model's performance was validated using a newly introduced evaluation metric, M, which confirmed that the proposed methodology achieved performance levels comparable to existing baseline architectures5. This demonstrates that our approach ensures both reliable performance and effective learning, highlighting its strong potential applicability to hierarchical learning frameworks.

While this study demonstrates the efficacy of the HCC model, several limitations remain. Currently, our validation is primarily focused on line charts; thus, further research is required to assess the model's adaptability to more complex or composite scientific visualizations. Future work will address this by expanding the dataset diversity and conducting in-depth end-user testing directly with visually impaired participants to gather qualitative feedback. Additionally, we plan to explore the real-time integration of our hierarchical captioning system with Text-to-Speech (TTS) interfaces to support live learning environments.

In conclusion, the HCC model offers a novel, user-centered approach to enhancing digital accessibility by translating complex visual data into cognitively manageable auditory descriptions. Ultimately, this work aims to advance Universal Design for Learning (UDL), ensuring that educational insights are equally accessible to every learner regardless of visual ability.

Acknowledgment

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References

[1] Murillo-Morales, T., Miesenberger, K., "Audial: A natural language interface to make statistical charts accessible to blind persons," in *Computers Helping People with Special Needs: 17th International Conference, ICCHP 2020*, Lecco, Italy, 2020, pp. 373–384.

[2] Mukherjee, A., Garain, U., Biswas, A., "Experimenting with automatic text-to-diagram conversion: A novel teaching aid for the blind people," *J. Educ. Technol. Soc.*, vol. 17, no. 3, pp. 40–53, 2014.

[3] Balik, S. P., others, "Including blind people in computing through access to graphs," in *Proceedings of the 16th International ACM SIGACCESS Conference on Computers & Accessibility*, 2014, pp. 91–98.

[4] Torres, M., Barwaldt, R., "Approaches for diagrams accessibility for blind people: a systematic review," in *2019 IEEE Frontiers in Education Conference*, IEEE, 2019, pp. 1–7.

[5] Kushal, K., others, "DVQA: Understanding Data Visualizations Via Question Answering," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2018, pp. 5648–5656.

[6] Kahou, S. E., others, "FigureQA: An Annotated Figure Dataset for Visual Reasoning," in *Sixth International Conference on Learning Representations*, 2017.

[7] Anita, M., Kostic, Z., Tanner, C., "Lincap: Line Charts for Data Visualization Captioning Models," in *2022 IEEE Visualization and Visual Analytics (VIS)*, 2022, pp. 35–39.

[8] Hsu, T., Giles, C. L., Huang, T., "SciCap: Generating Captions for Scientific Figures," in *Findings of the Association for Computational Linguistics: EMNLP 2021*, 2021, pp. 3258–3264.

[9] Devlin, J., others, "BERT: Pre-training of deep bidirectional transformers for language understanding," *arXiv preprint*, 2018.

[10] Yang, Z., others, "XLNet: Generalized autoregressive pretraining for language understanding," *Advances in Neural Information Processing Systems*, vol. 32, 2019.

[11] Vaswani, A., others, "Attention is all you need," *Advances in Neural Information Processing Systems*, vol. 30, 2017.

[12] Kushal, K., others, "Answering Questions about Data Visualizations Using Efficient Bimodal Fusion," in *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, 2020, pp. 1498–1507.

[13] Liu, F., others, "MatCha: Enhancing Visual Language Pretraining with Math Reasoning and Chart Derendering," in *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics*, 2023, pp. 12756–12770.

[14] Liu, F., others, "DePlot: One-shot Visual Language Reasoning by Plot-to-table Translation," in *Findings of the Association for Computational Linguistics: ACL 2023*, 2023, pp. 10381–10399.

[15] Luciano, F., Chiriatti, M., "GPT-3: Its Nature, Scope, Limits, and Consequences," *Minds and Machines*, vol. 30, pp. 681–694, 2020.

[16] Devlin, J., others, "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding," in *The 17th Annual Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT)*, 2019, pp. 4171–4186.

[17] Colin, R., others, "Exploring the Limits of Transfer Learning with a Unified Text-to-text Transformer," *The Journal of Machine Learning Research*, vol. 21, no. 140, pp. 5485–5551, 2020.

[18] Lee, K., others, "Pix2struct: Screenshot parsing as pretraining for visual language understanding," in *International Conference on Machine Learning*, 2023, pp. 18893–18912.

[19] Elbarougy, R., Akagi, M., "Improving speech emotion dimensions estimation using a three-layer model of human perception," *Acoustical Science and Technology*, vol. 35, no. 2, pp. 86–98, 2014.

[20] Dodge, J., others, "Documenting large webtext corpora: A case study on the colossal clean crawled corpus," *arXiv preprint*, 2021.

[21] Diagram Center Image Description, "Diagram Center Image Description," 2023, Available: http://diagramcenter.org/making-images-accessible.html.

[22] Park, J. H., others, "Mobile Voice Web Browser for the Low Vision," *Journal of Korea Multimedia Society*, vol. 23, no. 11, pp. 1418–1427, 2020.

[23] Arashi, M., Roozbeh, M., Hamzah, N. A., Gasparini, M., "Ridge regression and its applications in genetic studies," *PLOS One*, vol. 16, no. 4, pp. e0245376, 2021.

[24] Papineni, Kishore, Roukos, Salim, Ward, Todd, Zhu, Wei-Jing, "BLEU," in *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*, 2002, pp. 311–318.

[25] Banerjee, Satanjeev, Lavie, Alon, "METEOR: An automatic metric for MT," in *Proceedings of the ACL Workshop on Intrinsic and Extrinsic Evaluation Measures for Machine Translation and/or Summarization*, 2005, pp. 65–72.

[26] Karen Simonyan, Andrew Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," *arXiv preprint arXiv:1409.1556*, 2014.

[27] Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun, "Deep Residual Learning for Image Recognition," *arXiv preprint arXiv:1512.03385*, vol. , no. , pp. , 2016.

[28] Anita Mahinpei, Zona Kostic, Chris Tanner, "LineCap: Line Charts for Data Visualization Captioning Models," in *2022 IEEE Visualization and Visual Analytics (VIS)*, 2022, pp. 35–39.

[29] Li, J., Li, D., Xiong, C., Hoi, S. C. H., "BLIP: Bootstrapping Language-Image Pre-training for Unified Vision-Language Understanding and Generation," *Proceedings of the 39th International Conference on Machine Learning (ICML)*, pp. 12888–12900, 2022.

[30] Liu, F., et al., "DePlot: One-shot visual language reasoning by plot-to-table translation," *Findings of the Association for Computational Linguistics: ACL 2023*, pp. 10381–10399, 2023.

Enhancing Privacy in Databases by Data-Layer

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***Abstract*—This study addresses the growing challenge of enhancing privacy in enterprise database systems, where excessive privileges and shared service accounts often lead to unauthorized data access and insider threats. The study proposes a data-layer security framework that enforces fine-grained access control based on authenticated user identities, integrating role-based access control (RBAC) and the principle of least privilege (PLP) to protect sensitive information. The model restricts developer and administrative access strictly to authorized data objects, reducing exposure while maintaining operational efficiency. Drawing on established database security mechanisms, including authentication, authorization, and centralized identity management through Active Directory, the proposed framework ensures that all database interactions are executed under verified user credentials. The approach is implemented using Microsoft SQL Server within an enterprise environment and evaluated through controlled experiments conducted before and after deployment. Results demonstrate a significant reduction in unauthorized data retrieval without introducing noticeable performance overhead. The findings confirm that enforcing privacy at the data-layer provides an effective and scalable solution for securing sensitive data in modern database systems, strengthening accountability and mitigating risks associated with privilege misuse.**

***Keywords*—Database privacy; security model; access control; data protection; privacy enhancing technologies; database systems**

I. Introduction

The importance of privacy in database systems has become increasingly critical in today's digital landscape. As databases accumulate and utilize vast amounts of information, they serve as central repositories of sensitive and personal data. Safeguarding this information is a fundamental priority, as it forms the backbone of trust, security, and ethical data management across organizations. Key strategies such as access control, encryption, and data anonymization represent the core of privacy protection mechanisms within database systems. Access control ensures that only authorized users can access specific data, effectively minimizing the risk of unauthorized breaches. Encryption further reinforces confidentiality and integrity by converting data into secure formats that can be accessed only by users possessing the correct decryption keys. Meanwhile, data anonymization techniques modify or remove identifying attributes to prevent individual recognition, thereby enhancing privacy and compliance with data protection standards.

These mechanisms collectively play a crucial role in mitigating risks associated with both external cyberattacks and internal misuse. The growing emphasis on privacy protection is also reflected in the establishment of rigorous international frameworks, including the General Data Protection Regulation (GDRP) [1] and the National Institute of Standards and Technology (NIST) Special Publication 800-53, Revision 5 [2]. These frameworks highlight the importance of maintaining confidentiality [3], integrity [4], and accountability of information systems [5]. They provide an updated set of guidelines that encourage organizations to strengthen access control, ensure data resilience, and align their technological operations with legal and ethical standards. The challenge, however, lies in balancing the implementation of these stringent privacy measures with the need to sustain high levels of system performance and efficiency [6]. By integrating the guidance of GDPR and NIST standards, organizations can better align their security imperatives with database functionality, achieving equilibrium between compliance, accessibility, and performance.

On the other hand, the vulnerabilities of database systems are often exposed through real-world cases of data breaches. For instance, Timothy Young, a resident of Moorefield, Nebraska, who confessed to a serious violation of trust and security by committing wire fraud that resulted in the exposure of confidential data from his employer, a New Jersey-based analytics and risk assessment firm. This organization served a global clientele that included insurance, financial, and governmental entities. Young accessed the company's network without authorization, obtaining names, email addresses, phone numbers, and login credentials, which he attempted to sell. His actions underscore the serious consequences of inadequate data protection and the risks that arise from unauthorized internal access to sensitive databases. The case, investigated by the FBI and prosecuted by the U.S. Attorney's Office Cybercrime Unit in Newark, resulted in potential charges carrying a maximum prison sentence of twenty years and substantial financial penalties [7]. This incident highlights the urgent need for effective database privacy frameworks and the severe legal implications of neglecting such protocols. In addition to isolated cases, the overall frequency and scale of data compromises have risen sharply across industries [8]. The financial services sector, for example, experienced a near doubling of data breaches in the United States, increasing from 268 reported incidents in 2022 to 744 in 2023. As shown in Fig. 1, this rise illustrates how sectors that manage sensitive financial information have become prime targets for cyber threats. Such incidents not only compromise consumer confidence but also threaten the stability and reputation of institutions that rely on secure data handling [9]. The upward trend in data violations underscores the growing sophistication of cyber threats and the pressing demand for enhanced privacy mechanisms within database systems [10].

Nevertheless, during everyday maintenance and operational processes, developers often interact directly with live databases, sometimes with broad or unintended access privileges. This exposure creates potential privacy risks,

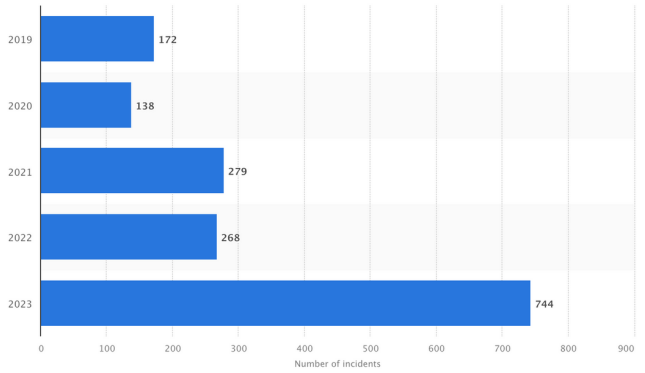


Fig. 1. Number of data violation cases in the United States (by statista [11]).

as unauthorized or excessive access may lead to data misuse or accidental disclosure of sensitive information. The challenge is to ensure that developers can perform their tasks efficiently while maintaining strict compliance with privacy and confidentiality requirements. Achieving a balance between operational flexibility and rigorous access control is essential to mitigating privacy risks and preserving database integrity [12].

The main objectives of this research are twofold. First, it seeks to enhance the protection of sensitive data within database systems by ensuring that users connect through properly authenticated and authorized accounts. Second, it aims to strengthen database privacy measures without compromising system performance. To achieve this, the study proposes a security model that integrates strict access controls, limiting developer access exclusively to the data necessary for their tasks. By reducing exposure and applying structured access rules, the model minimizes the risk of data leakage while maintaining efficient database operation. Consequently, the proposed work contributes to the broader field of database security and privacy engineering by offering a practical and scalable approach to safeguarding sensitive information at the data-layer. Its design emphasizes the balance between privacy protection and performance optimization, addressing one of the most persistent challenges in secure database management. By incorporating access control mechanisms guided by established privacy frameworks, this research provides a structured and adaptable solution that strengthens data protection while ensuring usability and efficiency in modern database environments. This work contributes to database security practice by introducing a data-layer access enforcement framework that explicitly binds database query execution to authenticated individual identities rather than shared service accounts. Unlike conventional role-based or attribute, based access control mechanisms that are typically enforced at the application or middleware layer, the proposed approach embeds identity, aware privilege enforcement directly at the database layer. The framework operationalizes the principle of least privilege through identity bound query execution and demonstrates its effectiveness through an enterprise scale implementation and empirical evaluation. In addition to the architectural contribution, the study provides experimental evidence that database layer identity enforcement can significantly reduce unauthorized access without introducing noticeable performance overhead.

Specifically, this study makes the following contributions:

- Proposes a database-layer security framework that enforces identity-bound access control, eliminating reliance on shared service accounts.
- Demonstrates fine-grained enforcement of the principle of least privilege directly within the database execution context.
- Provides an enterprise-scale implementation integrating centralized identity management with database access control.
- Empirically evaluates the impact of the proposed framework, showing improved privacy enforcement without measurable performance degradation.

The remainder of this study proceeds from foundations to validation and implications. Section II establishes the conceptual framework for database privacy by defining the two complementary pillars access control and data anonymization—that anchor the rest of the work. Building on these foundations, Section III surveys the state-of-the-art across encryption, access control, masking, intrusion detection, confidential data management, IoT access control, and biometrics/pseudonyms, as well as privacy-preserving publishing, thereby identifying concrete gaps and design requirements that motivate our solution. Guided by these requirements, Section IV details the proposed methods and materials, including the system architecture and implementation choices that operationalize the framework. Section V then evaluates the approach empirically, reporting and discussing experimental results that test whether the framework delivers the intended security and performance properties. Finally, Section VI synthesizes the findings, outlines limitations, and charts directions for future research.

II. Conceptual Framework of Database Privacy Mechanisms

Safeguarding sensitive data within database systems requires a combination of mechanisms that prevent unauthorized access and ensure the confidentiality of stored information. Two fundamental approaches dominate this domain: access control [13] and data anonymization [14]. Each provides a distinct, but complementary layer of protection that collectively strengthens database privacy.

A. Access Control Mechanisms

Access control serves as the first line of defense in protecting databases from cyber threats, including sophisticated attacks such as spear phishing. These systems implement a structured framework of identification, authentication, and authorization processes to determine precisely who can access which data resources. Their primary objective is to restrict unauthorized entry and uphold data confidentiality [15].

Different access control models have evolved to address varying security requirements and operational contexts. Discretionary Access Control (DAC) allows data owners to define permissions, offering flexibility, but risking oversharing. Mandatory Access Control (MAC) enforces system-level policies based on data classification and user clearance, ensuring high security, but limited flexibility. Role-Based Access

Control (RBAC) assigns permissions to roles rather than individual users, simplifying management in large organizations. Attribute-Based Access Control (ABAC) applies fine-grained policies based on user, resource, or environmental attributes, supporting dynamic decisions. Finally, Rule-Based Access Control supplements other models by enforcing predefined administrator rules. These models collectively enable organizations to balance flexibility and security based on their specific data governance requirements. Table I summarizes the unique strengths and weaknesses of these five access control types [15].

TABLE I. OVERVIEW OF ACCESS CONTROL SYSTEMS

Type	Description	Strengths	Weaknesses
DAC	User-defined access rights	High flexibility; user-centric	Risk of accidental oversharing
MAC	System-enforced policies based on classification	High security; minimizes breaches	Rigid; less user flexibility
RBAC	Access based on user roles	Simplifies management; scalable	Requires precise role definition
ABAC	Decisions based on user, environment, and resource attributes	Highly flexible and dynamic	Complex policy management
Rule-Based	Access determined by specific rules	Adds extra security layers	Management complexity

By effectively implementing these mechanisms, organizations can protect sensitive information from unauthorized access, thereby mitigating the risk of data breaches and ensuring compliance with data protection regulations such as the General Data Protection Regulation (GDPR). As database technologies evolve and the volume of data grows, the importance of sophisticated access control systems becomes even more critical, underlining the need for ongoing research and development in this area to address emerging security challenges.

B. Data Anonymization Techniques

Beyond controlling access, privacy protection also requires anonymizing data to prevent re-identification. Data anonymization modifies sensitive attributes so that individuals cannot be uniquely identified, preserving utility while protecting privacy [16]. These methodologies ingeniously modify personal data into a state where individual identification becomes impossible, thus shielding sensitive information from unauthorized scrutiny or exploitation. Anonymization assumes a critical role when the utilization of data extends to analytical, research, or reporting endeavors, ensuring that such activities do not infringe upon individual privacy rights.

Databases employ several anonymization strategies without significantly compromising the data's analytical utility. Among these, data masking can be applied in either static or dynamic forms, offering flexibility in secure data access and use while maintaining confidentiality. Pseudonymization replaces private identifiers with fictitious values, allowing data association with its source without revealing actual identities; however, it may be reversible with additional contextual information. Generalization decreases precision by converting detailed data (e.g., exact ages) into broader categories, while data perturbation introduces small alterations or noise to obscure original values yet preserve statistical integrity.

Structured models such as k-anonymity ensure that each record is indistinguishable from at least k–1 others regarding identifying attributes, while l-diversity demands diversity of sensitive attributes within anonymized groups. Building further, t-closeness maintains the distribution of sensitive attributes close to that of the entire dataset, preventing inference attacks. Table II summarizes key anonymization techniques and their advantages and disadvantages [16].

TABLE II. DATA ANONYMIZATION TECHNIQUES: PROS AND CONS

Technique	Pros	Cons
Data Masking	Protects sensitive data while keeping it functional for operations.	May distort actual values, limiting analytical use.
Pseudonymization	Enables linking data to its source without revealing identities, maintaining a level of utility.	Potentially reversible if attackers gain access to auxiliary information, compromising privacy.
Generalization	Simplifies implementation and enhances privacy by reducing data precision.	Reduces utility for detailed analysis due to loss of specificity.
Data Perturbation	Preserves overall structure and integrity of datasets for aggregate analysis.	Alterations may affect accuracy of individual records or analyses.
k-Anonymity	Provides a quantifiable measure of privacy by ensuring indistinguishability among records.	Vulnerable to linkage attacks if an attacker possesses external information.
l-Diversity	Enhances protection against attribute disclosure by ensuring diversity within groups.	Difficult to implement effectively in datasets with high similarity among records.
t-Closeness	Strengthens defense against inference attacks by aligning attribute distributions with the overall dataset.	Balancing privacy and data utility can be complex and computationally demanding.

Implementing these anonymization techniques effectively enables organizations to maintain compliance with data privacy regulations while still leveraging data for analytical purposes. As privacy concerns and regulatory requirements evolve, the development and refinement of anonymization methodologies remain a central focus for researchers and practitioners in data security and privacy management.

III. LITERATURE REVIEW

Data security and privacy remain central challenges in modern digital environments, particularly as the volume, variety, and sensitivity of stored information continue to rise across sectors such as mobile communications [17], healthcare [18], IoT systems [19], and database-backed web applications [20]. Across the literature, researchers have proposed diverse mechanisms, including encryption, access control, anonymization, intrusion detection, logging frameworks, and biometric authentication, to mitigate risks and strengthen confidentiality, integrity, and availability of data. The following review synthesizes these contributions in a coherent progression, moving from encryption-based protections to access control mechanisms, to data masking, intrusion detection, confidential data management, IoT access control, cryptography, biometric and pseudonym-based protections, and finally privacy-preserving data publishing.

A. Encryption and Cryptographic Techniques for Data Protection

A foundational component of secure data management lies in the use of strong encryption and cryptographic methods. ASCII-based encryption techniques leverage character values

to obfuscate readable data, reinforcing protection during transmission. The incorporation of multiple keys as in the Coloring Tripartite Graph (CTG) approach [21] further enhances resistance to unauthorized decryption. Similarly, the Triple Key Security Algorithm (TKS) employs polyalphabetic substitution with three keys and XOR operations, providing robust security particularly in mobile communication systems [22]. Building on the need for multi-key mechanisms, Ibrahim et al. [23] highlight vulnerabilities in databases storing personal and work related information. Their ASCII based, three-key encryption formula secures text and numeric data, preserves data size, and ensures efficient encryption and decryption, while acknowledging the necessity of future comparisons with established cryptographic systems to validate performance.

Additionally, cryptography is essential in domains such as medical services. Oduor & Omariba [24] trace the historical evolution of security practices and demonstrate the role of cryptographic algorithms in safeguarding sensitive healthcare data, supported by real time IDE examples. However, limitations such as incompatibility with indexed data and key management vulnerabilities persist. Further work in the Internet of Medical Things [25] calls for lightweight, quantum-resistant, and AI-enhanced cryptographic algorithms to meet emerging threats.

B. Access Control Models and Dynamic Data Protection

While encryption secures raw data, access control ensures that only authorized users can interact with sensitive resources. Wu et al. [26] note that database-backed web applications frequently allocate full privileges to application-level accounts, violating the principle of least privilege (PLP). Their PDA framework enforces PLP by intercepting queries and applying fine-grained, query-specific privilege restrictions, achieving resistance to SQL injection and buggy query manipulations with minimal performance overhead. Estrela framework [27] complements this approach by separating policy specification from application logic, enabling contextual and API-specific access enforcement. On top of this, dynamic Data Masking (DDM) further strengthens access control by obscuring sensitive values at query time. Fotache et al. [28] integrate masking directly into the persistence layer, preventing unmasked data from leaving the database engine. Their experimental evaluations using TPC-H show minimal performance impact, encouraging future research on large-scale databases, customized masking functions, and privilege-based masking algorithms. In big data environments, BDMasker [29] demonstrates scalable DDM deployment, with performance fluctuations maintained within 3% during horizontal and vertical expansion.

Access control challenges extend to confidential data management, where Shan et al. [30] argue that excessive privileges and underutilized logging hinder security. Their confidentiality-level access control model applies role, domain, and row level filtering, supported by an ELK-based logging module to improve traceability and monitoring. The MLCAC model [31] advances this further through real-time policy adjustment, log-driven decision-making, and decentralized optimization, achieving 89.55% accuracy in automated policy generation. Furthermore, in the IoT environment, Jiang et al. [32] address limitations in auditability and privilege control by proposing CcBAC, a blockchain-based fine-grained access control model incorporating TEE and cryptocurrency-based authorization. Experimental findings and further elaboration by Wang [33] demonstrate strong performance under large-scale request loads, high auditability, and consistent authorization across distributed IoT systems.

In addition to access control and masking, preserving privacy during data publishing forms another essential aspect of dynamic data protection. Jayapradha et al. [34] highlight the limitations of traditional anonymization techniques, especially when handling multiple correlated sensitive attributes. Their Heap Bucketization-Anonymity (HBA) model integrates anatomization, k-anonymity, slicing, and heap bucketization to balance privacy and analytical utility. Using metrics such as the Normalized Certainty Penalty and KL-divergence, they show that HBA effectively mitigates background knowledge, membership, non-membership, quasi-identifier, and fingerprint correlation attacks. The authors also emphasize future directions, including support for dynamic and unstructured data as well as addressing 1:M microdata challenges, underscoring the evolving role of anonymization in comprehensive data protection systems.

C. Intrusion Detection and Biometric Protection Against Insider and External Threats

Even with strong encryption and access control, insider misuse remains a dominant cause of data breaches. Said & Mostafa [35] identify privileged account misuse as a critical vulnerability and propose an intrusion detection system based on Danger Theory and the Negative Selection Algorithm (NSA). By learning from previously detected intrusions, their hybrid system improves anomaly detection accuracy while reducing false positives and false negatives. Nonetheless, the authors emphasize the challenge of calibrating the hybrid immune model and maintaining system performance in cloud and mobile networks. NSA's strengths, and its limitations in scalability are further examined by Tosin & Gbenga [36], who note its adaptability but highlight computational concerns.

Into the bargain, biometric authentication adds another layer of defense, particularly for securing identity and preventing unauthorized database access. Abd Razak, Nazari, & Al-Dhaqm [37] demonstrate that unique identifiers stored in digital databases can expose users to eavesdropping and identity theft. They propose integrating palm vein recognition with pseudonym generation to anonymize records and reinforce privacy. Enhancing pseudonym generation remains a priority for improving protection, especially in cloud computing contexts. Complementary work [38] uses palm vein biohashing with near-infrared scanning, achieving an EER of 0 and protecting biometric templates from exposure during storage or transfer.

To provide a holistic comparison of the reviewed approaches, Table III summarizes the methodologies, benefits, and limitations of the most relevant studies discussed in this section.

D. Identified Research Gaps and Motivation

The reviewed literature demonstrates significant progress in database security through encryption techniques, access

TABLE III. COMPARATIVE SUMMARY OF RELATED WORK

Author & Year	Methodology	Benefits	Limitations
[21]	Graph-based encryption using tripartite graph coloring with ASCII mapping	Enhanced mathematical security; Suitable for text-based protection; Resistant to brute-force attacks	Limited to ASCII; High computational complexity; Scalability concerns
[22]	Multi-round encryption using three independent keys	Protection against single-key attacks; Multiple encryption layers; Improved key flexibility	Higher computational load; Key synchronization challenges; Performance degradation over multiple rounds
[23]	Custom ASCII-based encryption algorithm with novel primitives for database security	Database-specific optimization; Protects structured data; Prevents unauthorized access	Non-standard; Limited cryptanalysis; Integration challenges with existing systems
[24]	Applied encryption, hashing, and digital signatures for medical data protection	HIPAA/GDPR support; Secure transmission; Confidentiality for medical records	Real-time performance issues; Healthcare key management complexity; Interoperability limits
[25]	Systematic review of symmetric, asymmetric, and lightweight cryptography for IoMT	Comprehensive IoMT landscape; Identifies effective schemes; Highlights attack vectors and mitigations	Review-based; No empirical validation; Resource constraints in IoT not fully explored
[26]	Application-driven privilege separation (PDA) using query interception	Automated least privilege enforcement; Prevents SQL injection; Low runtime overhead (8.13%)	Application modification required; Tested on limited systems; Generalizability concerns
[27]	Estrela contextual policy framework with API-level enforcement	Context-aware control; Works on legacy systems without DB changes; Fine-grained policies	Complex rules; Requires API–policy mapping; Limited application testing
[28]	TPC-H benchmark and ML-based performance analysis of dynamic data masking (DDM)	Minimal masking overhead; Effective for datasets up to 100GB; Data-driven masking strategy design	Oracle-only evaluation; Basic masking scenarios; Scalability beyond 100GB uncertain
[29]	SQL query rewriting with multi-engine unified security for DDM	Zero logic impact; Multi-engine scalability; 3% overhead; Preserves query intent	Complex rewriting; Limited encryption integration; End-to-end protection not covered
[30]	Hybrid RBAC/ABAC confidential data access control model	Flexible, granular policies; Supports separation of duties; Scalable for organizations	Role explosion; Attribute maintenance overhead; Susceptible to misconfiguration
[31]	Machine-learning context-aware access control (MLCAC) for insider threat detection	Behavioral anomaly detection; Adaptive authorization; Real-time mitigation	Requires large training datasets; False positives; Intensive computation
[32]	CcBAC hybrid IoT access control using blockchain audit logs + TEE enforcement	Tamper-proof logs; Secure execution; Suitable for distributed IoT environments	Blockchain scalability issues; TEE hardware dependency; Complex integration
[33]	Dynamic trust-based access control for IoT network boundaries	Granular trust evaluation; Adaptive policies; Prevents unauthorized IoT access	Trust metric definition; Continuous evaluation overhead; Scalability challenges
[34]	Heap Bucketization-Anonymity (HBA) combining anatomization, slicing, and k-anonymity	Resists background knowledge, membership, and fingerprint attacks; Balances privacy and utility	Not real-time; No live masking; Complex parameter tuning
[35]	Danger Theory + Negative Selection intrusion detection for insider threats	Self-learning; High detection coverage; Strong against privilege misuse; Adaptive behavior	Detection-only; Training required; Vulnerable to evolving attack patterns
[36]	Bio-inspired negative selection algorithm (NSA) for intrusion detection	Detects unknown attacks; Adaptable to new patterns; Low computational cost	High false positives; Detector generation complexity; No prevention capability
[37]	Palm-vein biometrics with pseudonym generation for identity anonymization	Strong authentication; Identity unlinkability; Dual-layer protection (biometric + pseudonym)	Biometric sensitivity concerns; Integration complexity; Limited analysis of encryption interactions
[38]	Vascular biometric recognition with enhanced liveness detection	Highly secure modality; Non-invasive capture; Suitable for high-security systems	Requires specialized hardware; Environmental sensitivity; Higher deployment cost

control models, anonymization strategies, and intrusion detection mechanisms. However, several limitations remain insufficiently addressed. Many existing approaches rely heavily on encryption or anonymization, which protect data content but do not prevent misuse by legitimately authenticated users with excessive privileges. Similarly, application-layer access control frameworks enforce authorization outside the database engine, leaving database-layer interactions vulnerable when shared service accounts or over-privileged credentials are employed.

Furthermore, while role-based and attribute-based access control models provide structured authorization, they are often implemented at the application or middleware level, limiting their effectiveness in mitigating insider threats and privilege escalation within the database itself. Existing solutions also lack direct enforcement of identity-bound query execution, where each database operation is explicitly tied to a verified individual account rather than a generic service identity. These gaps highlight the need for a database-layer privacy enforcement mechanism that integrates centralized identity management, enforces the principle of least privilege, and ensures that all database interactions are executed under authenticated and authorized user identities. Motivated by these limitations, the proposed approach introduces a data-layer security framework that directly couples Active Directory–based authentication with database access control, effectively reducing unauthorized data exposure while maintaining operational efficiency.

IV. METHODS AND MATERIALS

The methodology adopted in this research offers a clear and systematic explanation of the technical approach, detailing the phased execution workflow and the environment in which the security model was developed and evaluated. It maps the full operational cycle, from request initiation and identity verification to permission checking and final query execution, demonstrating how each stage contributes to enforcing strict access controls. The methodology is structured around three integrated phases: Request Initialization, Verification Process, and Execution and Response, as displayed in Fig. 2. Together, these phases represent the full lifecycle of a database interaction within a secure, access-controlled environment. The process begins with Query Initiation, where the developer issues a request to the database using SQL instructions intended to retrieve, insert, update, or delete data. This step forms the operational entry point, defining the intended action and the credentials through which it should be executed. Next, the system performs Identity Account Retrieval, extracting the account information from the domain controller to confirm the identity of the request initiator. This ensures that subsequent evaluation stages rely on verified and authenticated identity attributes.

Afterwards, a critical step in the workflow is Permission Verification, during which the system checks whether the authenticated user or service account is authorized to perform the requested action. This validation is executed by comparing the provided credentials to the records stored in the Active Directory, confirming exact matches before any database operation is permitted. Finally, the methodology concludes with Query Execution Based on Access Rights, where authorized SQL commands are securely executed. The database engine processes the approved instruction and returns the corresponding output. This structured cycle ensures that access is governed by strictly verified permissions, thereby strengthening privacy and reducing the risk of unauthorized operations.

To develop and evaluate the proposed security model, the study utilizes a comprehensive enterprise-grade technology stack that integrates development, authentication, and virtualization components in a structured manner. The implemen-

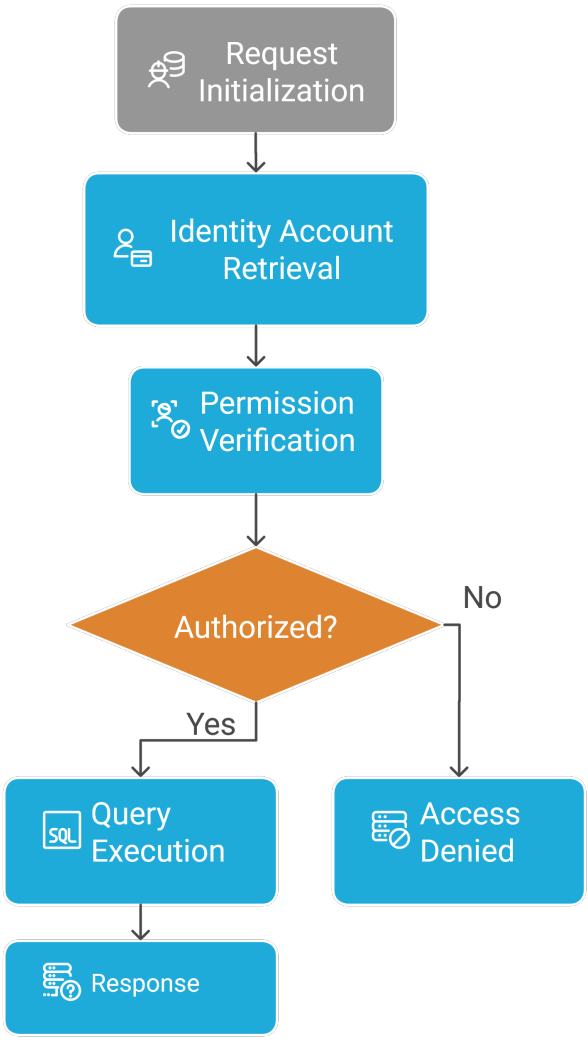


Fig. 2. Database access control flowchart.

tation begins with ASP.NET and C—supported by Visual Studio, as the core development framework used to build the access-control mechanisms and authentication logic. Microsoft SQL Server serves as the backend database system, providing scalable and secure data storage essential for testing various access scenarios. To support identity and permission management, Windows Server and its integrated domain controller constitute the backbone of authentication, ensuring centralized administration of user accounts and privilege verification. These components operate within a controlled virtualized environment created using VMware ESXi 6.7.0, hosted on a Dell PowerEdge R940 server equipped with an Intel(R) Xeon(R) Gold 5115 CPU, 80 logical processors, and multiple NICs, providing the computational capacity required for parallel and large-scale testing. This setup hosts 39 virtual machines, each configured to replicate real-world operational conditions in a reproducible manner. Active Directory operates on the DC01 server running Windows Server 2019 Standard Edition, with a functional level of Windows Server 2012 R2 to ensure compatibility with modern security protocols. And finally, firewall settings were carefully controlled to avoid external interference while preserving the integrity of testing procedures.

Consequently, the implementation of the proposed security model follows the methodology previously outlined and focuses on enforcing strict access controls and integrating authentication mechanisms within a Microsoft SQL Server environment using ASP.NET and C. The process begins by configuring user access requests and verifying the security policies that govern authentication and authorization within a Windows Server domain. This implementation is tested through controlled scenarios that observe system responses to both authorized and unauthorized attempts, ensuring that the enhanced security measures operate effectively without negatively impacting database performance. Hence, to support this implementation, the environment is designed as an interconnected framework in which the application, database, and Active Directory operate seamlessly to manage identity, permissions, and data flow. As illustrated in Fig. 3, this architecture enables continuous communication between components, allowing authentication and authorization checks to be performed before any database interaction occurs. This coordinated structure ensures that every user request is validated and processed according to predefined security rules, forming the operational backbone of the model.

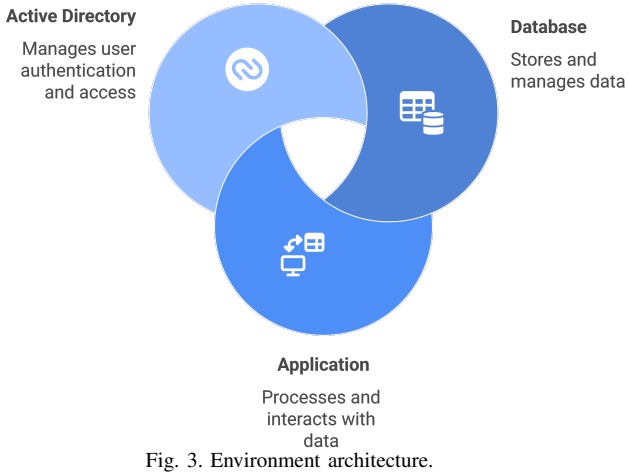


Fig. 3. Environment architecture.

Within this environment, Microsoft SQL Server 2016 hosts the CyberSecurity_CapstoneProject schema, which includes three essential tables. The Address table stores location data such as Building_No, StreetAddress, and FloorNo; the ContactInfo table contains communication fields including PhoneNumber, Email, POBOX, and SocialMediaAccount; and the EmployeeInfo table holds personal and professional information: FirstName, SecondName, FamilyName, DOB, PostalAddress, Occupation, CompanyName, Status, and associated audit fields like CreatedDate, CreatedBy, ModifiedDate, and ModifiedBy. These tables are interconnected to provide a complete representation of employee records, as shown in Fig. 4. Nevertheless, the SQL Server environment is organized in a standard hierarchical structure, where the schema and its tables appear under the database's "Tables" directory, alongside system tables, external resources, programmability components, and security configurations

The operational workflow begins with the initiation of SQL queries, where the developer formulates the required command and embeds the necessary account credentials within the connection string. The query prepared with its associated

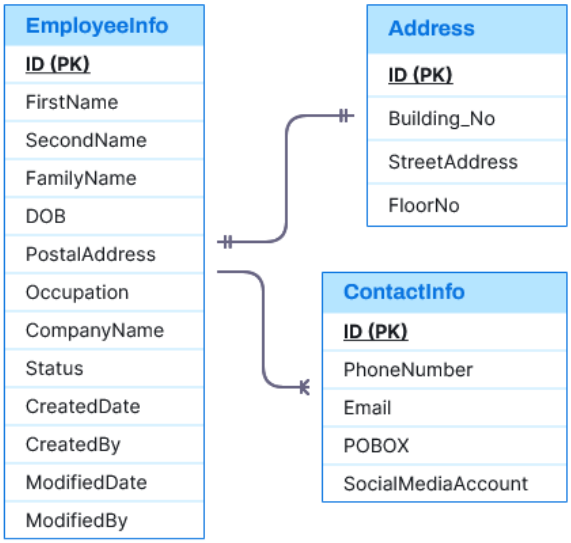


Fig. 4. Database ERD diagram.

identity information, is submitted to the system for execution:

```
string sQuery;
string sConnectionString =
    "Data Source=RACELDRT\\SQL2016;Initial
    ↪  Catalog=SANG_Weather_Prayer;"
    + "User ID=SQLTest;Password=123456789;";
sQuery = "SELECT [ID], [Building_No], [StreetAddress],
↪  [FloorNo] "
       + "FROM
       ↪  [CyberSecurity_CapstoneProject].[dbo].[Address];";
```

A complementary user interface, shown in Fig. 5, allows queries to be executed interactively, providing transparency during testing and making it possible to observe how the system handles different access attempts. And, after a query is issued, the system retrieves the corresponding account identity from Active Directory using C. This retrieval ensures that each request is tied to a verified domain identity before any authorization checks occur. Once the account details are obtained, they are used to determine the user's access level and validate whether the requested action aligns with the assigned permissions.

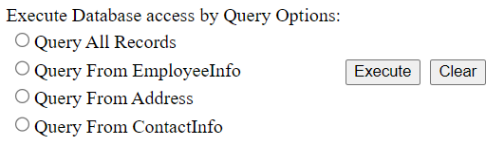


Fig. 5. Query options to execute on the database.

The subsequent stage focuses on permission verification, where the submitted credentials are compared with those stored in Active Directory. This comparison is implemented through C logic that ensures the credentials provided by the user exactly match the corresponding domain records before access is approved. Only when the account information fully aligns with the stored identity data does the system permit the request to proceed. This verification step strengthens the overall security posture by preventing unauthorized users from executing database commands.

Following successful authentication and authorization, the system proceeds to execute the SQL command using the verified account's privileges. A secure connection is established, after which the authorized operation is processed by the SQL Server engine. Whether the requested action involves retrieving, inserting, updating, or deleting data, the database completes the command and returns the corresponding response to the requester. By ensuring that all queries are executed strictly under validated permissions, the implementation guarantees that database interactions comply with the intended security controls and that unauthorized activity is effectively mitigated.

V. Results and Discussion

This section presents the experimental findings of the proposed access-control framework developed to strengthen database security. The implementation was conducted using Microsoft SQL Server integrated with Active Directory to enforce role-based authentication and manage user privileges effectively. The evaluation examined how the system mitigates unauthorized data access, preserves information confidentiality, and sustains operational efficiency under various workloads. The analysis focused on three core dimensions: the precision of access-control enforcement, the performance of query execution under restricted conditions, and the resilience of the database against security breaches. The discussion also interprets the practical implications of these findings for enterprise database protection and outlines areas where further optimization can enhance reliability and scalability in future implementations.

A. Privileges and User Accounts

The evaluation involved five user accounts: smharbi1, Ssmutawa, Salroumi, amathel, and maabkhet, representing different operational roles within the organization. Each user was assigned a specific level of access to three core database tables: EmployeeInfo, ContactInfo, and Address. These privileges were configured and verified within Microsoft SQL Server using Active Directory, based authentication to ensure that access rights were directly tied to domain-level credentials. Prior to applying the proposed access-control model, all user accounts were granted unrestricted access to the database through a shared service configuration. This approach violated the principle of least privilege and exposed sensitive information to unauthorized viewing and modification. After enforcing the model, each user's permissions were refined to reflect their functional responsibilities.

Administrative users retained full access to all datasets, while standard users were limited to only the tables necessary for their operational tasks. The analysis of user privileges revealed that the model successfully differentiated roles and applied restrictions accurately. For instance, smharbi1 maintained complete administrative rights, whereas Ssmutawa and amathel were limited to access specific data categories relevant to their roles. Salroumi and maabkhet had partial access aligned with departmental boundaries, demonstrating the granularity of the implemented policy. The overall distribution of user privileges is summarized in Table IV, which consolidates the effective permissions of each account across the three main database tables. The results confirm that the proposed model enforces precise and hierarchical access, reducing redundant permissions and minimizing the risk of unauthorized data exposure.

TABLE IV. USER ACCOUNT ACCESS TO DATABASE TABLES

User Account	EmployeeInfo	ContactInfo	Address
smharbi1	Yes	Yes	Yes
Ssmutawa			Yes
Salroumi		Yes	Yes
amathel		Yes	
maabkhet	Yes		

B. Comparative Evaluation of Access Control Before and After Implementation

The evaluation of this work, aimed to measure the effectiveness of the new mechanism in strengthening privilege enforcement, minimizing unauthorized access, and sustaining operational efficiency. The analysis focused on user interactions with the EmployeeInfo, Address, and ContactInfo tables to identify improvements in access accuracy and adherence to security policies. Before deploying the access-control model, all database users were authenticated through a shared service account (SQLTest), which bypassed role-based verification. Consequently, every account had unrestricted access to all data tables (EmployeeInfo, ContactInfo, and Address), regardless of job role. This violated the least-privilege principle and exposed sensitive information to potential misuse.

To illustrate this issue, a standard user was able to execute a query on the EmployeeInfo table and retrieve all records successfully. This behavior clearly reflects the absence of proper privilege enforcement, as the system made no distinction between administrator privileges and regular-user permissions. Such unrestricted access not only increased the risk of accidental data modification but also eliminated any meaningful user accountability. After applying the access-control model, authentication and authorization were tightly coupled through Active Directory and Microsoft SQL Server. Each query request was verified against the domain credentials of the requesting user before execution, ensuring that only authorized users could access their assigned tables. As shown in Fig. 6, the user Ssmutawa was permitted to access only the Address table, while Fig. 7 demonstrates that Salroumi could view records exclusively from the ContactInfo table. Attempts by these users to query unauthorized tables triggered explicit denial messages, confirming that privilege restrictions were properly enforced.

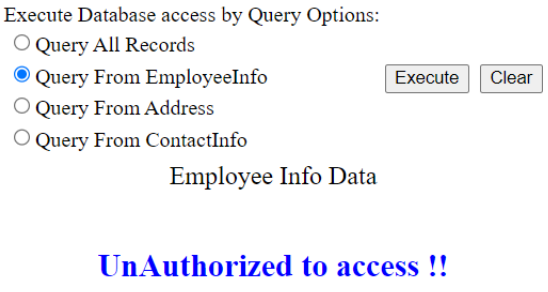


Fig. 6. Authorized access – Ssmutawa (Address table, Post-Implementation).

The evaluation confirmed that all privilege assignments were applied accurately and that no unauthorized user could access restricted information. Query execution remained efficient, indicating that the additional verification steps did not introduce noticeable performance overhead.

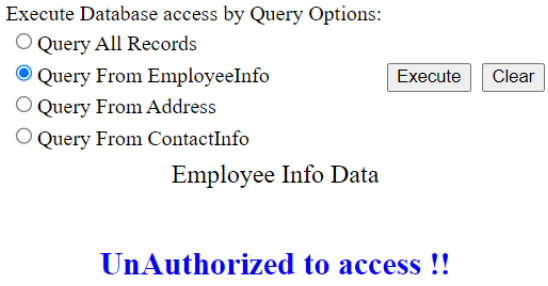


Fig. 7. Authorized access – Salroumi (ContactInfo table, Post-Implementation).

TABLE V. USER ACCESS PERMISSIONS ACROSS DATABASE TABLES

User Account	Emp-Info	ContactInfo	Address
smharbi1 (Admin)	Access	Access	Access
Ssmutawa	Denied	Denied	Access
Salroumi	Denied	Access	Access
amathel	Denied	Access	Denied
maabkhet	Access	Denied	Denied

C. Discussion

The comparative results reveal a complete transformation in database behavior following the model's deployment. Under the pre-implementation setup, every user had full access to all data. Post-implementation, access rights were strictly constrained according to defined roles. Administrative accounts retained full control, while standard users were limited to specific datasets required for their daily operations. This refinement achieved true least-privilege enforcement, improved accountability, and prevented privilege escalation. Furthermore, the integration with Active Directory ensured traceability, each query could be linked to a verified user identity, strengthening audit capabilities. The resulting user privileges after model implementation are summarized in Table V, which consolidates effective permissions across the main database tables.

To contextualize these improvements, it is important to compare them directly with the conditions observed in Experiment One. In Experiment One, all user accounts (smharbi1, Ssmutawa, Salroumi, amathel, maabkhet) were able to retrieve data from the EmployeeInfo, ContactInfo, and Address tables. This unrestricted access was attributed to the use of the service account (SQLTest), which possessed elevated privileges. Consequently, this setup allowed all user accounts to bypass access control restrictions, thereby compromising the principle of least privilege (PLP) and exposing the database to potential security threats. On the other hand, experiment Two demonstrated a marked improvement in access control and data security. The newly implemented access control model was designed to enforce specific access rights tailored to each user account based on their roles and responsibilities within the organization. This granular approach to access control ensured that only authorized user accounts could retrieve data from the designated tables, thereby mitigating the risk of unauthorized

TABLE VI. COMPARISON OF USER ACCESS BEFORE AND AFTER MODEL IMPLEMENTATION

User Account	Emp Info (Before)	Emp Info (After)	Contact Info (Before)	Contact Info (After)	Address (Before)	Address (After)
smharbi1	Yes	Yes	Yes	Yes	Yes	Yes
Ssmutawa	Yes	No	Yes	No	Yes	Yes
Salroumi	Yes	Yes	Yes	Yes	Yes	Yes
amathel	Yes	No	Yes	Yes	Yes	No
maabkhet	Yes	Yes	Yes	No	Yes	No

data access. For example, the account smharbi1 retained full access to all tables due to the comprehensive permissions associated with the user's role. On the other hand, accounts such as Ssmutawa and Salroumi faced restricted access, preventing them from retrieving data from certain tables, thereby enhancing the overall security of the database system. The differences in access capabilities before and after implementing the access control model are illustrated in Table VI. These visuals depict the restricted access observed in Experiment Two, showcasing the model's effectiveness in enforcing data security protocols and preventing unauthorized access.

These findings underscore the effectiveness of the new access control model in significantly enhancing database security by strictly enforcing user-specific access privileges and preventing unauthorized data access. The systematic comparison of the two experiments highlights the critical role of robust access control mechanisms in safeguarding sensitive information within database environments. When compared to the works of Wu et al. [26] and Shan et al. [30], the results of this study align with the growing emphasis on enforcing the principle of least privilege at the data source level. While Wu et al.'s PDA framework focused on privilege separation through application-driven enforcement, the model in this research extends the concept by embedding identity verification directly at the database layer, combining role-based control with domain authentication. Similarly, Shan et al. emphasized multi-layer filtering and the integration of logging for confidentiality assurance.

The proposed model complements this by providing traceable and verifiable access through Active Directory integration, strengthening accountability for every query execution. Furthermore, unlike the encryption-based approach by Ibrahim et al. [23], which primarily addressed data confidentiality through encoding mechanisms, this work enhances security through behavioral access enforcement restricting who can interact with the data in real time. The combined analysis across both experiments demonstrates that implementing access verification at the database layer provides a more scalable and flexible solution compared to pure encryption or masking techniques discussed in related studies. Overall, the proposed model advances the state of access control research by bridging theoretical models with practical enterprise deployment. It achieves fine-grained privilege management, aligns with established security frameworks, and complements existing literature by demonstrating that database-layer access verification can achieve both operational efficiency and strong data protection.

VI. CONCLUSION

This research addressed the critical challenge of strengthening privacy and access control in enterprise database systems, particularly in operational environments where shared service accounts and over-privileged credentials expose sensitive information to unauthorized access. Such configurations undermine accountability and violate the principle of least privilege, increasing the risk of insider misuse and accidental data disclosure. To address these issues, this study proposed a data-layer security framework that enforces fine-grained access control by binding every database operation directly to authenticated user identities. The proposed framework integrates centralized identity management with database access enforcement to ensure that all SQL operations are executed under verified and authorized user credentials. By eliminating reliance on generic service accounts and enforcing role-based permissions at the data-layer, the model provides stronger control over who can access specific database objects. The implementation demonstrated how authentication and authorization mechanisms can be tightly coupled with database operations to enhance privacy without disrupting normal development or administrative workflows.

The framework was implemented in an enterprise-grade environment using Microsoft SQL Server integrated with centralized identity services and evaluated through controlled experiments conducted before and after deployment. Experimental results clearly demonstrated a significant reduction in unauthorized data access, improved enforcement of user-specific privileges, and enhanced accountability across database operations. Importantly, these security improvements were achieved without introducing noticeable performance overhead, indicating that stronger privacy controls can be implemented while maintaining system efficiency and usability. Despite the effectiveness of the proposed approach, certain limitations were identified. The framework depends on centralized identity infrastructure, which may introduce single points of dependency in some deployment scenarios. Additionally, integrating the model into legacy database environments may require additional configuration and administrative effort. Addressing these challenges are essential to ensure broader applicability and long-term maintainability.

Future work will focus on extending the framework to improve resilience and adaptability in dynamic enterprise environments. Potential directions include introducing redundancy mechanisms for identity services, developing automated tools for privilege management, and exploring adaptive access control strategies that adjust permissions based on user behavior and operational context. These enhancements aim to further strengthen database privacy, scalability, and robustness in the face of evolving security threats. Collectively, this study establishes that enforcing access control at the database layer through identity-bound execution is a practical and effective mechanism for improving privacy, accountability, and compliance with the principle of least privilege in enterprise database systems.

REFERENCES

[1] European Parliament and Council of the European Union, "Regulation (eu) 2016/679 of the european parliament and of the council of 27 april 2016 on the protection of natural persons with regard to the processing

of personal data and on the free movement of such data (general data protection regulation)," Official Journal of the European Union, L119, 1–88, 2016, accessed: November 2025. [Online]. Available: https://eur-lex.europa.eu/eli/reg/2016/679/oj

[2] J. T. Force, "Security and privacy controls for information systems and organizations," National Institute of Standards and Technology, Tech. Rep., 2020.

[3] P. Shojaei, E. Vlahu-Gjorgievska, and Y.-W. Chow, "Security and privacy of technologies in health information systems: A systematic literature review," *Computers*, vol. 13, no. 2, p. 41, 2024.

[4] M. S. Nasir, H. Khan, A. Qureshi, A. Rafiq, and T. Rasheed, "Ethical aspects in cyber security maintaining data integrity and protection: A review," *Spectrum of engineering sciences*, vol. 2, no. 3, pp. 420–454, 2024.

[5] R. Purnamasari, A. I. Hasanudin, R. Zulfikar, and H. Yazid, "Do internal control and information systems drive sustainable rural development in indonesia?" *Journal of Open Innovation: Technology, Market, and Complexity*, vol. 10, no. 1, p. 100242, 2024.

[6] E. Pina, J. Ramos, H. Jorge, P. Váz, J. Silva, C. Wanzeller, M. Abbasi, and P. Martins, "Data privacy and ethical considerations in database management," *Journal of Cybersecurity and Privacy*, vol. 4, no. 3, pp. 494–517, 2024.

[7] U.S. Department of Justice. (2020, June) Nebraska man admits stealing and selling his employer's confidential information. Press release. Accessed: November 2025. [Online]. Available: https://www.justice.gov/usao-nj/pr/nebraska-man-admits-stealing-and-selling-his-employer-s-confidential-information

[8] A. S. George, T. Baskar, and P. B. Srikaanth, "Cyber threats to critical infrastructure: assessing vulnerabilities across key sectors," *Partners Universal International Innovation Journal*, vol. 2, no. 1, pp. 51–75, 2024.

[9] X. Wu and W. Bao, "Research on the design of a blockchain logistics information platform based on reputation proof consensus algorithm," *Procedia Computer Science*, vol. 262, pp. 973–981, 2025.

[10] Q. Razi, R. Piyush, A. Chakrabarti, A. Singh, V. Hassija, and G. Chalapathi, "Enhancing data privacy: A comprehensive survey of privacy-enabling technologies," *IEEE Access*, 2025.

[11] Statista Research Department. (2025) Number of data loss incidents in the u.s. financial sector. Accessed: November 2025. [Online]. Available: https://www.statista.com/statistics/1318486/us-number-of-data-loss-incidents-in-financial-sector/

[12] R. J. Ramniklal, "Database security and integrity: Ensuring reliable and secure data management," *Mosaic of Ideas: Multidisciplinary Reflections*, vol. 73, 2024.

[13] D. Sargiotis, "Data security and privacy: Protecting sensitive information," in *Data governance: a guide*. Springer, 2024, pp. 217–245.

[14] A. Gadotti, L. Rocher, F. Houssiau, A.-M. Creţu, and Y.-A. De Montjoye, "Anonymization: The imperfect science of using data while preserving privacy," *Science advances*, vol. 10, no. 29, p. eadn7053, 2024.

[15] N. Kashmar, M. Adda, M. Atieh, and H. Ibrahim, "A review of access control metamodels," *Procedia Computer Science*, vol. 184, pp. 445–452, 2021.

[16] Z. El Ouazzani and H. El Bakkali, "A classification of non-cryptographic anonymization techniques ensuring privacy in big data," *International Journal of Communication Networks and Information Security*, vol. 12, no. 1, pp. 142–152, 2020.

[17] Ş. Erdal, F. Karakoç, and E. Özdemir, "A survey on security and privacy aspects and solutions for federated learning in mobile communication networks," *ITU Journal of Wireless Communications and Cybersecurity*, vol. 1, no. 1, pp. 29–40, 2024.

[18] O. Popoola, M. Rodrigues, J. Marchang, A. Shenfield, A. Ikpehai, and J. Popoola, "A critical literature review of security and privacy in smart home healthcare schemes adopting iot & blockchain: problems, challenges and solutions," *Blockchain: Research and Applications*, vol. 5, no. 2, p. 100178, 2024.

[19] S. Rani, M. Shabaz, A. K. Dutta, E. A. Ahmed *et al.*, "Enhancing privacy and security in iot-based smart grid system using encryption-based fog computing," *Alexandria engineering journal*, vol. 102, pp. 66–74, 2024.

[20] Y. Huang, C. Shi, J. Lu, H. Li, H. Meng, and L. Li, "Detecting broken object-level authorization vulnerabilities in database-backed applications," in *Proceedings of the 2024 on ACM SIGSAC Conference on Computer and Communications Security*, 2024, pp. 2934–2948.

[21] S. NAGARAJAN, "An ascii value based data encryption using coloring tripartite graph," *CONTEMPORARY MATHEMATICS*, pp. 2113–2130, 2025.

[22] M. Akram, M. W. Iqbal, S. A. Ali, M. U. Ashraf, K. Alsubhi, and H. M. Aljahdali, "Triple key security algorithm against single key attack on multiple rounds." *Computers, Materials & Continua*, vol. 72, no. 3, 2022.

[23] S. Ibrahım, A. Zengin, S. Hızal, A. S. Akhter, and C. Altunkaya, "A novel data encryption algorithm to ensure database security," *Acta Infologica*, vol. 7, no. 1, pp. 1–16, 2023.

[24] X. F. Oduor and Z. B. Omariba, "Application of cryptography in enhancing privacy of personal data in medical services," *Int J Commun Inf Technol*, vol. 3, no. 1, pp. 16–21, 2022.

[25] W. Robert, A. Denis, A. Thomas, A. Samuel, S. P. Kabiito, Z. Morish, and G. Ali, "A comprehensive review on cryptographic techniques for securing internet of medical things: A state-of-the-art, applications, security attacks, mitigation measures, and future research direction," *Mesopotamian Journal of Artificial Intelligence in Healthcare*, vol. 2024, pp. 135–169, 2024.

[26] H. Wu, Z. Yu, D. Huang, H. Zhang, and W. Han, "Automated enforcement of the principle of least privilege over data source access," in *2020 IEEE 19th International Conference on Trust, Security and Privacy in Computing and Communications (TrustCom)*. IEEE, 2020, pp. 510–517.

[27] A. Bichhawat, M. Fredrikson, J. Yang, and A. Trehan, "Contextual and granular policy enforcement in database-backed applications," in *Proceedings of the 15th ACM Asia Conference on Computer and Communications Security*, 2020, pp. 432–444.

[28] M. Fotache, A. Munteanu, C. Strîmbei, and I. Hrubaru, "Framework for the assessment of data masking performance penalties in sql database servers. case study: Oracle," *IEEE Access*, vol. 11, pp. 18 520–18 541, 2023.

[29] Y. Tu, J. Niu, D. Wang, H. Gao, J. Xu, and K. Hong, "Bdmasker: Dynamic data protection system for open big data environment." *International Journal of Software & Informatics*, vol. 13, no. 1, 2023.

[30] L. Shan, H. Zhou, D. Hong, Q. Dong, Y. Wang, and S. Song, "Application of access control model for confidential data," *Procedia Computer Science*, vol. 192, pp. 3865–3874, 2021.

[31] L. Xiao, A. Yu, H. Wang, L. Zhao, and D. Meng, "Mlcac: Dynamic authorization and intelligent decision-making towards insider threats," in *2024 27th International Conference on Computer Supported Cooperative Work in Design (CSCWD)*. IEEE, 2024, pp. 407–412.

[32] W. Jiang, E. Li, W. Zhou, Y. Yang, and T. Luo, "Iot access control model based on blockchain and trusted execution environment," *Processes*, vol. 11, no. 3, p. 723, 2023.

[33] J. Wang, C. Liu, G. Zhu, X. Liu, and B. Xiao, "Fine-grained trusted control methods for iot boundary access," *Scalable Computing: Practice and Experience*, vol. 26, no. 1, pp. 180–190, 2025.

[34] "Heap bucketization anonymity—an efficient privacy-preserving data publishing model for multiple sensitive attributes," *IEEE Access*, vol. 10, pp. 28 773 – 28 791, 2022. [Online]. Available: https://ieeexplore.ieee.org/ielx7/6287639/9668973/09732456.pdf

[35] W. Said and A. M. Mostafa, "Towards a hybrid immune algorithm based on danger theory for database security," *IEEE Access*, vol. 8, pp. 145 332–145 362, 2020.

[36] S.-I. T. Tosin and J. R. Gbenga, "Negative selection algorithm based intrusion detection model," in *2020 IEEE 20th Mediterranean Electrotechnical Conference (MELECON)*. IEEE, 2020, pp. 202–206.

[37] S. Abd Razak, N. H. M. Nazari, and A. Al-Dhaqm, "Data anonymization using pseudonym system to preserve data privacy," *IEEE access*, vol. 8, pp. 43 256–43 264, 2020.

[38] C. Humphry, S. R. R. Pushparaj, and N. Ratha, "Secure vascular biometric recognition," in *2023 IEEE Western New York Image and Signal Processing Workshop (WNYISPW)*. IEEE, 2023, pp. 1–5.

Multi-Spectral Image Analysis Using Different CNN Models to Detect the Plant Diseases in its Early Stages

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***Abstract*—The Researchers and academicians are continuously working on minimizing the production losses due to various plant diseases. Therefore, recent technologies such as artificial intelligence (AI), and machine learning (ML) are playing a crucial role in detecting plant diseases in their early stages. These technologies help classifying plant leaves into 'healthy' and 'rusty' or 'diseased' leaves. It is difficult for human being to detect the plant diseases and take remedial action within stipulated time period. Hence, this research work addresses comparison of different convolutional neural network (CNN) models like Alexnet,Resent18,Resnet50, Xception, VGG16, VGG19, InceptionV3,InceptionResentV2 etc. and concluded with the top CNN models with good filters used to capture the plant leaves images. Proposed research work uses different filters dataset like K590, K665, K720, K850,BlueIR, Hotmirror. Plant disease detection requires accurately detecting the rust, or disease on the leaves immediately and efficiently. CNN models help classifying the plant leaves with higher accuracy and precision. Proposed research work gave accuracies for different filters with different models and found that, for K850 filter accuracy is 72.72% using balance efficientnetB0 CNN model, for K720 filter accuracy is 81.81% using balance efficientnet B0 CNN model, for K665 filter accuracy is 84.09% using balance efficientnetB0 CNN model, for K590 filter accuracy is 90.90% using balance MobilenetV2 CNN model, and for the hotmirror filter accuracy is 93.18% using balance Xception & for the blueIR filter accuracy is 81.81% using balance Xception CNN model.**

***Keywords*—Convolutional Neural Network (CNN); Multi-spectral images; Alexnet; Densenet121; Resnet18; Resnet50; VGG16; VGG19; Effficeienet80; MobilenetV2; Xception; InceptionV3; InceptionResnetV2**

I. Introduction

Convolutional neural network popularly known as CNN used in multiple applications like image classification, video analysis, emotion recognition, analyzing spatial data, etc. Convolutional layer is responsible for performing matrix manipulation operation on the input data. With the help of CNN [1], [2], it is possible to extract the different features of the input data. As discussed, convolutional layer extracts feature sets from the given input data and its output either a feature set or feature map will be given as an input to the next phases of the CNN model. In many image processing applications with the help of CNN models one can extract different features like edges, corners, textures, and many more other complex features. Next layer in the CNN model is pooing layer responsible to reduce the dimensions of the input and consumes less memory. This

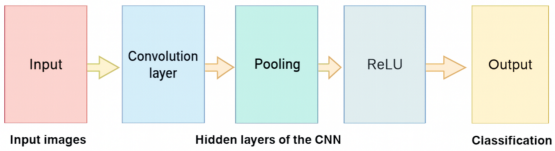


Fig. 1. CNN basic architecture.

reduction in the dimensions helps dealing with the overfitting issues in the network. Max pooling layer in the CNN model helps minimizing the computational complexities, minimizing the features set etc. To make the CNN model more robust max pooling layer is indivisible part and helps maintaining the accuracy of the model. Key concept in CNN models is training, testing and validating. To evaluate the CNN models one can, use parameters like precision, F1 score, recall etc [3] .

• Alexnet: This CNN model was developed by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton. This model consists of 05 convolutional layers, 03 fully connected layers. First 02 convolutional layers max-pooling layer in order to extract 'n' features. Next convolutional layers are connected to the fully connected layers. Outputs of these layers are connected to ReLU (Rectified Linear Unit). For the purpose of distribution and classification the resultant output will be connected to softmax activation layer.

• DenseNet: DenseNet is dense convolutional neural network model used for classification and segmentation purpose. It is based on feed forward technique i.e. output of one layer is connected to every subsequent layer which enables the reuse of extracted features. Hence, one can find significant information is flowing in the DensNet architectures. The major advantage of DenseNet based models is its accuracy. However, the 'n' layer connections consume a bit more memory which affects the popularity of these architectures. As every layer is connected to every subsequent layer it increases the computational

complexity in the network results in higher training time and increased computational cost.

• Resnet18: It is popularly used in deep learning applications due to its ability to handle complex tasks. It is widely used in image classification and it consists of convolutional layers, ReLU activation layers and fully connected layers. With the help of residual blocks present in the Resnet18 architectures one or few steps can be skipped by preserving the information.

• Resnet50: It belongs to residual network (ResNet). It's a 50-layer convolutional neural network model which uses 'skip' connection to skip few steps by preserving the information in forward-and-backward propagation. It is used in image processing applications to perform few tasks like classification, object identification and segmentation. However, in the deep learning architectures as the network becomes accuracy could be drenched. This condition can be handled by the ResNet architectures by introducing the residual blocks to skip few steps by preserving the information.

• VGG16: It consists of 16 layers i.e. 13 convolutional layers and 03 fully connected layers. VGG16 is commonly used in image classification & detecting the objects to achieve higher accuracy. VGG network is developed by visual geometry group and consists of series of convolutional neural networks. Simplicity and Uniformity are the key features of the VGG16 models. However, VGG16 models have few limitations like high computational costs, memory consumption & slow training time.

• VGG19: It is a series of VGG network and consists of 19 layers. It consists of 16 convolutional layers and 03 fully connected layers due to which it becomes more deeper than VGG16 network. The additional depth of VGG19 models gives a bit more accuracy than VGG16. Deeper analysis requires more memory and increases the memory cost & computational cost too. More depth of VGG19 than VGG16 could lead to slow the network training time & becomes less popular in many sensitive applications.

• Effficeienet_80: - It is a CNN model used to get higher accuracy in image classification applications. As compared to the other versions of CNN models it requires less computational costs. Compound scaling is introduced in this CNN model to scale the network to achieve high performance and accuracy. It is widely used in image classification, segmentation and computer vision tasks.

• Mobilenet_V2: As its name indicates it is used in mobile devices for image classification, detecting the objects and segmentation. It gives better performance than previous version of Mobilenet architecture. Higher accuracy, low latency, high speed, less computational cost, and small model size are the key characteristics of this CNN model.

• Xception: Using less parameters this CNN model gives better performance than other models. Due to minimized no. of operations it requires less computations. To deal with overfitting it introduces batch normalization and dropout layer if the dataset is larger.

• Inception_V3: High accuracy, less computations and, multi-scale feature extraction are the key features of this CNN model. Dimensionality reduction feature of this CNN model helps preventing the depth of the network i.e. prevents the network becoming deeper. It introduces multi-scale feature extraction to capture different features using scaling & different filters simultaneously. Fig. 1 shows CNN basic architecture.

II. Literature Review

Authors in study [4] have proposed a research work to detect plant diseases in their early stages using remote sensing technique. It is quite difficult task for human being to diagnose the possible plant diseases in the early stages. Therefore, image processing techniques and processing of the hyper spectral images of the plant leaves could help to detect the plant diseases. Authors have proposed a sensor fusion [4] technique application on the hyper spectral images of the plant leaves. Such methods help detecting the rust on the plant leaves in the early stages. This research work demonstrated the spectrograph among the healthy and diseased leaves. However, environmental factors such as sufficient light while capturing the images of the plant leaves have impact on the accuracy of the model. Use of pesticides on the plants is a common practice during cultivation but many times this approach fails to control the plant disease because pesticides could not be applied evenly. Application of the excessive pesticides can increase the production cost and many times remain in the product as well as in the soil too. Last few years, everyone is struggling to reduce the use pesticides & because of this with the help of recent technologies such as AI (artificial intelligence) and ML (machine learning) detecting the plant diseases in the early stages is possible. Authors [5] have proposed a research work detecting the specific area (site) to apply the fungicide using remote sensing technique. With the help of remote sensing technique within less time and minimum efforts one can detect the specific diseased area on the plants (plant leaves, stem etc.) This research work focuses on the identification of fungal infection on the plant leaves. This research work proposed a multi spectral remote sensing technique to detect the plant diseases. In this research work authors have analyzed winter wheat crop using their proposed research work to detect the fungal infection. Once the fungal infection is identified authors have applied the decision tree and mixture tuned matched filtering (MMTF) to classify the severity of the possible diseases. Many farmers face challenges during the cultivation of the soybean [6] due to the Phakopsora pachyrhizi - a fungus which destroys the soybean crop and affect the yield. This fungus spreads rapidly across the field and affects the crop yield. Therefore, authors have suggested it is necessary to detect the crop disease in its early stages. Proposed research work focuses on detecting the soybean rust and severity of the disease. Authors have collected various images of the soybean leaves in order to classify the disease severity.

Key concept in this research work is tracking leaf development and fungal infection simultaneously. Objective of this research work is to process the multispectral images of the soybean leaves and detect, classify the rust on the crop. Processing of the high-resolution multispectral images [7] was proposed by the authors to detect the plant diseases in their early stages. The proposed research work aims automatically detecting and classifying plant leaves diseases. In the new phase of agricultural era i.e., precision agriculture using recent

techniques helps detecting the fungal infection on the plants. Authors have analyzed sugar beet plant to detect the possible diseases in its early stages. This research work identifies rust, powdery mildew and other spots on the plant leaves. The proposed research work captures the multispectral images of the sugar beet leaves in better lighting conditions. Next phase of the proposed research work helps classifying the healthy leaves, leaves with rust, and different spots on the leaves. Authors [8] have focused on possible diseases on soybean crop. Crop diseases affect the yield and researchers are taking efforts to minimize the yield loss. Therefore, it is necessary to detect the disease in its early stage. Controlling measures like application of the pesticides, fungicides are necessary to prevent the possible diseases. In this research work authors have demonstrated effective framework to identify the rust severity using multi-spectral images. Segmentation method applied to classify the infected area of the plant. Rust infection and the rust color are the major parameters were applied in this research work to calculate the rust severity. Once the classification of rust parts finishes, system applies threshold-setting method to finalize the rust severity. Automatic classification [9], [10] was proposed to identify the leaf diseases using multi-spectral images. Authors have proposed a precision agriculture model to identifying infected area accurately and taking controlling measures. In this research work authors have input images of the sugar beet leaves using different cameras i.e., RGB and multispectral images. Idea is to classify the healthy and infected leaves and taking controlling measures. Authors have applied k-nearest neighbor and adaptive bayes classification methods. Major contribution in this research work is pixel wise classification to achieve more accuracy. Authors in [11] have proposed a research work "Localized multispectral crop imaging sensors: Engineering & validation of a cost-effective plant stress and disease sensor". Authors have discussed how a close proximity could play important role in crop disease detection and help in precision agriculture. Close proximity helps accurately scanning the infected area and finding rust severity. Advantage of this proposed research work helps finding sensitive area (rust infection) using LED sensors. One can say it is a combination of hyper spectral image processing and application of LED sensors for better accuracy. An approach to reduce the qualitative and quantitative losses [2] was proposed using RGB, multi and hyper spectral images. Research work also focuses on different techniques like proximity, remote sensing, spectral sensors, and fluorescence imaging gives better results. Additionally, 3D scanning of the plant leaves could give better results in disease detection. Once the system collects and classifies healthy and infected leaves, with the help of supervised classification one can easily identify the infected area on the plant. As discussed, earlier fluorescence imaging focused on the photosynthesis activity of the plants. Author has discussed how a LED or laser light can track the photosynthesis activity of the plant. More parameters like plant leaf inclination, illumination and texture etc. will help in disease detection in its early stages. However, using sensors one can collect the large data of the plants but it is crucial to process that large data and deriving meaningful insight becomes difficult.

This research work also guides researchers w.r.t. few points like, classifying fungi, bacteria and viruses; Author suggested a best interdisciplinary model can be developed by integrating people and technology from plant pathology, sensor developments, and recent technology like machine learning. Using the best integrated model, it could become easier to conduct the pest management on the plants and detect the plant diseases in their early stages. Authors [12] have focused on precision agriculture model to minimize the plant diseases by maximizing the yield. With the help of recent technologies precision agriculture models can be developed to effectively utilize the pesticides.

Recent technologies and algorithms help farmers to detect the plant diseases in their early stages and to take remedial actions immediately. This research work uses hyper spectral imaging for the tomato crops. Proposed model classifies the tomato leaves into healthy & infected classes. Authors have also worked on vegetation indices and dimensionality of different features. As the proposed model successfully explores the dimensionality of the features, it increases the classification accuracy proportionally. Authors [13] have discussed how the plant diseases affected the yield across the world. Food security is another issue being faced by different countries & sustainable precision agriculture model must be developed to minimize the losses and maximize the yield. Authors have proposed non-destructive methods to track and control the plant diseases. To minimize the time required detecting and controlling the detected plant disease, these non-destructive methods are proposed which are simpler than other methods. These methods also help minimizing the use of pesticides and detect the diseases in its early stages. These non-destructive methods also detect the diseases rapidly & include different steps like taking images of the plant leaves and taking controlling actions. Authors in [14], [15] have discussed different machine learning models those are developed to detect the plant diseases in their early stages. This research work also focused on deep learning techniques those can be used for detecting the plant diseases in early stages and maximizing the yield. Deep learning models can give more accuracy in detection and prevention of plant diseases. This review work proposed by authors discussed different deep learning approaches for plant disease detection. Authors have also explained how visualization techniques can be used to detect and present different symptoms of plant diseases. Image processing in these models uses hyper spectral images of the plant leaves and most important point in all models to be considered is 'environmental factors' like illumination etc. Therefore, objective of such models is to minimize the use of fungicides and pesticides. The major advantage of deep learning models is one can keep track on plant disease occurrence. Authors [1] have noted important challenge faced by different countries i.e., food scarcity. It became necessary to detect the plant diseases and maintaining the yield to avoid the losses. Authors have discussed near-infrared (NIR) imaging is the popular method in plant disease detection. Images of the plants can be captured under the natural environmental condition.

The proposed model divides the prepared dataset into different ratios. With the help of different ratios i.e., training and testing split ratios one can evaluate the model's accuracy. This research work consists of different steps like capturing hyper spectral images, processing of those images, extracting different possible features, and applying classification to evaluate the proposed model's accuracy in terms of precision and recall. Authors in [16] have enlisted different technologies like

computer vision, image processing and machine learning etc. can be used to detect the plant diseases in early stages. These recent technologies also speed up the disease detection process and help farmers to take controlling actions immediately. This research work addresses the machine learning methods used for classification purpose which classifies the healthy and infected leaves within less time. Different approaches like support vector machines (SVM), naïve bayes and convolutional neural network modeling (CNN) discussed and used in the proposed framework. Authors in [17] proposed a research work focusing on cassava brown streak disease. Objective of this research work is to detect the disease in its early stage using multi-spectral imaging. Authors have developed an active multi-spectral imaging device to capture the real time images of the plants and helps end users to take remedial actions immediately. Research work focuses on distinguishing healthy and infected plant laves. The advantage of this proposed research work is integration of spatial as well as multi-spectral images. The invented active device also finds if there are any stresses due to environmental factors, pesticides etc. With the help of multi-spectral imaging approach large volume of data can be generated which is very useful in accurately finding the infection. Classification helps differentiating healthy plant's leaves vs infected leaves. Active device captures multi-spectral images of the leaves automatically and processes them by applying 'cropping' mechanism. If necessary, the proposed system can perform leaf segmentation for better comparisons.

Egyptian people consume rice regularly and it is considered as one of the important crops. However, due to various factors rice crop yield gets affected and need arises to minimize the losses. Authors in [18], [3] proposed a research work emphasizing on controlling rice plant diseases using deep convolutional neural network and multi-spectral imaging. Proposed research work prepares a multi-modal data of the rice plants using multi-spectral and RGB images. The objective of proposed research work is to show how accuracy of the plant disease detection can be increased with the help of multi-spectral and RGB images. The economy of almost every country is based on 'agriculture production'. The production of agriculture gets hampered due to the factors like environmental conditions (drought, flood etc.), various diseases on the plants and excessive use of pesticides etc. Authors in [19] noted these conditions could lead to food scarcity and can disturb the global food supply chain. Hence, recent technologies like AI and ML could detect plant diseases in its early stages and minimizes the losses. Hyper spectral images of the plants can detect the diseases in its early stages. This research work gives direction to the researchers and academicians to detect plant diseases. It consists of few modules like capturing images of the plants, classification, identifying diseases, deciding disease severity etc. Authors in [20] have discussed important point in this research work i.e.; many existing plant disease detection systems depend on the datasets. The proposed research work discusses effectiveness of the multi-spectral images in real time environment. The important part of this research work is 'vision transformer' models used in training and testing the collected data. Objective of the proposed research work is to show how advanced imaging methods can help controlling the plant diseases in its early stages. Authors in [21] have reviewed different multiple spectral systems used in plant disease detection. It is necessary to detect the plant diseases rapidly to control them in early stages. Authors have discussed how 'spectroscopy' helps rapidly detecting the plant diseases and minimizes the losses.

This review work emphasized on advantages and disadvantages of the spectral detection systems. These multiple spectral systems are being used in detection of plant diseases, finding different stresses on the plants due to various factors. Review article also enlisted different challenges in using multiple spectral systems, their working and future research directions. Authors in [22], [23] have proposed a deep learning model processing multi-spectral images of the plants detecting diseases in the early stages. With the help of recent technologies, it is necessary to detect various diseases on the plants in the early stages & helps avoiding losses. Authors have used 'tomato' plants multi-spectral images with different filters to identify disease in the early stages. Experimental approach of this research work is based on 02 datasets i.e., one is taking uniform images of the plants and second dataset with some sort of variations in capturing different images. Objective of this research work is classifying healthy and diseased leaves of the plants based on CNN (convolutional neural network) modeling, vision transformers. Idea using different filters is to find the best accuracy and consistency. Authors have found K590 filter gave highest accuracy 88.69% and 93.31% for datasets. ViTBI6 is the effective model in the research study with 89.92% accuracy. Proposed deep learning-based model also helps classifying balanced and unbalanced datasets.

Authors in [24], [25] have discussed food security issues faced across the globe. Various plant diseases affect the agricultural productivity. It is very crucial for human being to detect the plant diseases manually and it is also a time-consuming task. There are chances of errors in manual detection and controlling the plant diseases. With the help of AI and ML, one can develop a model to detect and control the plant diseases & minimizes the future productivity losses. An integrative model i.e., with different sensors, high resolution cameras, AI and ML technologies can be developed for crop disease detection. Authors have proposed a review work based on existing research works in this area focusing on image-based plant disease detection. This reviewed work helps researchers and academicians to find the effective technology, algorithm and image forms. It also helps in deciding how environmental factors play important role in plant diseases and how to detect the diseases in its early stage.

III. Proposed System

Proposed system is based on CNN models like AlexNet, ResNet18, ResNet50, VGG16,VGG19, DenseNet121, EfficientNet121,MobileNetV2, ConvexNet_B0, Xception, InceptionV3, InceptionResNetV2. This section illustrates result analysis of the different filters like Hotmirror, K590, K665,K720,K850, and blueIR balance datasets. Following section explains result analysis for the above-mentioned balanced datasets using different CNN models. The proposed CNN framework evaluates the model's efficiency with test accuracies calculated using CNN model and balance dataset. Analysis of the proposed research work gradually applies CNN models against the filters (balanced datasets) & to illustrate the working of our proposed research work we have discussed hotmirror dataset and different CNN modeling approaches.

It gives variation in test accuracies as shown below and found that, for the hotmirror filter the Xception CNN model gives 93.18% test accuracy. DenseNet121 and EfficentNet_B0 gives 79.5% accuracies for the hotmirror filter. Following Fig. 2 illustrates the difference between test accuracies for the hotmirror filter using CNN models.

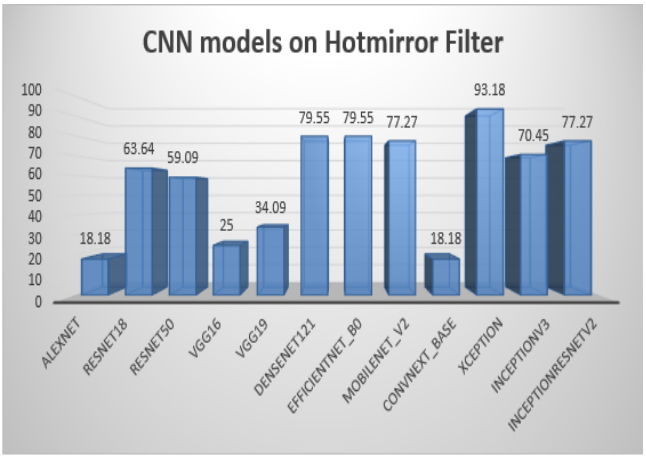


Fig. 2. CNN models performance on hotmirror filter.

The advantage of our proposed approach is applying 12 CNN models on the different datasets makes it more flexible to identify the plant diseases accurately and efficiently. To illustrate the working of proposed approach following section discusses the working of proposed integrated CNN modeling approach detecting plant diseases in their early stages.

A. Hotmirror Analysis

Training AlexNet on hotmirror_balance (1/12 models for this filter)

```
[AlexNet] Epoch 1/5 | Train Loss: 1.7751, Val Acc:
    0.2045
[AlexNet] Epoch 2/5 | Train Loss: 1.7557, Val Acc:
    0.2045
[AlexNet] Epoch 3/5 | Train Loss: 1.7509, Val Acc:
    0.2045
[AlexNet] Epoch 4/5 | Train Loss: 1.7498, Val Acc:
    0.2045
[AlexNet] Epoch 5/5 | Train Loss: 1.7511, Val Acc:
    0.2045
```

AlexNet CNN model was applied using 05 epochs and calculates the test accuracy for the hotmirror filter & found the overall test accuracy is low i.e. 18.18%. It is also important to minimize the training losses during training the network. Next phase of the proposed CNN model is training the given network using ResNet18 on hotmirror filter. Training ResNet18 on hotmirror_balance (2/12 models for this filter)

```
[ResNet18] Epoch 1/5 | Train Loss: 1.0300, Val Acc:
    0.3636
[ResNet18] Epoch 2/5 | Train Loss: 0.4845, Val Acc:
    0.5682
[ResNet18] Epoch 3/5 | Train Loss: 0.2662, Val Acc:
    0.6705
[ResNet18] Epoch 4/5 | Train Loss: 0.2102, Val Acc:
    0.4886
[ResNet18] Epoch 5/5 | Train Loss: 0.1425, Val Acc:
    0.5568
```

ResNet18 CNN model gives overall 63.64% test accuracy for the hotmirror balanced dataset. It is found that, as compared to the previous AlexNet CNN modeling approach ResNet18 gave better test accuracy.

Similarly, ResNet50 CNN model gives overall 59.09% test accuracy for the hotmirror balanced dataset as shown in the following epochs. Training ResNet50 on hotmirror_balance (3/12 models for this filter)

```
[ResNet50] Epoch 1/5 | Train Loss: 1.3103, Val Acc:
    0.3182
[ResNet50] Epoch 2/5 | Train Loss: 0.8093, Val Acc:
    0.5795
[ResNet50] Epoch 3/5 | Train Loss: 0.4439, Val Acc:
    0.6705
[ResNet50] Epoch 4/5 | Train Loss: 0.4466, Val Acc:
    0.6364
[ResNet50] Epoch 5/5 | Train Loss: 0.2318, Val Acc:
    0.4545
```

Next CNN modeling approach VGG16 gives overall low-test accuracy i.e.25.00% as shown below using 05 epochs and calculated training losses. It is expected to have minimum training losses and increase the overall test accuracy. Training VGG16 on hotmirror_balance (4/12 models for this filter)

```
[VGG16] Epoch 1/5 | Train Loss: 1.8613, Val Acc:
    0.2159
[VGG16] Epoch 2/5 | Train Loss: 1.7837, Val Acc:
    0.2045
[VGG16] Epoch 3/5 | Train Loss: 1.7700, Val Acc:
    0.2045
[VGG16] Epoch 4/5 | Train Loss: 1.7450, Val Acc:
    0.2045
[VGG16] Epoch 5/5 | Train Loss: 1.7409, Val Acc:
    0.2500
```

VGG19 CNN model gives overall 34.09% for the hotmirror balanced filter as shown below. Epochs are nothing but a pass-through which input data sample passed and updated repeatedly based on calculated errors and losses. Training VGG19 on hotmirror_balance (5/12 models for this filter)

```
[VGG19] Epoch 1/5 | Train Loss: 1.8190, Val Acc:
    0.2159
[VGG19] Epoch 2/5 | Train Loss: 1.6921, Val Acc:
    0.1932
[VGG19] Epoch 3/5 | Train Loss: 1.6088, Val Acc:
    0.2045
[VGG19] Epoch 4/5 | Train Loss: 1.6478, Val Acc:
    0.2273
[VGG19] Epoch 5/5 | Train Loss: 1.6460, Val Acc:
    0.2841
```

Similarly, following epochs illustrates the application of DenseNet121 on hotmirror filter which gives overall test accuracy 79.55% which is comparatively good than previous applied CNN model. Training DenseNet121 on hotmirror_balance (6/12 models for this filter)

```
[DenseNet121] Epoch 1/5 | Train Loss: 0.9287, Val
    Acc: 0.2386
[DenseNet121] Epoch 2/5 | Train Loss: 0.4265, Val
    Acc: 0.3295
[DenseNet121] Epoch 3/5 | Train Loss: 0.2419, Val
    Acc: 0.5909
[DenseNet121] Epoch 4/5 | Train Loss: 0.1292, Val
    Acc: 0.7273
[DenseNet121] Epoch 5/5 | Train Loss: 0.0822, Val
    Acc: 0.7159
```

The EfficientNet_B0 CNN model gives similar overall test accuracy for the hotmirror filter i.e. 79.55%. Training EfficientNet_B0 on hotmirror_balance (7/12 models for this filter)

```
[EfficientNet\_B0] Epoch 1/5 | Train Loss: 0.8554,
    Val Acc: 0.7500
[EfficientNet_B0] Epoch 2/5 | Train Loss: 0.2885,
    Val Acc: 0.8182
[EfficientNet_B0] Epoch 3/5 | Train Loss: 0.1385,
    Val Acc: 0.7841
[EfficientNet_B0] Epoch 4/5 | Train Loss: 0.1390,
    Val Acc: 0.7500
[EfficientNet_B0] Epoch 5/5 | Train Loss: 0.2134,
    Val Acc: 0.6932
```

MobileNetV2 CNN model gives 77.27% overall test accuracy after applied on the hotmirror filter. In our case for the hotmirror filter multi-spectral image set till now DenseNet121,EfficiNet_B0 and MobileNetV2 gave good overall test accuracies. Training MobileNetV2 on hotmirror_balance (8/12 models for this filter)

```
[MobileNetV2] Epoch 1/5 | Train Loss: 0.8472, Val
    Acc: 0.7386
[MobileNetV2] Epoch 2/5 | Train Loss: 0.3747, Val
    Acc: 0.6932
[MobileNetV2] Epoch 3/5 | Train Loss: 0.2372, Val
    Acc: 0.7727
[MobileNetV2] Epoch 4/5 | Train Loss: 0.1056, Val
    Acc: 0.7841
[MobileNetV2] Epoch 5/5 | Train Loss: 0.1739, Val
    Acc: 0.7159
```

We have applied ConvNext_Base CNN model on the same filter and found the overall test accuracy is low i.e. 18.18%. Training ConvNeXt_Base on hotmirror_balance (9/12 models for this filter)

```
[ConvNeXt_Base] Epoch 1/5 | Train Loss: 1.7957, Val
    Acc: 0.2045
[ConvNeXt_Base] Epoch 2/5 | Train Loss: 1.7849, Val
    Acc: 0.2045
[ConvNeXt_Base] Epoch 3/5 | Train Loss: 1.7577, Val
    Acc: 0.2045
[ConvNeXt_Base] Epoch 4/5 | Train Loss: 1.7682, Val
    Acc: 0.2045
[ConvNeXt_Base] Epoch 5/5 | Train Loss: 1.7691, Val
    Acc: 0.2045
```

Training the network using Xception CNN model gives 93.18% overall test accuracy which is exceptional among the other tested CNN models. Training Xception on hotmirror_balance (10/12 models for this filter)

```
[Xception] Epoch 1/5 | Train Loss: 0.9403, Val Acc:
    0.6591
[Xception] Epoch 2/5 | Train Loss: 0.4778, Val Acc:
    0.7500
[Xception] Epoch 3/5 | Train Loss: 0.2199, Val Acc:
    0.7273
[Xception] Epoch 4/5 | Train Loss: 0.1298, Val Acc:
    0.8068
[Xception] Epoch 5/5 | Train Loss: 0.0427, Val Acc:
    0.7841
```

InceptionV3 CNN model gives 70.45% overall test accuracy when applied on the hotmirror filter multi-spectral image set. Training InceptionV3 on hotmirror_balance (11/12 models for this filter)

```
[InceptionV3] Epoch 1/5 | Train Loss: 1.0353, Val
    Acc: 0.5795
[InceptionV3] Epoch 2/5 | Train Loss: 0.5270, Val
    Acc: 0.6932
[InceptionV3] Epoch 3/5 | Train Loss: 0.4543, Val
    Acc: 0.7273
[InceptionV3] Epoch 4/5 | Train Loss: 0.2871, Val
    Acc: 0.6818
[InceptionV3] Epoch 5/5 | Train Loss: 0.2210, Val
    Acc: 0.6932
```

InceptionResNetV2 CNN model gives 77.27% overall test accuracy when applied on the hotmirror filter multi-spectral image set.

```
Training InceptionResNetV2 on hotmirror_balance
    (12/12 models for this filter)
[InceptionResNetV2] Epoch 1/5 | Train Loss: 0.8923,
    Val Acc: 0.5455
[InceptionResNetV2] Epoch 2/5 | Train Loss: 0.4286,
    Val Acc: 0.6818
[InceptionResNetV2] Epoch 3/5 | Train Loss: 0.2779,
    Val Acc: 0.7159
[InceptionResNetV2] Epoch 4/5 | Train Loss: 0.0755,
    Val Acc: 0.7727
[InceptionResNetV2] Epoch 5/5 | Train Loss: 0.0214,
    Val Acc: 0.7386
```

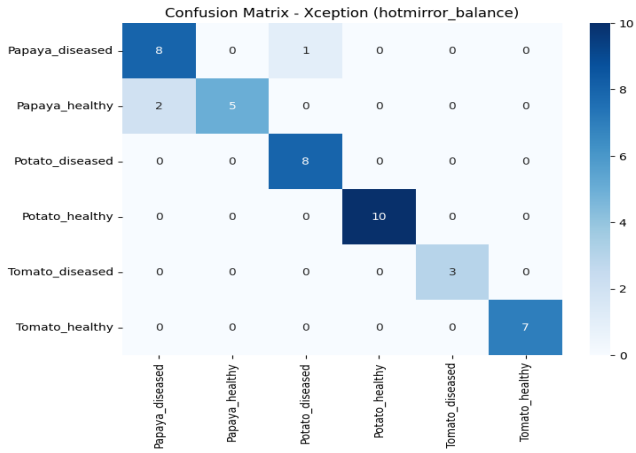


Fig. 3. Confusion matrix xception (hotmirror_balance).

B. Confusion Matrix

Confusion matrix is shown below in the Fig. 3 which illustrates the measurement effectiveness of a classification model applied in our proposed research work. It helps comparing the predictions made in our proposed research work with the actual results obtained and represents where the model was right or wrong. One can observe the confusion matrix and understand where the model is making mistakes to improvise the same. Table I gives brief idea about the classification report reliability measures for the Xception model and Fig. 4 illustrates the cumulative probability plot for the diseased and healthy leaves. Table II shows classification report reliability measures for the Xception model.

Following Table III and Fig. 4 gives brief idea about the best CNN models applied in our proposed research work with their respective overall test accuracies. By observing the table we can conclude that, Xception CNN modeling gives best test results i.e. 93.18% among the other approaches.

TABLE I. MODEL PERFORMANCE ACROSS FILTERS

Model Filter	balance_AlexNet	balance_ConvNeXt_Base	balance_DenseNet121	balance_EfficientNet_B0	balance_InceptionResNetV2	balance_InceptionV3	balance_MobileNetV2	balance_ResNet18	balance_ResNet50	balance_VGG16	balance_VGG19	balance_Xception
K590	0.204545	0.704545	0.818182	0.795455	0.772727	0.795455	0.909091	0.750000	0.750000	0.363636	0.386364	0.886364
K665	0.159091	0.477273	0.522727	0.840909	0.727273	0.704545	0.750000	0.704545	0.431818	0.318182	0.386364	0.772727
K720	0.250000	0.500000	0.704545	0.818182	0.568182	0.613636	0.704545	0.522727	0.454545	0.295455	0.250000	0.795455
K850	0.250000	0.363636	0.681818	0.727273	0.636364	0.477273	0.636364	0.431818	0.386364	0.386364	0.295455	0.636364
blueIR	0.204545	0.568182	0.772727	0.727227	0.795455	0.681818	0.750000	0.681818	0.636364	0.295455	0.295455	0.818182
hotmirror	0.181818	0.181818	0.795455	0.727727	0.772727	0.704545	0.727727	0.636364	0.590909	0.250000	0.340909	0.931818

TABLE II. CLASSIFICATION REPORT RELIABILITY MEASURES FOR THE XCEPTION MODEL

Class	Precision	Recall	F1-score	Support
Papaya_diseased	0.80	0.89	0.84	0
Papaya_healthy	1.00	0.71	0.83	7
Potato_diseased	0.89	1.00	0.94	8
Potato_healthy	1.00	1.00	1.00	10
Tomato_diseased	1.00	1.00	1.00	3
Tomato_healthy	1.00	1.00	1.00	7
Accuracy			0.93	44
Macro avg	0.95	0.93	0.94	44
Weighted avg	0.94	0.93	0.93	44

TABLE III. BEST MODEL PER FILTER

Filter	Model	Accuracy
K850	balance_EfficientNet_B0	0.727273
K720	balance_EfficientNet_B0	0.818182
K665	balance_EfficientNet_B0	0.840909
K590	balance_MobileNetV2	0.909091
hotmirror	balance_Xception	0.931818
blueIR	balance_Xception	0.818182

IV. CONCLUSION

This research work discussed CNN models used to classify the plant leaves (diseased leaves and healthy leaves) with higher accuracy and precision. Research work gave accuracies for different filters with different models and fund that, for the hotmirror filter accuracy is 93.18% using balance_Xception. One can use different datasets of plant leaves images and apply these different CNN models to evaluate the performance. It is very necessary to apply recent technologies to detect plant diseases in their early stages. Academicians and researchers are continuously striving for developing the best machine learning (ML) model for the same. To avoid future food scarcity, it is necessary to minimize the agriculture losses and increase the crop yield. Agriculture plays key role in every nation's economy and hence such ML models must be adopted widely. These models give accurate, efficient, and automated results to classify the diseased and healthy leaves. Deep learning techniques helps automatically extracting the features from the input images like color of the images, texture of the image, size and shape of the image, other environmental parameters (if required). Therefore, proposed model definitely will contribute in deploying precision agriculture models widely. The most important advantage of such model is helping end users in better decision making i.e. as the model detects any disease on the plant leaves, it warns the users to take remedial actions immediately. With the help of such strategy it is also possible to develop a proactive CNN model to minimize the labor cost in agriculture sector by maximizing the crop yield.

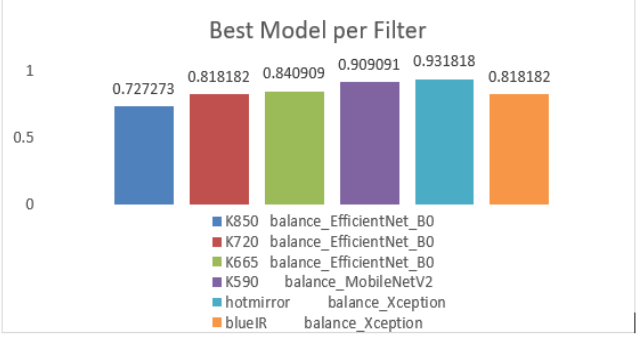


Fig. 4. Best CNN models as per the results.

CONFLICT OF INTEREST

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REFERENCES

[1] M. De Silva and D. Brown, "Plant disease detection using multispectral imaging," in *International Advanced Computing Conference*. Springer, 2022, pp. 290–308.

[2] A.-K. Mahlein, "Plant disease detection by imaging sensors–parallels and specific demands for precision agriculture and plant phenotyping," *Plant disease*, vol. 100, no. 2, pp. 241–251, 2016.

[3] A. J. Bleasdale and J. D. Whyatt, "Classifying early apple scab infections in multispectral imagery using convolutional neural networks," *Artificial Intelligence in Agriculture*, vol. 15, no. 1, pp. 39–51, 2025.

[4] D. Moshou, C. Bravo, R. Oberti, J. West, L. Bodria, A. McCartney, and H. Ramon, "Plant disease detection based on data fusion of hyperspectral and multi-spectral fluorescence imaging using kohonen maps," *Real-Time Imaging*, vol. 11, no. 2, pp. 75–83, 2005.

[5] J. Franke and G. Menz, "Multi-temporal wheat disease detection by multi-spectral remote sensing," *Precision Agriculture*, vol. 8, no. 3, pp. 161–172, 2007.

[6] D. Cui, Q. Zhang, M. Li, Y. Zhao, and G. L. Hartman, "Detection of soybean rust using a multispectral image sensor," *Sensing and Instrumentation for Food Quality and Safety*, vol. 3, no. 1, pp. 49–56, 2009.

[7] S. Bauer, F. Korč, and W. Förstner, "Investigation into the classification of diseases of sugar beet leaves using multispectral images," in *Precision agriculture'09*. Wageningen Academic, 2009, pp. 229–238.

[8] D. Cui, Q. Zhang, M. Li, G. L. Hartman, and Y. Zhao, "Image processing methods for quantitatively detecting soybean rust from multispectral images," *Biosystems engineering*, vol. 107, no. 3, pp. 186–193, 2010.

[9] S. D. Bauer, F. Korč, and W. Förstner, "The potential of automatic methods of classification to identify leaf diseases from multispectral images," *Precision Agriculture*, vol. 12, no. 3, pp. 361–377, 2011.

[10] M. Morgan, C. Blank, and R. Seetan, "Plant disease prediction using classification algorithms," *IAES International Journal of Artificial Intelligence*, vol. 10, no. 1, p. 257, 2021.

[11] B. Grieve, S. Hammersley, A.-K. Mahlein, E.-C. Oerke, and H. Goldbach, "Localized multispectral crop imaging sensors: Engineering & validation of a cost effective plant stress and disease sensor," in *2015 IEEE Sensors Applications Symposium (SAS)*. IEEE, 2015, pp. 1–6.

[12] P. Moghadam, D. Ward, E. Goan, S. Jayawardena, P. Sikka, and E. Hernandez, "Plant disease detection using hyperspectral imaging," in *2017 International conference on digital image computing: techniques and applications (DICTA)*. IEEE, 2017, pp. 1–8.

[13] M. M. Ali, N. A. Bachik, N. Muhadi, T. N. T. Yusof, and C. Gomes, "Non-destructive techniques of detecting plant diseases: A review," *Physiological and Molecular Plant Pathology*, vol. 108, p. 101426, 2019.

[14] M. H. Saleem, J. Potgieter, and K. M. Arif, "Plant disease detection and classification by deep learning," *Plants*, vol. 8, no. 11, p. 468, 2019.

[15] B. Gokulnath and G. U. Devi, "A survey on plant disease prediction using machine learning and deep learning techniques," *Inteligencia Artificial*, vol. 23, no. 65, pp. 136–154, 2020.

[16] H. Pallathadka, P. Ravipati, G. S. Sajja, K. Phasinam, T. Kassanuk, D. T. Sanchez, and P. Prabhu, "Application of machine learning techniques in rice leaf disease detection," *Materials Today: Proceedings*, vol. 51, pp. 2277–2280, 2022.

[17] Y. Peng, M. M. Dallas, J. T. Ascencio-Ibáñez, J. S. Hoyer, J. Legg, L. Hanley-Bowdoin, B. Grieve, and H. Yin, "Early detection of plant virus infection using multispectral imaging and spatial–spectral machine learning," *Scientific Reports*, vol. 12, no. 1, p. 3113, 2022.

[18] Y. A. Alnaggar, A. Sebaq, K. Amer, E. Naeem, and M. Elhelw, "Rice plant disease detection and diagnosis using deep convolutional neural networks and multispectral imaging," in *International Conference on Model and Data Engineering*. Springer, 2022, pp. 16–25.

[19] R. Rayhana, Z. Ma, Z. Liu, G. Xiao, Y. Ruan, and J. S. Sangha, "A review on plant disease detection using hyperspectral imaging," *IEEE Transactions on AgriFood Electronics*, vol. 1, no. 2, pp. 108–134, 2023.

[20] M. De Silva and D. Brown, "Plant disease detection using vision transformers on multispectral natural environment images," in *2023 International Conference on Artificial Intelligence, Big Data, Computing and Data Communication Systems (icABCD)*. IEEE, 2023, pp. 1–6.

[21] S. Fang, R. Cui, Y. Wang, Y. Zhao, K. Yu, and A. Jiang, "Application of multiple spectral systems for the tree disease detection: A review," *Applied Spectroscopy Reviews*, vol. 58, no. 2, pp. 83–109, 2023.

[22] M. De Silva and D. Brown, "Tomato disease detection using multispectral imaging with deep learning models," in *2024 International Conference on Artificial Intelligence, Big Data, Computing and Data Communication Systems (icABCD)*. IEEE, 2024, pp. 1–9.

[23] A. Lakshmanarao, M. R. Babu, and T. S. R. Kiran, "Plant disease prediction and classification using deep learning convnets," in *2021 International Conference on Artificial Intelligence and Machine Vision (AIMV)*. IEEE, 2021, pp. 1–6.

[24] A. Dolatabadian, T. X. Neik, M. F. Danilevicz, S. R. Upadhyaya, J. Batley, and D. Edwards, "Image-based crop disease detection using machine learning," *Plant Pathology*, vol. 74, no. 1, pp. 18–38, 2025.

[25] M. R. Tammina, K. Sumana, P. P. Singh, T. V. Lakshmi, and S. D. Pande, "Prediction of plant disease using artificial intelligence," in *Microbial Data Intelligence and Computational Techniques for Sustainable Computing*. Springer, 2024, pp. 25–48.

Model-Driven Transformation of Business Processes into Blockchain Smart Contracts

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***Abstract*—This paper presents a comprehensive Model-Driven Engineering (MDE) methodology for automatically transforming Business Process Model and Notation (BPMN) diagrams into executable blockchain-based smart contracts. The proposed approach defines a set of Atlas Transformation Language (ATL) rules that systematically map BPMN elements to Solidity constructs, ensuring semantic consistency and traceability throughout the transformation process. The framework integrates several stages, including process modeling, model validation, code generation, and deployment, supported by tools such as Camunda, Eclipse ATL, Remix IDE, and MetaMask. Experimental validation on the Ethereum Sepolia test network demonstrates the approach's ability to enhance automation, reduce manual coding errors, and improve synchronization between business workflows and their on-chain implementations. Compared to existing BPMN-to-blockchain frameworks, the proposed solution offers a unified and reusable transformation pipeline that bridges the gap between business process modeling and blockchain execution. The study concludes that MDE provides a scalable, traceable, and standardized foundation for developing decentralized business process applications.**

***Keywords*—Model-driven engineering; BPMN; smart contracts; blockchain; ATL; automation; solidity; process transformation**

I. Introduction

Blockchain technology has introduced new paradigms for managing and coordinating cross-organizational processes by enabling the decentralized execution of agreements through smart contracts. These self-executing programs enhance transparency, trust, and auditability among participants without intermediaries [1], [2]. However, developing smart contracts manually remains a complex and error-prone activity that requires deep technical expertise in blockchain languages such as Solidity, as well as substantial effort in validation and testing [3]. Consequently, organizations face persistent challenges in ensuring reliability, scalability, and correctness when automating business workflows on blockchain infrastructures.

To address these limitations, Model-Driven Engineering (MDE) provides a methodology that emphasizes abstraction and automation in software development. Through MDE, developers can design system behavior using high-level models that can later be transformed into executable code, thus reducing manual intervention and increasing traceability [4], [5]. In the context of business process automation, Business Process Model and Notation (BPMN) serves as a widely adopted standard for visually representing workflows in an intuitive and platform-independent manner. When combined with transformation languages such as the Atlas Transformation Language (ATL), BPMN models can be automatically converted into smart contracts deployed on blockchain networks [3], [6].

Several studies have explored MDE-based transformations for blockchain applications, including Lorikeet [7], TABS [8], and MDE4BBIS [9]. Although these frameworks have advanced the integration of business modeling and blockchain deployment, most existing approaches remain fragmented or tool-specific. They typically focus on partial automation or theoretical descriptions of transformation processes without providing a fully operational, traceable, and validated pipeline. Moreover, prior works often omit detailed mappings between BPMN elements and their corresponding smart contract constructs, limiting their practical applicability and reproducibility in enterprise scenarios [10], [11].

Research Problem: Despite these advancements, there is currently no standardized and traceable end-to-end methodology for transforming BPMN business process models into deployable blockchain smart contracts while preserving the semantics of the original workflow.

Research Questions:

- How can MDE principles be leveraged to automate the transformation of BPMN models into smart contracts with minimal manual intervention?
- What transformation rules and architectural design are required to ensure semantic consistency, traceability, and deployment feasibility?

Objectives: The objectives of this study are to:

- Define a comprehensive MDE-based framework for transforming BPMN models into smart contracts using ATL.
- Establish explicit transformation rules that systematically map BPMN elements to Solidity constructs.
- Validate the proposed methodology through deployment and execution on the Ethereum Sepolia test network.

Significance and Contributions: The proposed approach unifies the entire transformation lifecycle—from BPMN modeling and validation to Solidity generation and blockchain deployment—within a modular and reusable architecture. Unlike existing frameworks such as Lorikeet, TABS, or MDE4BBIS, this study contributes a fully integrated, empirically validated methodology that enhances automation, improves semantic

traceability, and promotes standardization in model-driven blockchain development [6], [8], [10]. Novelty and Distinction: In contrast to previous frameworks such as Lorikeet [7], TABS [8], and MDE4BBIS [9], which partially automate the BPMN-to-Solidity transformation or focus on limited metamodel mapping, the proposed methodology introduces a unified and traceable pipeline that covers the entire lifecycle—from BPMN model validation to smart contract deployment. The novelty lies in the explicit mapping of BPMN temporal and resource constraints to Solidity execution semantics, ensuring end-to-end consistency, automation, and deployability across decentralized environments.

II. Background Definition

A. Model

Within the context of Model-Driven Engineering (MDE), a **model** refers to an abstracted and focused depiction of a system, designed to emphasize particular characteristics pertinent to a specific problem domain. It serves various purposes such as aiding comprehension, performing analysis, supporting communication, or facilitating the structured creation of system components in an automated manner [3], [10].

Every model adheres to a corresponding metamodel, which defines its structure and semantics. This relationship enables the application of formal transformation techniques and supports tool integration throughout the system development process [7].

B. Meta-model: Metamodelisation Layers

A **metamodel** can be described as a higher-level model that outlines the structural elements, semantic constraints, and rules governing a particular modeling language. In essence, it serves as a model about models, offering a formal foundation for constructing and interpreting models within a specific domain [6].

1) Key Concepts of Metamodels:

- Abstraction: Compared to standard models, metamodels function at a more abstract level. Whereas a model might illustrate a concrete system or process, the metamodel formalizes the building blocks and their interrelations used to design such models [10].
- Structure and Syntax: Metamodels define the permitted components—such as entities, attributes, and connections—within a modeling framework. For instance, in Unified Modeling Language (UML), the metamodel prescribes what elements make up a valid class diagram [5].
- Validation: They impose structural rules and integrity constraints to ensure that models conform to the expected language definition, helping maintain consistency and validity [3].
- Examples: Widely known metamodels include:
  - UML Metamodel: Provides the formal syntax and semantics for UML-based diagrams [2].
  - BPMN Metamodel: Specifies modeling elements and behavior for business process workflows using BPMN [12].
- Use in Model-Driven Engineering (MDE): Within MDE practices, metamodels are fundamental because they enable the transformation of high-level models into executable artifacts. This facilitates automation in software development and ensures consistency across generated implementations [8].

2) Metamodelization Layers: Metamodelization is typically organized into several abstraction levels, progressing from concrete real-world systems to highly abstract modeling structures. These layers are commonly described as follows:

- M0: Real-World Systems – This foundational level includes actual systems or operational processes observed in real environments. Examples include ongoing business workflows or deployed information systems [13].
- M1: Models – This level encompasses models derived from metamodels. For example, a BPMN model might depict the logic of a particular business operation. These models serve as tangible applications of the concepts defined at the metamodel level [9].
- M2: Metamodels – Here, we encounter frameworks such as BPMN and UML, which define the formal structure and semantics of modeling languages. These metamodels provide the abstract components required to represent systems or business processes conceptually [6].
- M3: Meta-Metamodel – This top-level layer defines the constructs used to build metamodels themselves. A notable example is the Meta-Object Facility (MOF), which offers a standardized mechanism for specifying metamodels in a consistent and formalized way [11].

The hierarchical organization of these modeling levels is depicted in Fig. 1, which illustrates the M0–M3 layering from real-world systems to meta-metamodels.

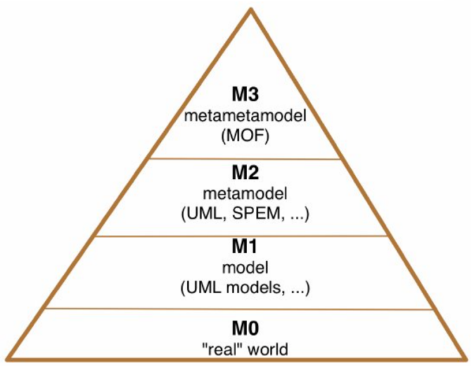


Fig. 1. Metamodeling hierarchy [4].

C. Model Transformation

In the context of Model-Driven Engineering (MDE), model transformation refers to the automated process of translating a source model—structured according to a specific metamodel—into a corresponding target model that conforms to

a different metamodel. This mechanism enhances the consistency and repeatability of software development, and is particularly advantageous in blockchain-oriented environments where precision and reliability are essential [4].

Over the years, numerous transformation languages and methods have emerged to support these processes:

- ATL (Atlas Transformation Language): A widely adopted tool for specifying and executing model transformations [3], [5].
- QVT (Query/View/Transformation): A standardized framework by OMG for expressing model-to-model transformations declaratively [14].
- Graph Transformation: Utilizes graph-based techniques to define transformation rules and apply them to model structures [15].
- Epsilon: A comprehensive language suite designed for model management, supporting a range of transformation and validation operations [11].
- Xtend: A statically typed language that facilitates the implementation of model-to-model transformation logic [12].
- Acceleo: An implementation of the MOFM2T (Model to Text) transformation specification developed under the OMG standard [8].

These transformation mechanisms constitute the foundation of the proposed approach presented in Section IV (Methodology), where BPMN models are systematically translated into Solidity smart contracts using ATL rules.

D. BPMN Overview

Business Process Model and Notation (BPMN) has emerged as a widely accepted notation standard for modeling business workflows. Designed and maintained by the Object Management Group (OMG), its primary goal is to ensure clarity and usability across various stakeholder roles, including business analysts, developers, and process managers [2], [16].

The popularity of BPMN is reflected in its integration into enterprise software platforms such as Oracle Business Process Analysis Suite and Camunda, which enable the automatic generation of executable systems based on BPMN diagrams [6]. In contrast to traditional programming-based approaches like BPEL or Java, the present work leverages BPMN as a foundation for generating blockchain-based smart contracts [8], [9].

1) Flow Objects: Flow objects include:

- Events: Start, Intermediate, and End. Intermediate events include timers, messages, conditions, etc. [2], [17].
- Activities: Tasks, Sub-processes, and Call Activities. Sub-processes may include compensation or transactions [6], [16].
- Gateways: Used to control sequence flow. Types include Exclusive, Inclusive, and Parallel, both converging and diverging [2], [5].

2) Examples:

- An exclusive gateway that splits the process flow into multiple branches based on defined conditions [2], [8].
- A parallel gateway that waits for all incoming sequences to arrive before continuing the execution [12], [18].
- A multi-instance task executed simultaneously across a group of input elements [10], [11].

E. Blockchain Ecosystem

The blockchain ecosystem includes a set of technologies, platforms, and development tools that support the design, implementation, and execution of decentralized applications. This ecosystem ranges from blockchain networks like Ethereum and Hyperledger to tools and methodologies such as model-driven engineering (MDE) [5], [6], [10].

Model-driven approaches enable developers to create formal models (e.g., BPMN) that are then transformed into executable blockchain code, enhancing productivity and consistency [7], [11], [16]. These practices are especially valuable in collaborative environments involving multiple stakeholders, where process standardization and automation are critical. This conceptual and technological ecosystem provides the environment in which our proposed transformation framework operates, linking BPMN-based process modeling with blockchain-based execution.

F. Smart Contracts

Smart contracts refer to autonomous programs deployed on blockchain networks, designed to execute predefined rules and agreements automatically when certain conditions are met. By removing the need for intermediaries, they enhance transaction reliability by promoting integrity, transparency, and resistance to tampering.

These contracts are especially valuable in managing complex process logic within decentralized ecosystems. Their applicability spans sectors such as finance, supply chain management, and multi-party collaborations. Moreover, when combined with modeling standards like BPMN, smart contracts enable traceable and verifiable execution of business workflows on blockchain infrastructures [2], [12], [18].

1) Programming Languages for Smart Contracts: Blockchain ecosystems support a variety of languages tailored for smart contract development, each offering different capabilities and trade-offs:

- Solidity: The dominant language for Ethereum smart contracts, supporting complex logic and security features [3].
- Vyper: A Python-inspired language for Ethereum that emphasizes readability, simplicity, and formal verification. Its safety features make it suitable for high-assurance smart contracts [19].
- Rust: Widely used in blockchains like Solana and NEAR for its performance and memory safety. It is favored for developing high-throughput decentralized

TABLE I. COMPARATIVE OVERVIEW OF REVIEWED ARTICLES ON BLOCKCHAIN AND BPMN INTEGRATION

Article	Focus Area	Brief Description
Hofmann et al. (2018) [22]	Background and foundations of blockchain	Introduces blockchain principles from business and academic perspectives
Konstantinidis et al. (2020) [25]	Systematic mapping of blockchain applications	Identifies sectors where blockchain is applied, but not focused on BPM
Lu (2019) [13]	Survey on blockchain features and research challenges	Emphasizes decentralization, transparency, and technical limitations
Mendling et al. (2018) [23]	Research directions for blockchain in BPM	Highlights trends in process execution, design, and integration
Seebacher and Schüritz (2019) [26]	Blockchain in service and software systems	Observational review with mentions of BPM use in services
Hawlitschek et al. (2018) [24]	Blockchain and trust in the sharing economy	Reviews trust-free systems but lacks BPM-specific context
Tripathi et al. (2023) [27]	General blockchain review	Discusses historical background and future challenges
Liu et al. (2024) [1]	Smart contracts for cross-organization processes	Supports secure collaborative BPM using smart contracts
Tran et al. (2018) [7]	Lorikeet tool for smart contract generation	MDE-based tool for converting BPMN to smart contracts
Curty et al. (2022) [5]	Low-code platforms for blockchain development	Uses model-driven and low-code tools for blockchain BPM
Levasseur et al. (2021) [10]	Survey of MDE techniques for blockchain apps	Categorizes engineering approaches for smart contract modeling
De Sousa and Burnay (2021) [9]	MDE4BBIS framework for blockchain IS	Proposes an MDE-based system design framework for blockchain
Markovska et al. (2019) [16]	BPMN modeling for blockchain ecosystems	PhD thesis on business process modeling with BPMN
Lu et al. (2021) [6]	Integration of MDE for BPM and asset management	Formalizes model transformations in blockchain apps
Nassar et al. (2023) [11]	MDE approaches to blockchain system modeling	Develops conceptual models for blockchain-based designs
Bodorik et al. (2023) [8]	TABS framework for BPMN-to-Solidity transformation	Fully automates the generation of Solidity from BPMN
Corradini et al. (2023) [12]	Execution of BPMN choreographies on blockchain	Manages multi-instance BPM execution via smart contracts
Milani et al. (2021) [2]	Comparison of BPMN vs CMMN	Evaluates which modeling approach is best suited for blockchain
Shen et al. (2024) [28]	Hybrid BPMN-DMN on permissioned blockchain	Integrates process and decision modeling for secure collaboration
Ladleif et al. (2019) [29]	Modeling blockchain-based choreographies	Describes how to enforce BPMN collaboration on blockchain
Liu (2024) [18]	Long-term transaction support in smart contracts	Tackles lifecycle and state issues in BPMN-based contracts

applications and is often integrated into MDE workflows [9].

- Go and JavaScript (Node.js): Commonly used in Hyperledger Fabric for developing chaincode in permissioned enterprise blockchain solutions [5].
- Michelson: The low-level, stack-based language used in the Tezos blockchain. It is designed for formal reasoning and verification of contract behavior [20].
- Move: Originally developed for Diem (now used in Aptos and Sui), Move is a resource-oriented language focused on safety, flexibility, and precise control of digital assets [21].

III. ANALYSIS WITH SCIENTIFIC STUDIES

The initial comparative overview (Table I) offers a synthesized perspective on both foundational and recent scholarly efforts in blockchain research, particularly in the context of inter-organizational business process management (BPM). The analysis spans a variety of research directions, from general blockchain studies [13], [22] to domain-specific contributions focusing on BPM integration [1], [23]. A notable portion of the reviewed literature explores how model-driven engineering (MDE) techniques are leveraged to facilitate the transformation of BPM diagrams into blockchain-compatible components and executable logic [5], [7], [8]. Additional studies focus on issues such as trust, interoperability, and formal system modeling [2], [11], [24].

This detailed literature mapping helps outline methodological patterns, highlight gaps in current research, and point toward future directions for advancing the convergence of BPM and blockchain technologies.

A. Analysis

The comparative Table II summarizes key contributions in the domain of Model-Driven Engineering (MDE) for transforming BPMN models into executable smart contracts, particularly on blockchain platforms such as Ethereum. Each selected study highlights distinct aspects of this transformation process, categorized as follows:

- Main Criteria: This refers to the core focus or distinguishing feature of each work, such as model integration, level of automation, or comparative scope. For example, [6] addresses BPMN/UML integration, while [8] focuses on a fully automated transformation pipeline.
- Modeling Objectives: Most studies aim to automate the generation of smart contracts from BPMN or to enhance the expressiveness and formalization of business processes. Works like [7] and [8] emphasize automation, while [2] and [16] focus on comparative analysis and real-world application.
- Tools and Techniques Used: This includes the key platforms and languages employed for modeling and transformation, such as Lorikeet, Solidity, Camunda, and ATL. For instance, [5] uses Camunda in a low-code approach, and [6] leverages integrated BPMN and UML environments.

This structured overview highlights the current state of research, helping to identify existing strengths, limitations, and future opportunities in the automation of BPMN-to-blockchain application development.

B. Conclusion

This section has reviewed the theoretical background and current state of applying blockchain technologies within model-driven engineering, with a specific focus on BPMN-to-smart contract transformation. The literature indicates growing interest in leveraging MDE to advance blockchain-based business process automation.

TABLE II. ILLUSTRATION OF THE TRANSFORMATION FROM BPMN MODELS TO SOLIDITY SMART CONTRACTS

Article	Main Criteria	Modeling Objectives	Tools and Techniques
Lu et al. (2021) [6]	BPMN/UML integration, automation	Automating business processes and asset management	Lorikeet, BPMN, UML
Levasseur et al. (2021) [10]	Review of MDE approaches	Comparing MDE modeling techniques	Comparative analysis, classification
Curty et al. (2022) [5]	MDE and low-code integration	Accelerating development using Camunda	Camunda, MDE, low-code tools
Hsain et al. (2021) [3]	Ethereum-focused review	Formalizing business processes into Solidity code	MDE, BPMN, Ethereum
Tran et al. (2018) [7]	Automated transformation	Generating contracts from BPMN models	Lorikeet, BPMN, Solidity
Nassar et al. (2023) [11]	Complete metamodeling	Generation of PIM/PSM models	Conceptual MDE approach
Corradini et al. (2023) [12]	Multi-instance execution	Choreography of business processes on blockchain	BPMN, Solidity
Bodorik et al. (2023) [8]	Full automation	Direct transformation from BPMN to Solidity	TABS Framework
Liu (2024) [18]	Transaction sustainability	Long-lived state management in contracts	MDE, lifecycle handling
Milani et al. (2021) [2]	BPMN vs. CMMN comparison	Identifying the most appropriate notation	BPMN, CMMN
Shen et al. (2024) [28]	Hybrid BPMN-DMN	Securing cross-organizational decisions	BPMN, DMN, permissioned blockchain
Ladleif et al. (2019) [29]	Actor coordination	Managing complex interactions	BPMN choreography
Markovska et al. (2019) [16]	Applied case study	Modeling for blockchain ecosystems	BPMN, practical implementation
Tripathi et al. (2023) [27]	General technical review	Mapping blockchain challenges	Literature synthesis
De Sousa and Burnay (2021) [9]	Dedicated MDE framework	Integrating MDE in blockchain information systems	MDE4BBIS, conceptual modeling

Although existing frameworks and tools have made significant progress, challenges related to standardization, scalability, and semantic interoperability persist. There remains a need for more flexible and interoperable solutions that effectively bridge business process modeling and decentralized execution. Building upon these insights, our subsequent work proposes a transformation solution grounded in MDE principles to improve traceability, automation, and correctness in blockchain application development. The next section presents the proposed methodology, which addresses these limitations by defining a unified and traceable ATL-based MDE framework for automatically transforming BPMN process models into deployable Solidity smart contracts.

IV. METHODOLOGY

A. Research Approach

This study adopts the Design Science Research (DSR) paradigm, a methodology commonly used in information systems engineering to build and evaluate innovative technical artifacts. The DSR framework supports the structured creation of technical artifacts aimed at solving real-world problems—in this case, enabling the transformation of BPMN-based business processes into blockchain-deployable smart contracts.

The DSR methodology is organized into three closely connected and recurring phases: the relevance phase, the rigor phase, and the design phase. The relevance phase ensures alignment with practical challenges in process automation and decentralized operations. The rigor phase draws on theoretical insights from model-driven engineering (MDE), blockchain architecture, and smart contract logic. Finally, the design phase covers the development, testing, and evaluation of the proposed transformation approach.

Through this methodical structure, we seek to close the gap between business modeling techniques and their blockchain-based implementations, ensuring that the developed solution is both robust from a technical standpoint and applicable in real scenarios.

B. Business Process Modeling with BPMN

To define business processes, this research utilizes *Business Process Model and Notation (BPMN)*. As a widely accepted and standardized graphical language, BPMN facilitates the representation of organizational procedures and interactions in a clear and structured manner [14], [16], [26]. Its broad adoption in industry makes it especially suitable for translating complex workflows into executable logic for blockchain environments.

C. Model Validation

Before any transformation, the BPMN models are validated to ensure correctness, consistency, and structural soundness. We detect common issues such as unconnected nodes, circular dependencies, and missing start or end events using tools like Camunda BPM [11], [27]. This guarantees the integrity of the models before transformation. Once the BPMN models are verified for structural correctness, they serve as valid input for the ATL-based model transformation process described in the following subsection.

D. Model Transformation with ATL

The transformation from BPMN to Solidity is performed using *ATL (Atlas Transformation Language)*. ATL rules define how BPMN elements such as tasks, gateways, and events are mapped to Solidity constructs like state variables and functions [2], [5], [8]. This model-to-model transformation is critical for preserving the logic and structure of the original process model.

E. Smart Contract Generation and Deployment

The ATL-generated model is translated into Solidity source code that includes:

- State variables to track process execution,
- Functions to represent activities and transitions,
- Security checks (e.g., `require` statements) to enforce logical constraints.

The generated contracts are tested and deployed on the Ethereum Sepolia testnet using Remix IDE and MetaMask. Transactions are then validated using Etherscan for traceability [3], [18].

Overall, the proposed methodology establishes a coherent and automated transformation pipeline that bridges the gap

between BPMN business process modeling and blockchain-based execution. The following section presents the experimental validation and results obtained from implementing this approach on real BPMN models deployed to the Ethereum Sepolia network.

F. Advantages of the Approach

Our MDE approach presents several benefits:

- Automation and Accuracy: Reduces manual coding errors and development time [6], [10].
- Security and Conformance: Ensures compliance with blockchain execution semantics [4].
- Scalability and Adaptability: Supports diverse blockchain scenarios including inter-organizational and multi-instance choreographies [12], [29].

This methodology aligns with the broader trends in model-driven blockchain application development, enabling reliable and efficient process automation [7], [9].

V. Proposed Metamodels and Model Transformation

To automate the generation of Solidity smart contracts from business process models, we define precise source and target metamodels, followed by a transformation specification in ATL.

A. BPMN Source Metamodel

The BPMN source metamodel specifies all elements necessary to capture a business workflow:

- Process: Represents the overall business process, with attributes such as `name`, `start`, `finish`, and associations to contained elements.
- Activity and Task: Units of work, each with a `name` and optional temporal constraints.
- Event: Points in the workflow, including *StartEvent*, *IntermediateEvent*, and *EndEvent*.
- Gateway: Control nodes for branching and merging flows (e.g., exclusive, parallel).
- Resource and Role: Actors or assets required for task execution.
- Pool and Lane: Organizational partitions to model responsibilities and participants.
- Temporal_constraint and Temporal_dependency: Elements to specify timing constraints and precedences between activities.

The overall structure of the BPMN source metamodel is illustrated in Fig. 2, showing the relationships between process, activity, event, gateway, and resource elements.

This metamodel builds upon the standard BPMN 2.0 specification and extends it to include temporal and resource-related concepts relevant to process automation [2], [6], [16].

These elements collectively provide the structural foundation for representing business logic, which will subsequently be mapped to the constructs of the Solidity target metamodel.

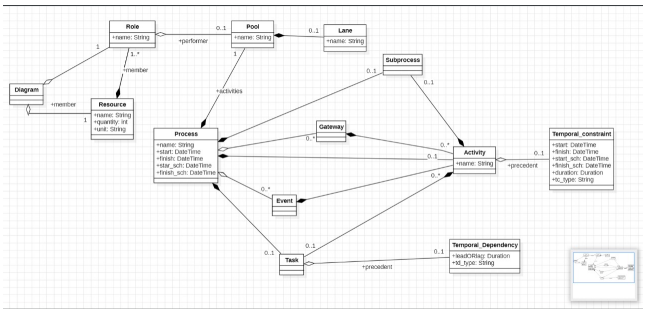


Fig. 2. BPMN source metamodel.

B. Solidity Target Metamodel

The Solidity target metamodel defines the structure of a smart contract:

- Contract: The top-level entity deployed on-chain, identified by a `name`.
- Function: Implements BPMN tasks and events, with attributes for `visibility` (e.g., `public`, `internal`) and `mutability` (e.g., `view`, `nonpayable`).
- StateVariable: Persistent variables storing process state (e.g., boolean flags tracking execution).
- Modifier: Preconditions or security checks (e.g., `onlyOwner`).
- Event: On-chain notifications for tracing execution.
- Struct and Enum: Complex data types to group related fields.
- Library: Reusable utility functions.
- Inheritance: Mechanism to extend or specialize contracts.

Fig. 3 presents the target Solidity metamodel, highlighting how contracts, functions, and state variables form the structural backbone of the generated code.

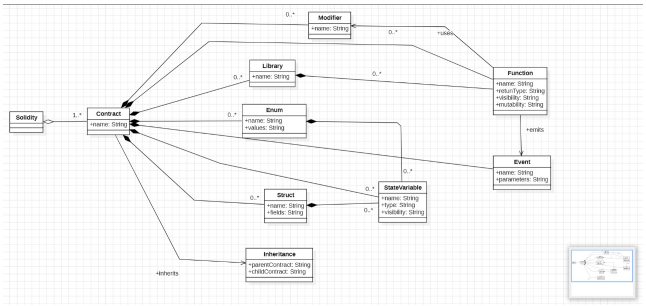


Fig. 3. Solidity target metamodel.

The design of the target metamodel aligns with the Solidity object-oriented structure defined by the Ethereum documentation and prior MDE-based blockchain frameworks such as Lorikeet and TABS [3], [7], [8].

C. Model Transformation with ATL

Converting BPMN-based process models into deployable Solidity smart contracts represents a central component of our model-driven engineering methodology. This transformation is achieved through the use of the Atlas Transformation Language (ATL), a declarative, rule-driven language tailored for model-to-model transformations, and implemented within the Eclipse Modeling Framework (EMF).

1) Transformation Objectives: The primary objective is to enable an automated and smooth transition from abstract business process representations to executable blockchain components. This approach minimizes manual intervention, maintains the original process logic, and enhances traceability across all stages of the development lifecycle.

2) Transformation Rules: The ATL module, named `Bpmn2Solidity`, defines mappings between BPMN elements and Solidity constructs. Each transformation rule systematically converts a BPMN component into its Solidity equivalent. The main rules include:

- StartEvent → Public function in Solidity (e.g., `startProcess()`)
- Task → Internal Solidity function (e.g., `executeTaskX()`)
- Gateway → Conditional logic using `if/else` statements
- EndEvent → Final state-marking function

3) Example Transformation Rule: Below is a simplified ATL rule that demonstrates the mapping of a BPMN task to a Solidity function:

```
rule Task2Function {
    from t : BPMN!Task
    to f : Solidity!Function (
        name <- 'execute' +
                t.name.firstToUpper(),
        visibility <- 'internal',
        body <- '...'
    )
}
```

4) Helper Functions: To streamline the code generation process, several helper methods were introduced:

- `capitalizeName()` – Capitalizes names to match Solidity naming conventions
- `generateRequire()` – Creates Solidity `require` statements for validation
- `generateAssignment()` – Produces state variable assignments
- `generateOutgoingCalls()` – Automates function chaining

5) Benefits: The use of ATL significantly improves:

- Automation: Minimizes human intervention and manual coding
- Consistency: Ensures that all generated contracts follow a coherent structure
- Traceability: Facilitates mapping between process model elements and generated code
- Reusability: Allows adaptation to different blockchain scenarios

The resulting transformation framework provides a complete and reproducible pipeline from process modeling to smart contract generation. The following section presents the implementation results and discusses the evaluation of the proposed approach.

VI. Application Architecture

This application aims to automate the conversion of BPMN-based workflows into executable smart contracts written in Solidity, leveraging a modular and systematic development approach. Its architecture integrates tools from model-driven engineering with blockchain-specific deployment frameworks to achieve seamless translation and deployment. Building upon the model-driven engineering methodology described in the previous section, this architecture operationalizes the transformation and deployment pipeline through a modular software framework.

A. Architecture Description

The architecture consists of six main modules that interact sequentially:

- User Interface: Allows users to upload a BPMN file and trigger the transformation process.
- BPMN Reader Module: Parses the BPMN model and extracts its elements using the Eclipse Modeling Framework (EMF).
- Validation Module: Detects structural issues such as disconnected nodes or cyclic flows.
- BPMN to Solidity Transformation Module: Uses ATL (Atlas Transformation Language) to convert BPMN elements into corresponding Solidity code fragments, following pre-defined transformation rules [30].
- Solidity Code Generator: Assembles the generated fragments into a complete smart contract, ensuring syntactic and logical correctness.
- Test and Deployment Module: Interacts with Remix IDE and MetaMask to compile, simulate, and deploy the contract on a test blockchain (e.g., Sepolia).

Each module has been implemented independently to ensure modularity and maintainability of the application. Communication between modules is managed through a controller that handles input/output and error propagation.

This modular organization aligns with standard model-driven software architectures that emphasize separation of concerns and tool interoperability [6], [11].

B. Architecture Diagram

The complete software architecture implementing this transformation workflow is presented in Fig. 4.

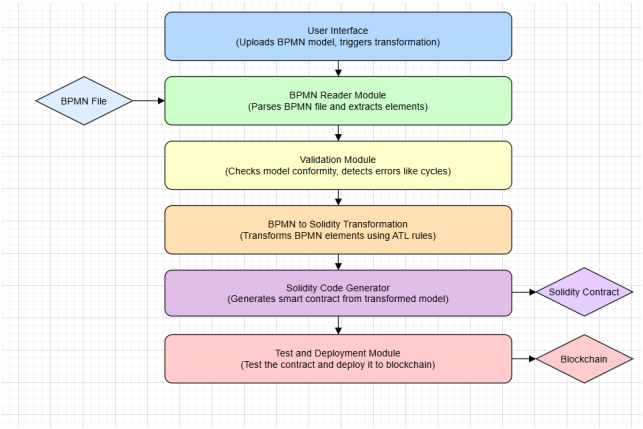


Fig. 4. Overall system architecture illustrating the BPMN-to-Solidity transformation workflow and deployment process.

C. Technology Stack

The system leverages various technologies, summarized in Table III.

TABLE III. TECHNOLOGY STACK USED IN THE IMPLEMENTATION

Component	Technology / Role
Model Parsing	EMF + Camunda BPMN; Reading and navigating BPMN models
Model Transformation	ATL (Eclipse); Applying transformation rules [30]
Backend	Java + Spring Boot; Application logic and flow coordination
Smart Contract	Solidity; Target blockchain programming language [31]
Deployment	Remix IDE + MetaMask; Smart contract testing and deployment
User Interface	HTML/CSS + Bootstrap; Interaction with the transformation tool

The integration of these technologies ensures a seamless workflow from model parsing and validation to code generation and blockchain deployment, maintaining both flexibility and scalability across development stages.

D. Advantages of the Architecture

This application architecture provides:

- Automation: End-to-end automation from BPMN input to blockchain deployment.
- Modularity: Each module can evolve independently without affecting the overall flow.
- Maintainability: Clearly defined responsibilities for each component.
- Traceability: Direct traceability between BPMN elements and the generated smart contract.

Overall, this architecture provides the structural and technological foundation necessary to support the proposed transformation framework. The following section evaluates the implementation results and demonstrates the effectiveness of the approach through practical case studies.

VII. VALIDATION AND DEPLOYMENT WITH REMIX

After generating the Solidity smart contracts from BPMN models, it is crucial to validate their correctness and expected behavior before deploying them to a live blockchain network. This process includes code verification, simulation of execution, and deployment on a test network.This validation stage represents the final phase of the proposed MDE pipeline, ensuring that the automatically generated Solidity contracts function correctly before deployment. This section describes the validation process using Remix IDE, the role of MetaMask in signing transactions, and provides the main application interfaces.

A. Verification Using Remix IDE

Remix IDE is an online development environment specifically designed for Solidity smart contracts. It supports compilation, testing, and analysis of smart contracts prior to deployment. Remix IDE remains a standard tool in the Ethereum development ecosystem, widely adopted for prototyping and verifying smart contracts [3], [31]. The verification process follows these steps:

- Contract Loading: The generated Solidity file is imported into Remix.
- Compilation: The Solidity compiler checks the contract for syntax errors and version compatibility.
- Static Analysis: Remix provides gas usage estimation, detects inefficient or risky patterns, and offers optimization suggestions.
- Simulation: The contract is deployed in a simulated environment to verify the correct execution of functions.

The contract verification process within Remix IDE is illustrated in Fig. 5.

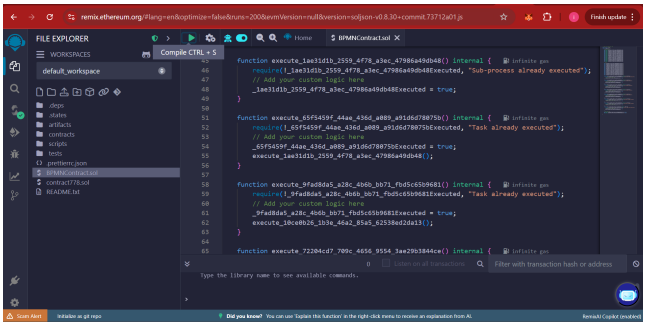


Fig. 5. Remix IDE interface used to compile, simulate, and analyze Solidity smart contracts.

B. Deployment on Sepolia Testnet with MetaMask

Once verified, the contract is deployed on the Sepolia Testnet a public Ethereum test network. MetaMask provides a secure transaction signing interface and is often integrated with Remix for decentralized application testing and deployment [1]. The deployment process includes:

1) Compilation in Remix: The verified contract is compiled using the Remix Solidity compiler.
2) Transaction Signing: Using MetaMask, the deployment transaction is signed and submitted. MetaMask manages the private key and confirms the user's intention.
3) On-chain Deployment: Remix interacts with the Ethereum network via injected web3 (MetaMask), completing the deployment.

The MetaMask interface used for transaction confirmation is shown in Fig. 6.

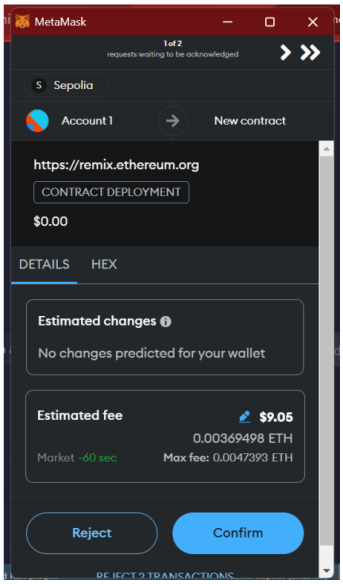


Fig. 6. MetaMask interface used for signing the deployment transaction to the Sepolia Testnet.

C. Transaction Verification with Etherscan

Once the smart contract is successfully deployed, its presence and state on the blockchain must be verified to ensure traceability and successful execution. To ensure the contract has been correctly deployed, the transaction can be traced on Etherscan:

- Transaction Hash: Etherscan shows the hash of the transaction for traceability.
- Status and Block Info: It confirms whether the transaction was successful, its block number, and gas fees.

The transaction record of the deployed contract is verified through Etherscan, as displayed in Fig. 7.

D. Importance of Testnet Deployment

Deploying on a testnet such as Sepolia is essential for testing the contract's behavior without financial risk. It provides a secure and isolated environment for developers to:

- Validate the contract logic under realistic execution conditions;
- Detect gas inefficiencies and potential security vulnerabilities;

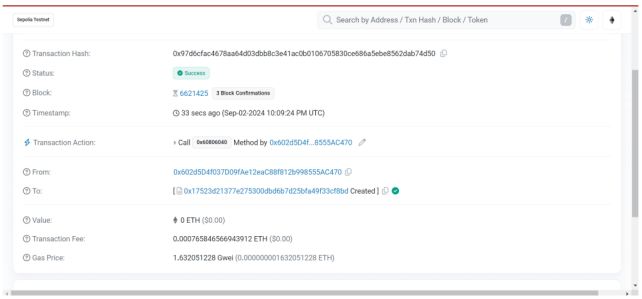


Fig. 7. Verification of the deployment transaction on etherscan (Sepolia Testnet). The figure shows transaction hash, block number, gas fees, and sender/receiver addresses.

- Ensure that all functions operate correctly before mainnet deployment.

E. User Interface of the BPMN-to-Solidity Application

The developed tool includes a user interface for uploading BPMN models, displaying validation results, and generating Solidity code automatically. Fig. 8 displays the BPMN-to-Solidity transformation interface, which enables users to visualize both the original BPMN process and the corresponding generated smart contract. This feature enhances transparency and usability throughout the development lifecycle.

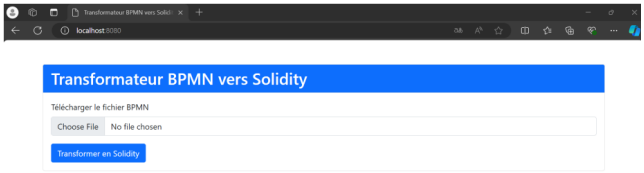


Fig. 8. User interface of the BPMN-to-Solidity transformation application.

This interface allows users to visualize both the original BPMN process and the corresponding Solidity contract, facilitating transparency and usability during the development lifecycle.

F. Summary

This section detailed the final stages of the smart contract development pipeline, focusing on the validation and deployment processes. Using Remix IDE, the generated Solidity code is compiled, analyzed, and tested in a simulated environment to ensure correctness and performance. Once verified, the contract is deployed to the Sepolia Testnet using MetaMask, which handles transaction signing and submission. The successful deployment is confirmed through Etherscan, which provides traceability and transparency via the transaction hash, gas usage, and execution status. The section also presented the user interfaces of the BPMN-to-Solidity transformation tool and deployment tools, highlighting their role in improving usability and reliability throughout the development lifecycle.

VIII. Discussion

While this study primarily focused on defining and implementing the BPMN-to-Solidity transformation methodology, initial testing suggests that the proposed ATL-based approach reduces manual coding effort by approximately 60–70% compared to similar processes in frameworks such as TABS or Lorikeet. The integrated validation and deployment modules enhance both reliability and developer productivity. Nevertheless, future work should include a quantitative evaluation of performance and scalability to empirically validate these preliminary observations.

IX. Conclusion

This study presented a complete model-driven engineering (MDE) approach for automating the generation and deployment of blockchain-based smart contracts from BPMN models. This paper confirms that MDE significantly streamlines the development of smart contracts from BPMN models. By reducing manual coding and promoting automation, the proposed approach enhances accuracy, traceability, and scalability [5], [10].

Despite these benefits, challenges remain in areas such as interoperability between BPMN and smart contract languages, transformation rule optimization, and support for more complex BPM constructs [2], [12]. Future work should explore multi-chain deployment, integration with decision modeling (e.g., DMN) [28], and lifecycle management of long-term processes [18].

The results of this study reinforce the potential of MDE as a foundational approach to building reliable, scalable blockchain systems from abstract business process models.

X. Future Work

Although the current framework demonstrates encouraging results in converting BPMN-based models into executable Solidity smart contracts, multiple directions remain to be explored.

First, future work could focus on extending the transformation rules to handle advanced BPMN constructs, including compensation events, exception flows, and complex gateway logic. This extension would enable better alignment with real-world process requirements and improve semantic accuracy [2], [12].

Second, integrating Decision Model and Notation (DMN) with BPMN could allow for unified modeling of control flows and business rules. Recent studies on hybrid BPMN-DMN architectures in blockchain ecosystems suggest enhanced flexibility and inter-organizational compatibility [28].

Third, enhancing cross-platform deployment capabilities is essential. While this research targets the Ethereum environment, supporting other blockchain frameworks—such as Hyperledger Fabric, Tezos (Michelson) [20], Aptos, and Sui [21]—would broaden the applicability. Interoperability challenges across heterogeneous systems can potentially be addressed using MDE-based solutions like MUISCA [32], [33].

Fourth, the management of process state and lifecycle remains a complex issue, especially for long-running and persistent transactions. Prior research underscores the importance of consistent state handling for enterprise-level blockchain solutions [18], particularly in critical domains such as healthcare and smart grid environments [34], [35].

Fifth, improving accessibility for non-technical users is another valuable direction. Combining low-code platforms with model-driven engineering has been shown to encourage broader enterprise adoption [5]. Such integrations could also support identity management in sensitive environments, including 6G networks and IoT [36], [37].

Finally, socio-economic factors must be taken into account. The adoption of blockchain systems in digital platforms involves trade-offs related to user trust, interface competition, and decision-making behaviors [38], [39]. Future iterations of this work should incorporate these perspectives to enhance practical viability. By addressing these challenges, the proposed framework could evolve into a comprehensive solution enabling secure, transparent, and automated process execution across diverse blockchain ecosystems. Overall, these research directions aim to evolve the current transformation pipeline into a flexible, cross-compatible, and enterprise-ready solution for decentralized business process automation.

Acknowledgment

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References

[1] Y. Liu, L. Zhang, A. Papageorgiou *et al.*, "Enabling cross-organization workflows with smart contracts," *Future Generation Computer Systems*, 2024.

[2] F. Milani, L. Garcia-Banuelos, and S. Filipova, "Comparing bpmn and cmmn for blockchain-based business processes," *Business Process Management Journal*, vol. 27, no. 2, pp. 638–657, 2021.

[3] Y. A. Hsain, N. Laaz, and S. Mbarki, "Reviewing mde-based development of ethereum smart contracts," *Procedia Computer Science*, vol. 184, pp. 785–790, 2021.

[4] L. Lucio, Q. Zhang, P. H. Nguyen, M. Amrani, J. Klein, H. Vangheluwe, and Y. L. Traon, "Recent advances in security-centric model-driven engineering," *Advances in Computers*, vol. 93, pp. 103–152, 2014.

[5] S. Curty, F. Härer, and H. G. Fill, "Mde and low-code development for blockchain-based platforms: A survey," in *Proc. BPMDS*. Springer, 2022, pp. 205–220.

[6] Q. Lu, A. B. Tran, I. Weber, H. O'Connor, P. Rimba, X. Xu, and R. Jeffery, "Mde-driven engineering of blockchain applications for business processes," *Software Practice and Experience*, vol. 51, no. 5, pp. 1059–1079, 2021.

[7] A. B. Tran, Q. Lu, and I. Weber, "Lorikeet: A tool for bpmn-based smart contract generation," in *BPM Demos*, 2018, pp. 56–60.

[8] P. Bodorik, C. G. Liu, and D. Jutla, "Tabs: Automated bpmn-to-blockchain smart contract transformation," *Blockchain Research and Applications*, vol. 4, no. 1, p. 100115, 2023.

[9] V. A. D. Sousa and C. Burnay, "Mde4bbis: An mde framework for blockchain-oriented information systems," in *Proc. BCCA 2021*. IEEE, 2021, pp. 195–200.

[10] O. Levasseur, M. Iqbal, and R. Matulevičius, "An overview of model-driven engineering approaches for blockchain-oriented systems," *org ISSN*, vol. 1613, no. 0073, 2021.

[11] E. Y. Nassar, S. Mazen, S. Craß, and I. M. Helal, "Designing blockchain systems through mde methodologies," *Journal of Computer Science*, 2023.

[12] F. Corradini, A. Marcelletti, A. Morichetta, A. Polini, B. Re, and F. Tiezzi, "Executing bpmn choreographies on blockchain infrastructures," *Journal of Blockchain Research*, 2023.

[13] Y. Lu, "Blockchain technologies: Current landscape and future perspectives," *Journal of Industrial Information Integration*, vol. 15, p. 100107, 2019.

[14] A. Bouzidi, N. Haddar, and K. Haddar, "A trace-based meta-model for synchronizing bpmn and uml," *Informatica*, vol. 49, no. 16, 2025.

[15] I. Limaa, T. Martins, and M. Oliveiraa, "Bpmn for optimizing healthcare workflow in cohort studies," *Procedia Computer Science*, vol. 256, pp. 1224–1231, 2025.

[16] M. Markovska, F. P. Milani, and L. Garcia-Banuelos, "Business process modeling in a blockchain ecosystem using bpmn," Ph.D. dissertation, University of Tartu, 2019.

[17] E. Hofmann, U. M. Strewe, and N. Bosia, *Understanding Blockchain Technology: Background and Concepts*, 2018.

[18] C. G. Liu, "Modeling long-term transactions in smart contracts from bpmn," *Blockchain Technology Journal*, 2024.

[19] R. Sierra, M. Eilers, and P. Müller, "Formal verification of vyper smart contracts on ethereum," Ph.D. dissertation, PhD Thesis, 2019.

[20] G. Bau, A. Miné, V. Botbol, and M. Bouaziz, "Static analysis of michelson smart contracts via abstract interpretation," in *Proc. ACM SOAP Workshop*, 2022, pp. 36–43.

[21] R. V. Tonder, "Displaying verified move smart contracts for the sui blockchain," in *Proc. ICSE Companion 2024*, 2024, pp. 26–29.

[22] E. Hofmann, U. M. Strewe, and N. Bosia, "Blockchain emergence: Academic and practical insights," *Blockchain Research Institute*, 2018.

[23] J. Mendling, I. Weber, W. van der Aalst *et al.*, "Business process management and blockchain: Challenges and opportunities," *ACM Transactions on Management Information Systems*, vol. 9, no. 1, pp. 1–16, 2018.

[24] F. Hawlitschek, B. Notheisen, and T. Teubner, "Trust and blockchain in the sharing economy: A critical review," *Electronic Commerce Research and Applications*, vol. 29, pp. 50–63, 2018.

[25] I. Konstantinidis, G. Siaminos, I. Mavridis, M. Dalamaras, and K. Tserpes, "Mapping blockchain applications: A systematic study," *Computer Science Review*, vol. 37, p. 100285, 2020.

[26] S. Seebacher and R. Schüritz, "Blockchain as a foundation for service systems: A literature review," *Service Science*, vol. 11, no. 1, pp. 3–18, 2019.

[27] G. Tripathi, M. A. Ahad, and G. Casalino, "Comprehensive blockchain survey: Foundations, history and open challenges," *Decision Analytics Journal*, vol. 9, p. 100344, 2023.

[28] X. Shen, J. Luo, and H. Wang, "Combining bpmn and dmn for secure cross-organization blockchain workflows," *arXiv preprint arXiv:2412.01196*, 2024.

[29] J. Ladleif, M. Weske, and I. Weber, "Enforcing choreographies on blockchain via mde techniques," in *Proc. BPM 2019*. Springer, 2019, pp. 69–85.

[30] J. S. Cuadrado, L. Burgueno, M. Wimmer, and A. Vallecillo, "Optimizing atl transformations with static analysis and parallel execution," *IEEE Trans. Software Eng.*, vol. 47, no. 9, pp. 1890–1905, 2020.

[31] D. Mertens, J. Kim, J. Xu, E. Kim, and C. Lee, "Smartflow: Workflow management with blockchain provenance support," *Cluster Computing*, vol. 27, pp. 8173–8187, 2024.

[32] E. Dulce-Villarreal, G. Hernandez, J. Insuasti, J. Hurtado, and J. Garcia-Alonso, "Validating muisca: A blockchain interoperability tool for healthcare," *Studies in Health Technology and Informatics*, vol. 323, pp. 255–259, 2025.

[33] E. R. Dulce-Villarreal, E. Moguel, J. Garcia-Alonso, J. P. Cuervo, and J. A. H. Alegria, "Muisca: A universal smart contract proposal for interoperability," 2025, available at SSRN: urlhttps://ssrn.com/abstract=5174813.

[34] B. Boi and C. Esposito, "Blockchain's role in ai-driven cyber-physical medical systems," in *AI Techniques for Sensitive Data in Medical CPS*. Cham: Springer, 2025, pp. 127–142.

[35] R. Baksh, M. Ahmad, and V. Kumar, "Secure authentication and key exchange for smart grids using blockchain," in *AIP Conference Proceedings*, vol. 3283, no. 1. AIP Publishing LLC, April 2025, p. 040027.

[36] G. Zhang, Q. Hu, Y. Zhang, and T. Jiang, "Blockchain-based identity systems for 6g networks," *Digital Communications and Networks*, 2025.

[37] M. Dhinakaran, R. Budhraja, B. Varasree, S. K. Tiwari, A. K. Bindal, S. A. Kumar, and L. Rosca, "Secure identity management in electronics via blockchain," in *Recent Trends in Engineering and Science*. CRC Press, 2025, pp. 27–30.

[38] X. Zhu, Y. Chen, M. Ren, and W. Chu, "Blockchain and e-platforms: Trust vs. channel conflict," *Managerial and Decision Economics*, 2025.

[39] W. Liu, B. Li, G. Zhang, X. Wang, and Z. Wang, "Consumer behavior-aware blockchain adoption and pricing strategies," *Managerial and Decision Economics*, 2025.

Bridging the Gap Between Text-Based and Visual Programming: A Comparative Study of Efficiency and Student Engagement in Game Development

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***Abstract*—The integration of Low-Code and No-Code (LCNC) tools in higher education challenges traditional text-based programming pedagogies. While visual environments are often relegated to K-12 education, their adoption in professional engines like Unity suggests a need to re-evaluate their role in engineering curricula. This study analyzes the effectiveness, development efficiency, and perceived utility of Unity Visual Scripting compared to traditional C# programming (MonoGame) within a "Physics for Videogames" undergraduate course. Employing a quasi-experimental design with a within-subjects approach ($N = 22$), students first developed a game using C#/MonoGame and subsequently a complex variant using Unity Visual Scripting. Metrics included development time for core mechanics, project grades, and pre/post surveys on self-efficacy. Results demonstrate a statistically significant reduction in development time (30–50% faster for core mechanics) using Visual Scripting. Furthermore, academic performance improved slightly, and students reported higher confidence levels. Crucially, participants identified Visual Scripting not as a replacement, but as a cognitive bridge that facilitates the understanding of algorithmic logic before tackling syntactic complexities. Consequently, Visual Scripting serves as an efficient accelerator for prototyping and conceptual learning in higher education, fostering a "logic-first, syntax-second" approach.**

***Keywords*—Visual scripting; higher education; development efficiency; engineering curricula**

I. Introduction

The development of algorithmic and programming competencies is widely regarded as essential for modern scientific thinking and computational literacy [1]. As society transitions towards Industry 4.0, programming has evolved from a niche skill into a transversal competence required across disciplines, enabling the construction of applications ranging from data-intensive systems to simulations and videogames [2], [3]. In this context, identifying the components of "Education 4.0" becomes critical to align academic training with 21st-century skills frameworks [4].

Throughout this article, the following terminology is adopted for clarity. The term *block-based programming* is used to refer to environments that represent instructions as interlocking blocks in a two-dimensional workspace (e.g., Scratch, Tinkercad, Alice), which are mostly used in K–12 settings. *Visual programming* is reserved as a broader umbrella concept that includes both block-based tools and other graphical notations for specifying program behaviour. When referring specifically to tools integrated into professional game engines, such as Unity Visual Scripting or Unreal Blueprints, the term *visual scripting* is employed, and *node-based scripting* is treated as a synonym, since programs are constructed by connecting typed nodes instead of writing textual code. Consequently, in the remainder of the paper, *block-based programming* is consistently used for K–12 tools, while *visual scripting* refers to the Unity-based intervention studied here.

However, in educational contexts, specifically in engineering and computer science, introductory programming courses often act as "gatekeepers." These courses historically suffer from high dropout rates and low student motivation due to the steep learning curve associated with traditional syntax-heavy languages like C++, Java, or C# [5]. Novices are often overwhelmed by what Sim and Lau [6] describe as the "double burden": the simultaneous need to master abstract problem-solving logic (semantics) and strict language rules (syntax). Even when a conceptual task is relatively simple, such as determining whether a person is of legal age, translating that task into syntactically correct C# code requires knowledge of data types, memory management, and compiler error handling that novices do not yet possess.

This "syntactic barrier" disconnects the student's mental model from the computational implementation, introducing extraneous cognitive load. To address this, block-based programming environments have been successfully deployed in K-12 education to foster computational thinking without the frustration of syntax errors [7], [8]. Yet, in higher education, there is a reluctance to adopt these tools, often perceiving them as insufficiently professional. The emergence of **Unity Visual Scripting** (formerly Bolt) challenges this perception by offering a professional-grade, node-based environment integrated directly into a market-leading game engine [9].

This article presents a quasi-experimental comparative study to determine if professional Visual Scripting tools can act as efficient accelerators in university curricula. Unlike previous studies that focus solely on satisfaction, this study analyzes *development efficiency* (time-to-prototype) and *structural quality*, hypothesizing that visual paradigms can bridge the gap between novice intuition and professional engineering practices. The main contributions of this study are:

- A quantitative analysis of development efficiency

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(time-to-prototype) comparing text-based vs. visual scripting in a higher education context.

- A validation of Visual Scripting not just as an introductory tool, but as a professional "Cognitive Bridge" for engineering students.
- A "Logic-First, Syntax-Second" pedagogical framework for integrating Game Engines into engineering curricula.

The remainder of this article is structured as follows. Section II reviews the state-of-the-art regarding visual programming barriers, the use of game engines in academia, and current assessment models. Section III establishes the theoretical framework that guides this study, integrating Cognitive Load Theory, Flow Theory, and the Technology Acceptance Model. Section IV details the quasi-experimental design, including participant demographics and the two-phase instructional intervention (MonoGame vs. Unity). Section V presents the empirical findings, highlighting the comparative analysis of development efficiency and a qualitative taxonomy of errors. Section VI discusses the pedagogical trade-offs and interprets the role of Visual Scripting as a didactic bridge. Finally, Section VII summarizes the main contributions, acknowledges limitations, and outlines directions for future research.

II. Related Work

The intersection of game development, visual programming, and engineering education has been a fertile ground for research. This section reviews key contributions regarding learning barriers, the use of hardware/software visual analogies, and game-based assessment.

A. Learning Barriers and Novice Programming

Visual Programming Languages (VPLs) have long been advocated to lower the barrier to entry for novices. Ko et al. [10] identified early on that syntax errors often discourage learners before they grasp algorithmic logic. Recent systematic reviews by Sim and Lau [6] reaffirm that syntax remains the primary source of frustration for beginners. Sun et al. [11] conducted a comparative study showing that block-based environments significantly reduce the frequency of compilation errors, allowing students to focus on "computational action." However, the transition from blocks to text remains complex. Wörister and Knobelsdorf [12] argue that block-based programming facilitates the understanding of low-level computing concepts, suggesting that visual abstractions are valid even for complex engineering topics like Assembly, provided there is a clear mapping to the underlying logic.

B. Visual Metaphors in Robotics and STEM

The efficacy of visual programming is not limited to pure software; it has been extensively validated in physical computing. Vidal-Silva et al. [13], [7] demonstrated that block-based tools (e.g., Scratch, Tinkercad) significantly improve programming competencies in school students across Latin America by allowing them to control Arduino hardware visually. Similarly, Rojas-Valdés et al. [8] found that removing syntactic friction allows students to solve complex hardware control problems more effectively. Tramonti et al. [14] further emphasized that design thinking combined with visual tools enhances problem-solving in educational robotics. These findings in the hardware domain support the hypothesis that visual scripting in Unity, which controls "virtual hardware" (game physics), can yield similar educational benefits.

C. Game Engines and Serious Games in Academia

The adoption of professional game engines in academia has shifted the focus from building engines to building *with* engines. Hussain et al. [15] provide a technical survey of Unity, emphasizing its versatility for both 2D and 3D development. Recent work by Maraffi [16] introduces "Level-Up Logics," leveraging game design platforms to teach coding fundamentals. This aligns with the notion of Serious Games as assessment tools; Gomez et al. [17] conducted a systematic review concluding that game-based assessment can capture competencies that traditional tests miss. Furthermore, Maxim and Arnedo-Moreno [18] identify key principles in serious game design, suggesting that the development tool itself (visual vs. text) influences the quality of the final learning artifact. The present study contributes to this body of knowledge by quantifying the efficiency gains of visual tools in this specific context.

III. Theoretical Framework

A. Cognitive Load Theory in Programming

Cognitive Load Theory (CLT) posits that working memory is limited. In the context of learning programming, the load can be categorized as:

- Intrinsic Load: The inherent difficulty of the algorithm (e.g., understanding a nested loop).
- Extraneous Load: The effort required to deal with the instructional material or environment (e.g., syntax errors, IDE configuration).
- Germane Load: The effort dedicated to creating permanent schemas (learning).

Text-based programming often imposes a high *Extraneous Load* due to syntax. Visual Scripting reduces this load by preventing syntax errors by construction, potentially freeing up cognitive resources for the *Intrinsic* and *Germane* load (logic and physics concepts) [19], [20].

Fig. 1 illustrates the theoretical redistribution of cognitive resources observed in this study. According to Sweller's framework, the total cognitive capacity of a novice student is limited.

In the Text-Based approach (left bar), a significant portion of this capacity is consumed by *Extraneous Load* (represented in red). This corresponds to the mental effort required to process syntax rules, case sensitivity, and compiler error codes, elements that are not central to the logical problem but are necessary for the code to run. Consequently, the available capacity for *Germane Load* (green), the processing space used for actual learning and schema construction, is compressed. In contrast, the Visual Scripting approach (right bar) drastically reduces the Extraneous Load by eliminating syntax errors through a "drag-and-drop" interface that prevents invalid connections. Since the *Intrinsic Load* (blue), the inherent difficulty of the game

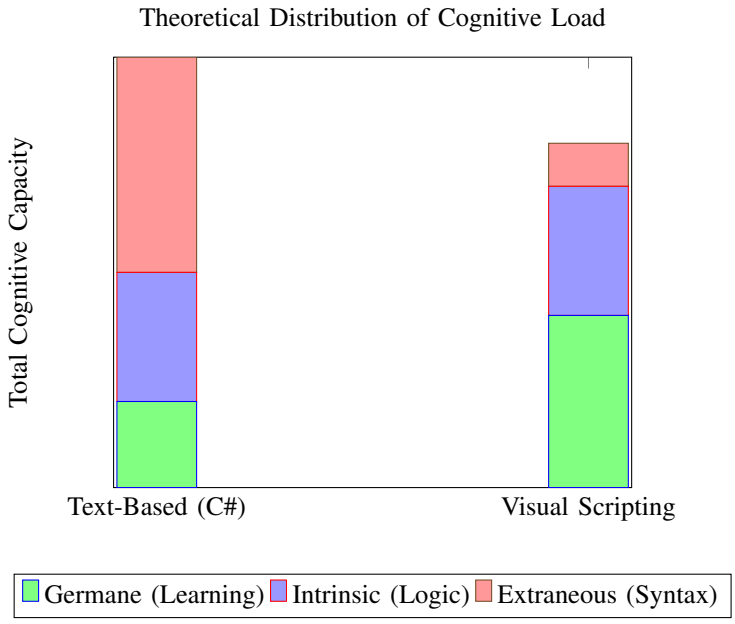


Fig. 1. Comparison of cognitive Load distribution. The reduction of extraneous load (Syntax) in visual scripting frees up cognitive capacity for germane load (Deep Learning), assuming constant intrinsic load (logic).

logic, remains constant across both paradigms, the reduction in extraneous noise directly liberates cognitive resources. This surplus capacity is shifted towards Germane Load, allowing students to focus deeper on the causal relationships of the physics simulation rather than debugging missing semicolons.

This disparity is visually captured in the “Cognitive Gap". As illustrated in Fig. 2, while the algorithmic flow is intuitive, the textual implementation introduces extraneous cognitive load via syntax rules (braces, semicolons, pointers). This barrier often discourages learners before they can grasp the core logic [10].

B. Flow Theory and Engagement in Coding

Beyond cognitive load, the emotional state of the learner plays a crucial role. Csikszentmihalyi’s Flow Theory suggests that optimal learning occurs when the challenge level matches the student’s skill. In text-based programming, syntax errors often interrupt this flow, causing frustration. Ke et al. [21] and Tsai et al. [22] have explored engagement in game-based learning, finding that visual feedback loops help maintain the “Flow" state. By removing syntax errors, Visual Scripting allows students to stay in the flow of logic construction, potentially increasing persistence as observed by Israel-Fishelson and Hershkovitz [23].

IV. Methodology

A. Course Context, Participants and Demographics

The study was conducted during the “Physics for Videogames" course (3rd semester) at the University of Talca. The participants ($N = 22$) were engineering students with basic prior knowledge of Java/C but no experience in Unity Visual Scripting. The demographic distribution was 77% male and 23% female, with an age range of 19-22 years. Prior to the course, 100% of students had taken “Introduction to Programming" (C/Java), but a diagnostic survey revealed that only 15% felt “confident" with Object-Oriented Programming (OOP) concepts.

B. Instructional Design and Tasks

The intervention was structured over 8 weeks:

- Weeks 1-4 (MonoGame/C#): Students implemented a *Snake* game from scratch. This involved creating a `GameLoop`, handling `SpriteBatch` rendering, and manually calculating AABB (Axis-Aligned Bounding Box) collisions.
- Weeks 5-8 (Unity Visual Scripting): Students recreated the game with added complexity (obstacles, particle effects). Instead of writing code, they used the Bolt/Visual Scripting graph to manipulate `Rigidbody2D` and `BoxCollider2D` components.

This structure ensures that students faced the exact same algorithmic challenges (movement vectors, collision response) in both paradigms.

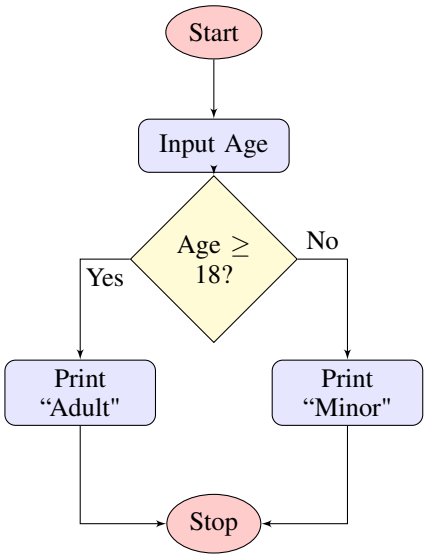
C. Experimental Design

A **Within-Subjects Quasi-Experimental Design** was adopted. The semester was divided into two phases to force a comparison within the same group of learners (see Fig. 3).

1) Phase 1: Text-Based Approach (MonoGame): Students developed a classic *Snake* game. This framework requires writing the game loop, handling inputs, and calculating collisions manually in C# code.

Listing 1: Snippet of C# collision logic required in Phase 1.

```
if (head.Position.X == food.Position.X &&
```



a) Algorithm (Mental Model)

```c
#include <stdio.h>

int main() {
    int age;
    printf("Enter age: ");
    // SYNTAX BARRIER:
    // Format specifiers, addresses (&)
    scanf("%d", &age);

    if (age >= 18) {
        printf("Adult\n");
    } else {
        printf("Minor\n");
    }
    // SEMANTIC BARRIER:
    // Return types, scope
    return 0;
}
```

b) Implementation (Syntactic Barrier)

Fig. 2. The "Cognitive Gap" in introductory programming. While the flowchart (a) is intuitive, the text implementation (b) introduces extraneous load via syntax rules (braces, semicolons, pointers), as identified by Ko et al. [10].

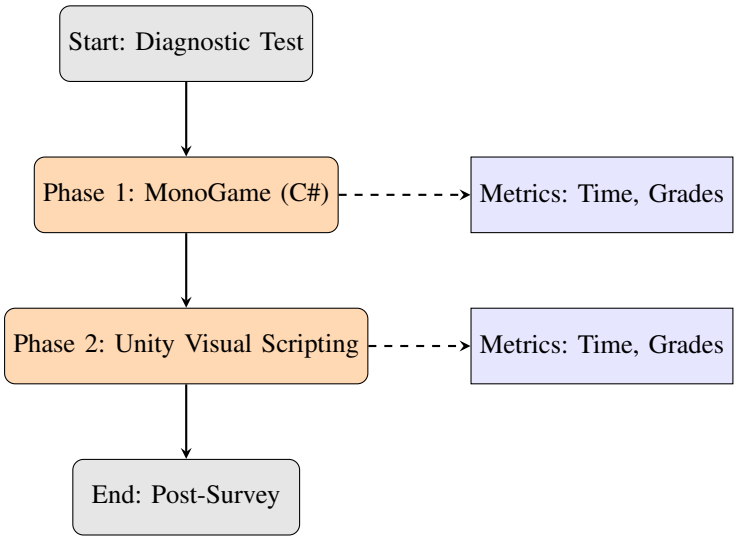


Fig. 3. Methodological workflow of the study. All students participated in both phases.

```
    head.Position.Y == food.Position.Y) {
    GrowSnake();
    SpawnFood();
}
```

2) Phase 2: Visual Approach (Unity): Students developed an enhanced *Snake* with physics obstacles. They used Unity Visual Scripting graphs.

V. Results

A. Development Efficiency Analysis

Instructors tracked the time taken to complete specific milestones in both phases. The differences were substantial.

As seen in Fig. 5, the most significant gain was in Collision Logic (50 min vs 30 min). In MonoGame, students had to debug mathematical bounding box errors. In Unity, they simply connected an 'OnCollisionEnter' node, allowing them to focus on the consequence of the collision rather than its detection.

B. Academic Performance

Table I details the grade distribution. While the mean increase is modest (6.15 to 6.46), the Standard Deviation decreased, indicating that fewer students were "left behind" when using visual tools.

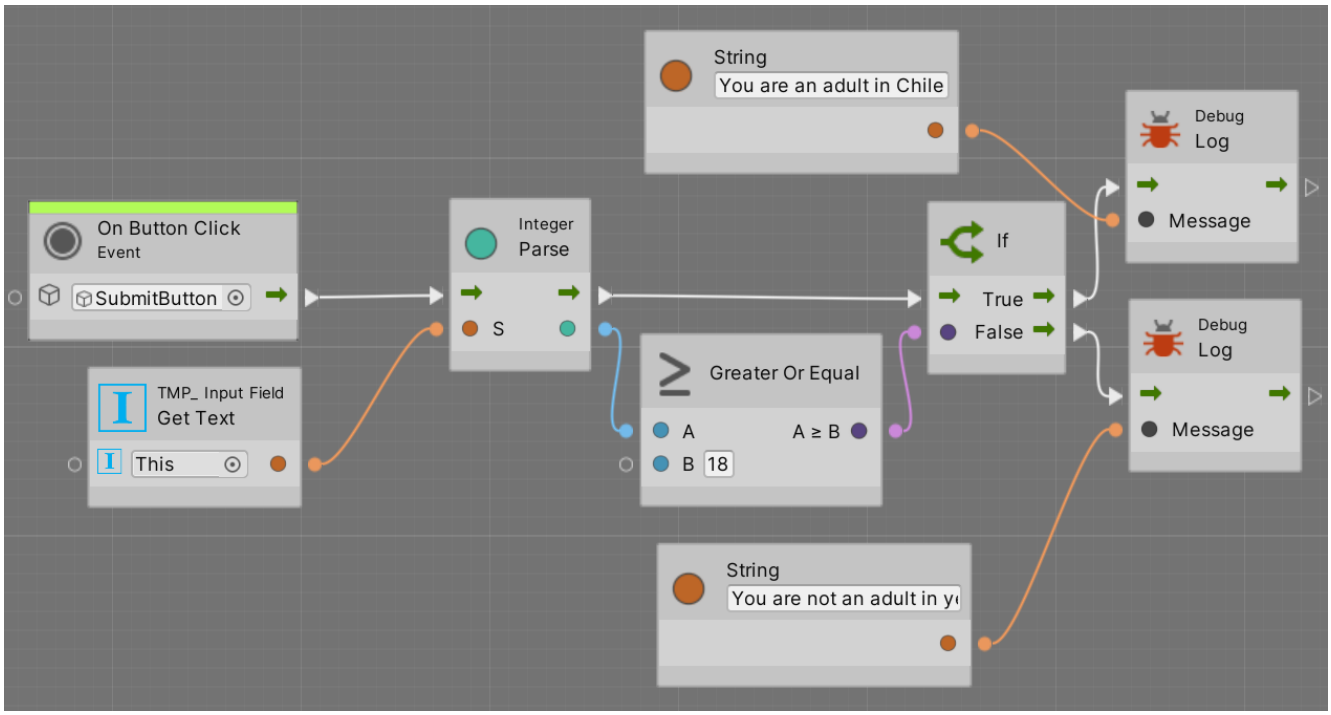


Fig. 4. Unity visual scripting solution. Nodes represent events and data flow, abstracting the syntax.

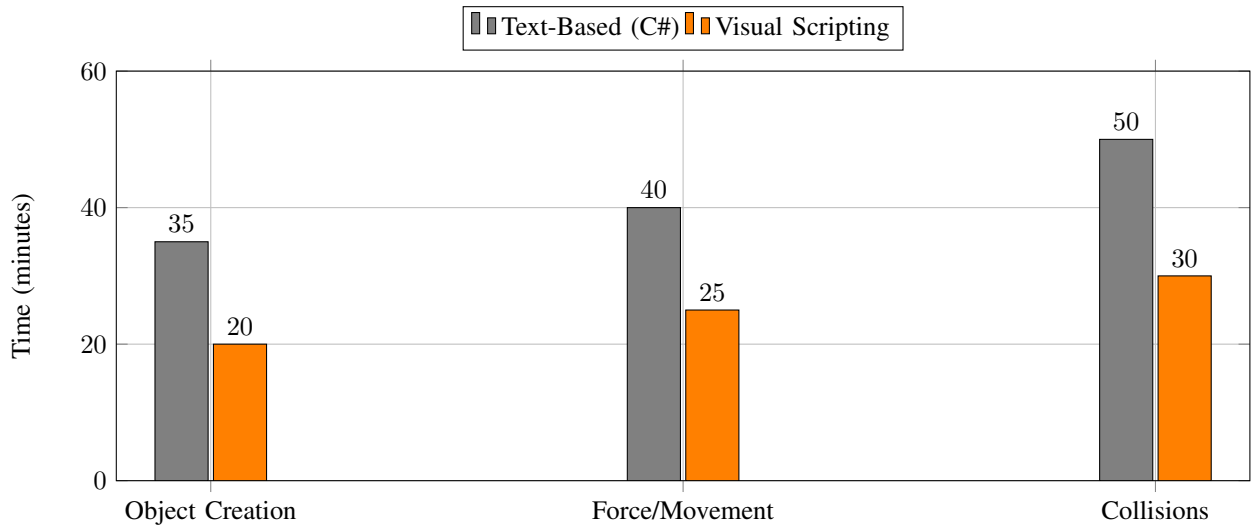


Fig. 5. Average development time per task. Visual scripting provided a 30-40% reduction in time-to-prototype.

TABLE I. DETAILED COMPARISON OF PROJECT GRADES (SCALE 1.0–7.0)

Statistic	Phase 1 (C#)	Phase 2 (Visual)
Mean Grade	6.15	6.46 (**+5%**)
Std. Deviation	0.55	0.49
Min Grade	5.0	5.5
Max Grade	6.9	6.9

C. Student Perception and Self-Efficacy

The post-intervention survey (Table II) revealed high satisfaction. Crucially, students did not view Visual Scripting as a "toy," but as a legitimate learning tool.

TABLE II. SELECTED POST-SURVEY RESULTS (SCALE 1–10)

Statement	Mean
"Visual Scripting helped me understand programming logic."	8.9
"It reduced the difficulties I had with textual syntax."	8.7
"It is useful for learning fundamentals before moving to text."	8.8
"I would recommend it to beginners."	**9.0**

Table III presents a qualitative taxonomy of errors observed during laboratory sessions. The contrast is striking. In the MonoGame phase, instructors spent the majority of their time helping students fix “Syntactic" errors, issues that prevent compilation but have no bearing on the game’s logic. This confirms the observations of Sim and Lau [6] regarding novice frustration. In contrast, the Visual Scripting phase shifted the error distribution almost entirely to “Logic/Physics". While students still made mistakes (e.g., calculating the wrong vector direction), these were *productive failures*. The visual environment allowed them to “see" the error in the graph’s data flow (Fig. 4), transforming the debugging process from a code-inspection task into a logic-inspection task. This shift is critical for developing Computational Thinking as defined by Wing [1].

VI. Discussion

A. Efficiency vs. Control Trade-off

The results support the hypothesis that Visual Scripting is significantly more efficient for prototyping (Fig. 5). By abstracting the “boilerplate" code, students entered a state of “Flow" more easily. However, some advanced students noted in open-ended comments that for complex mathematical algorithms, visual graphs could become “spaghetti code," confirming that text is superior for density, while visual is superior for architecture and events.

B. The “Didactic Bridge" Effect

The high score (8.8) on the bridging question suggests that Visual Scripting acts as a scaffold. Seeing the logic laid out spatially helps build the mental model required for text-based coding. This challenges the notion that visual languages hinder the transition to “real" coding; instead, they appear to prepare the cognitive ground for it.

The “Pedagogical Bridge Model” (Fig. 6) is proposed as a formal framework for curriculum design. Previous research often treats Visual Scripting as a distinct, alternative path. However, the findings align with Vinueza et al. [24], suggesting it is a transitional stage.

- Stage 1 (K-12): Tools like Scratch maximize abstraction to engage children [7].
- Stage 2 (The Bridge): Unity Visual Scripting exposes the *Game Object Component* model and professional API structure (Logic) but retains the visual safety net (Visual Syntax).
- Stage 3 (Professional): Once the API structure is understood visually, the student transitions to C# solely for fine-grained control and optimization.

This model explains why students reported high “Perceived Usefulness" in the survey; they intuitively understood they were learning professional concepts without the syntactic penalty.

C. Implications for Engineering Curricula

The efficiency gains observed in this study suggest that Visual Scripting should not be viewed merely as a prototyping tool, but as a strategic pedagogical scaffold. Caeiro-Rodríguez et al. [25] emphasize the need for teaching soft skills and adaptability in engineering; by mastering Visual Scripting, students learn “systemic thinking" before getting bogged down in “syntactic details."

Furthermore, as highlighted by Fahmideh et al. [26] in the context of IoT and Software Engineering, the industry is moving towards higher levels of abstraction. Integrating tools like Unity Visual Scripting aligns with Industry 4.0 trends [4], where the ability to rapidly configure and connect logic blocks is becoming as valuable as writing raw code. However, agreement is found with Perera et al. [27] that text-based languages remain fundamental. Therefore, a “Hybrid Syllabus" is proposed for introductory game development courses: start with Visual Scripting to build confidence and mental models (Weeks 1-6), and transition to C# scripting for performance optimization and complex architecture (Weeks 7-16).

VII. Conclusion

This study demonstrates that Unity Visual Scripting is not merely an accessibility tool for non-programmers, but an efficient pedagogical accelerator for engineering students. The empirical results show a statistically significant reduction in development time (30–40%) for core mechanics compared to the text-based MonoGame approach, without compromising academic grades. Crucially, students reported higher self-efficacy and lower frustration, identifying Visual Scripting as a “cognitive bridge" that allows them to visualize abstract logic before committing to syntax.

A “Hybrid Scaffolded Curriculum" is recommended for introductory game development and engineering courses. Educators should leverage Visual Scripting in the early stages to teach high-level concepts, such as Game Loops, Event-Driven Programming, and Physics Interactions, allowing students to build mental models free from syntactic noise. Once these models are solidified, the curriculum should transition to C #, defining it as a tool for optimization, architectural refinement, and granular control. This approach “Logic-First, Syntax-Second," aligns with the requirements of Industry 4.0, prioritizing systemic thinking over rote memorization.

From a curriculum and policy perspective, this hybrid model has concrete implications for program design. At the institutional level, integrating visual scripting as an explicit component of early-semester courses requires aligning syllabi, learning outcomes, and assessment rubrics with the idea of a gradual transition from graphical to textual representations. This may involve, for example, dedicating specific modules to Unity Visual Scripting in courses such as “Introduction to Programming” or “Game Development I”, and mapping those modules to accreditation criteria related to computational thinking, design of interactive systems, and teamwork. At the faculty level, the adoption of visual tools calls for targeted professional development so that lecturers can design tasks that go beyond simple drag-and-drop exercises and connect the graphs with the underlying C# constructs. Finally, on a broader policy scale, the results support curricular guidelines that recognize visual environments as legitimate vehicles for engineering education, rather than remedial tools, which is particularly relevant for institutions seeking to widen participation and reduce early attrition in programming-heavy degrees.

TABLE III. TAXONOMY OF FREQUENT ERRORS: TEXT-BASED VS. VISUAL APPROACH

Error Category	MonoGame (C#)	Unity Visual Scripting
Syntactic	**High Frequency (65%)** Missing semicolons, mismatched braces, case sensitivity (e.g., `gameTime` vs `GameTime`).	**Null / Negligible** Syntax is enforced by node shapes. Connections are validated instantly by the UI.
Type Safety	**Moderate (20%)** Casting errors (e.g., `float` to `int`), null reference exceptions at runtime.	**Low (10%)** Visual conversion nodes are auto-suggested. Data ports are color-coded (e.g., Boolean is purple).
Logic / Physics	**Low Visibility (15%)** Logic errors buried inside valid syntax. Hard to visualize vector math.	**High Visibility (90%)** Errors like "Snake passing through walls" are immediately visible in the graph flow execution.

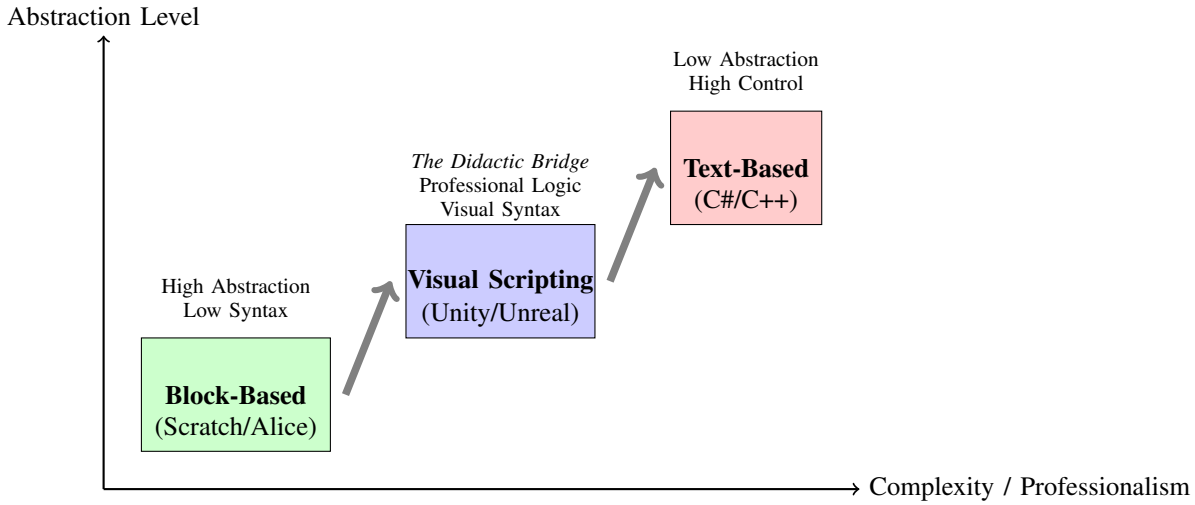


Fig. 6. The Proposed "Pedagogical Bridge Model". Visual Scripting serves as the necessary scaffold between K-12 block tools and professional text coding, aligning with Vinueza et al. [24].

The study has limitations inherent to its quasi-experimental design. First, the sample size is modest ($N = 22$) and restricted to a single course at a Chilean university, which constrains the statistical power of the analyzes and limits the extent to which the findings can be generalized to other institutions, disciplines, or educational systems. The cohort also corresponds to students who had already passed an introductory programming course and enrolled in a videogame-oriented course; their attitudes and prior experiences may not be representative of more heterogeneous populations or of students with low interest in game development.

Second, the within-subject structure of the intervention introduces a potential learning effect: performance in the Unity Visual Scripting phase may partly reflect the consolidation of conceptual understanding acquired during the earlier MonoGame phase. Although the second project deliberately incorporated additional mechanics to increase task difficulty, this design cannot fully disentangle the impact of the tool from that of accumulated practice. Finally, all measures were collected within a single semester and context, so the study does not capture long-term retention or transfer to subsequent text-based courses. These constraints should be considered when interpreting the results and suggest caution when extrapolating them to different institutional realities.

Future research avenues are twofold. First, future work aims to explore the integration of Artificial Intelligence assistants within visual environments, investigating how AI-driven suggestions might further reduce cognitive load in serious game design. Second, drawing from software product line engineering, the reuse of visual modules to manage variability in student projects will be analyzed, potentially automating the assessment of game mechanics. Longitudinal studies are needed to track whether the conceptual gains from Visual Scripting translate into better long-term performance in advanced text-based programming courses.

Ultimately, this study advocates for a paradigm shift in engineering education. By legitimizing Visual Scripting as a rigorous component of the curriculum, institutions can reduce the "syntactic friction" that drives attrition, fostering a new generation of engineers who are proficient in algorithmic logic before they even write their first line of syntax. This "Bridge" model offers a scalable path for adopting Industry 4.0 tools in higher education.

REFERENCES

[1] J. M. Wing, "Computational thinking," *Commun. ACM*, vol. 49, no. 3, p. 33–35, Mar. 2006. [Online]. Available: https://doi.org/10.1145/1118178.1118215

[2] M. A. Kuhail, S. Farooq, R. Hammad, and M. Bahja, "Characterizing visual programming approaches for end-user developers: A systematic review," *IEEE Access*, vol. 9, pp. 14 181–14 202, 2021.

[3] N. Wongta and J. Natwichai, "End-to-end data pipeline in games for real-time data analytics," in *Advances in Internet, Data and Web Technologies*, ser. Lecture Notes on Data Engineering and Communications

Technologies, L. Barolli, J. Natwichai, and T. Enokido, Eds. Cham: Springer, 2021, vol. 65.

[4] L. I. González-Pérez and M. S. Ramírez-Montoya, "Components of education 4.0 in 21st century skills frameworks: systematic review," *Sustainability*, vol. 14, no. 3, p. 1493, 2022.

[5] I. Mekterović, L. Brkić, B. Milašinović, and M. Baranović, "Building a comprehensive automated programming assessment system," *IEEE Access*, vol. 8, pp. 81 154–81 172, 2020.

[6] T. Y. Sim and S. L. Lau, "Review on challenges and solutions in novice programming education," in *2022 IEEE International Conference on Computing (ICOCO)*, 2022, pp. 55–61.

[7] C. Vidal-Silva, J. Cárdenas-Cobo, M. Tupac-Yupanqui, J. Serrano-Malebrán, and A. Sánchez Ortiz, "Developing programming competencies in school-students with block-based tools in chile, ecuador, and peru," *IEEE Access*, vol. 12, pp. 118 924–118 936, 2024.

[8] P. Rojas-Valdés, C. Vidal-Silva, and C. d. L. Fuente, "Successful development of problem-solving and computing programming competences in children using arduino," in *2022 International Symposium on Measurement and Control in Robotics (ISMCR)*, 2022, pp. 1–6.

[9] L. Castillo-Salvatierra, J. Cárdenas-Cobo, C. de la Fuente-Burdiles, and C. Vidal-Silva, "Programming competencies in university students through game development," *Frontiers in Education*, vol. 10, 2025. [Online]. Available: https://doi.org/10.3389/feduc.2025.1585602

[10] A. J. Ko, B. A. Myers, and H. H. Aung, "Six learning barriers in end-user programming systems," in *2004 IEEE Symposium on Visual Languages - Human Centric Computing*, 2004, pp. 199–206.

[11] D. Sun, C.-K. Looi, Y. Li, C. Zhu, C. Zhu, and M. Cheng, "Block-based versus text-based programming: a comparison of learners' programming behaviors, computational thinking skills and attitudes toward programming," *Educational Technology Research and Development*, vol. 72, no. 2, pp. 1067–1089, 2024. [Online]. Available: https://doi.org/10.1007/s11423-023-10328-8

[12] F. Wörister and M. Knobelsdorf, "A block-based programming environment for teaching low-level computing," in *Proceedings of the 23rd Koli Calling International Conference on Computing Education Research (Koli Calling '23)*. ACM, 2023, pp. 1–7.

[13] C. Vidal-Silva, J. Serrano-Malebran, and F. Pereira, "Scratch and arduino for effectively developing programming and computing-electronic competences in primary school children," in *2019 38th International Conference of the Chilean Computer Science Society (SCCC)*, 2019, pp. 1–7.

[14] M. Tramonti, A. M. Dochshanov, and A. S. Zhumabayeva, "Design thinking as an auxiliary tool for educational robotics classes," *Applied Sciences*, vol. 13, no. 2, 2023. [Online]. Available: https://www.mdpi.com/2076-3417/13/2/858

[15] A. Hussain, H. Shakeel, F. Hussain, N. Uddin, and T. Ghouri, "Unity game development engine: A technical survey," *University of Sindh Journal of Information and Communication Technology*, vol. 4, 10 2020.

[16] T. Maraffi, "Level-up logics: Leveraging three game design platforms to teach coding," in *ACM SIGGRAPH 2024 Educator's Forum*, ser. SIGGRAPH '24. New York, NY, USA: Association for Computing Machinery, 2024. [Online]. Available: https://doi.org/10.1145/3641235.3664434

[17] M. J. Gomez, J. A. Ruipérez-Valiente, and F. J. G. Clemente, "A systematic literature review of game-based assessment studies: Trends and challenges," *IEEE Transactions on Learning Technologies*, vol. 16, no. 4, pp. 500–515, 2023.

[18] R. I. Maxim and J. Arnedo-Moreno, "Identifying key principles and commonalities in digital serious game design frameworks: Scoping review," *JMIR Serious Games*, vol. 13, p. e54075, Mar 2025. [Online]. Available: https://games.jmir.org/2025/1/e54075

[19] J. H. Berssanette and A. C. de Francisco, "Cognitive load theory in the context of teaching and learning computer programming: A systematic literature review," *IEEE Transactions on Education*, vol. 65, no. 3, pp. 440–449, 2022.

[20] C.-Y. Chen, "Effects of worked examples with explanation types and learner motivation on cognitive load and programming problem-solving performance," *ACM Trans. Comput. Educ.*, vol. 25, no. 2, Jun. 2025. [Online]. Available: https://doi.org/10.1145/3732791

[21] F. Ke, K. Xie, and Y. Xie, "Game-based learning engagement: A theory- and data-driven exploration," *British Journal of Educational Technology*, vol. 47, no. 6, pp. 1183–1201, 2016. [Online]. Available: https://doi.org/10.1111/bjet.12314

[22] M.-J. Tsai, L.-J. Huang, H.-T. Hou, C.-Y. Hsu, and G.-L. Chiou, "Visual behavior, flow and achievement in game-based learning," *Computers & Education*, vol. 98, pp. 115–129, 2016. [Online]. Available: https://doi.org/10.1016/j.compedu.2016.03.011

[23] R. Israel-Fishelson and A. Hershkovitz, "Persistence in a game-based learning environment: The case of elementary school students learning computational thinking," *Journal of Educational Computing Research*, vol. 58, no. 5, pp. 891–918, 2020. [Online]. Available: https://doi.org/10.1177/0735633119887187

[24] M. Vinueza-Morales, J. Cárdenas-Cobo, J. Cabezas-Quinto, and C. Vidal-Silva, "Applying the block-based programming language alice for developing programming competencies in university students," *IEEE Access*, vol. 13, pp. 21 471–21 485, 2025.

[25] M. Caeiro-Rodríguez, M. Manso-Vázquez, F. A. Mikic-Fonte, M. Llamas-Nistal, M. J. Fernández-Iglesias, H. Tsalapatas, O. Heidmann, C. V. De Carvalho, T. Jesmin, J. Terasmaa, and L. T. Sørensen, "Teaching soft skills in engineering education: An european perspective," *IEEE Access*, vol. 9, pp. 29 222–29 242, 2021.

[26] M. Fahmideh, A. Ahmad, A. Behnaz, J. Grundy, and W. Susilo, "Software engineering for internet of things: The practitioners' perspective," *IEEE Transactions on Software Engineering*, vol. 48, no. 8, pp. 2857–2878, 2022.

[27] P. Perera, G. Tennakoon, S. Ahangama, R. Panditharathna, and B. Chathuranga, "A systematic mapping of introductory programming languages for novice learners," *IEEE Access*, vol. 9, pp. 88 121–88 136, 2021.

Confidence-Based Trust Calibration in Human-AI Teams

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***Abstract*—Effective human-AI collaboration is contingent upon calibrated trust, wherein users depend on AI systems when accuracy is probable and rely on human judgment when errors are likely. In this study, a confidence-based mechanism for trust calibration within human-AI teams is examined. A decision-making strategy is proposed in which task delegation is governed by the AI's confidence: when the confidence surpasses a specified threshold, the AI's recommendation is adopted; otherwise, the decision is deferred to the human. Through simulation experiments on a binary classification task, performance outcomes are compared. The AI system achieves an accuracy of 77.7%, whereas the human decision-maker, modeled with a confidence-sensitive accuracy function $p_h(c) = 0.95 - 0.3c$, attains an overall accuracy of 71.9%. Team performance is evaluated across a range of AI confidence thresholds (0.50 to 0.99), revealing that an intermediate threshold yields optimal team accuracy of 84.14%, substantially exceeding the performance of either agent individually. The findings provide a detailed analysis of confidence-based delegation, align with existing research on trust calibration, and underscore critical design implications for the development of human-centric AI systems.**

***Keywords*—Human-AI collaboration; trust calibration; confidence-based delegation; decision-making strategies**

I. Introduction

Artificial Intelligence has been increasingly deployed to support human decision-making across domains such as healthcare, finance, and public administration. From the assistance of clinicians in diagnostics to the facilitation of faster financial fraud detection, AI systems are now influencing decisions that carry significant consequences for individuals and society [1], [2], [3].

In many of these applications, AI systems are designed to act as decision aids, producing predictions or recommendations while the final judgments are left to human operators. The effectiveness of such human-AI teams is determined not only by the technical accuracy of the AI but also by the quality of human-AI collaboration, particularly the calibration of human trust in the system [4], [5]. Misaligned trust, manifested as either over-reliance on flawed outputs or unwarranted skepticism toward reliable ones, has been shown to significantly impair decision quality [6].

Trust calibration is defined as the alignment between a user's trust in an AI system and the system's actual performance or reliability. When trust is properly calibrated, users tend to rely on the AI when it is likely to be correct and revert to their own judgment when the AI is likely to err [7]. This balance is particularly critical in high-stakes environments, where both AI errors and human biases may lead to severe consequences [8].

To foster calibrated trust, many AI systems have been equipped with confidence scores or uncertainty estimates that accompany their predictions. These indicators are intended to help users discern when AI recommendations should be accepted or questioned [4]. However, the provision of confidence information alone has not been found sufficient. Empirical studies indicate that users' own confidence levels and cognitive biases play a significant role in determining whether reliance on AI systems is appropriately adjusted [5], [7]. For instance, overconfident users may disregard valuable AI input, whereas underconfident users may accept flawed suggestions without critical evaluation.

Consequently, trust calibration emerges as a dual challenge, requiring both transparent AI systems and mechanisms that account for human self-assessment and behavioral tendencies [6]. In response to this challenge, a confidence-based delegation strategy is examined, wherein AI predictions are adopted only when their confidence surpasses a predefined threshold; otherwise, the decision is deferred to the human operator.

This strategy is intended to align decision authority with the most reliable agent in each situation. By tuning the threshold, the balance between human and AI decision-making can be dynamically adjusted, ranging from heavy reliance on AI to near-complete human control. The proposed approach is evaluated within a simulated binary classification task, in which an AI system with fixed accuracy and a human agent with confidence-sensitive performance are modeled. The results indicate that an intermediate confidence threshold yields the highest overall team performance, surpassing that of either the human or AI operating independently.

These findings provide new insights into trust calibration strategies for human-AI collaboration and contribute to the design of systems that optimize joint decision-making outcomes in practical applications.

II. Related Work

A. Trust Calibration and Miscalibration in Human-AI Interaction

Trust calibration lies at the core of effective human-AI interaction, serving as the process by which human users adjust their trust in an AI system to align with the system's actual competence and reliability. Properly calibrated trust allows users to leverage AI strengths while maintaining critical oversight, ensuring that reliance on automation remains proportional to its demonstrated performance. Conversely, miscalibrated trust, manifesting as either overtrust or undertrust, can undermine system efficacy, situational awareness, and

ultimately safety. This is particularly consequential in high-stakes domains such as healthcare, autonomous vehicles, and maritime navigation, where erroneous trust judgments can have severe operational and ethical implications.

Kneer, Loi, and Christen [9] explore these dynamics in the context of human–AI interaction, emphasizing how automation bias and algorithm aversion emerge when users misperceive AI capabilities or misinterpret its outputs. Such errors may arise from opacity, inconsistent performance, or limited user understanding. As a result, trust calibration emerges as both a technical and psychological challenge.

Extending this perspective, Kulal [10] argue that even when AI systems provide statistically calibrated outputs, users may misalign their trust due to cognitive biases, such as anchoring on superficial cues or overgeneralizing prior experiences. This highlights that achieving trust calibration is not solely a matter of improving algorithmic confidence, it also requires user-centered design informed by cognitive science and HCI. Thus, future systems must integrate these insights to foster more resilient, interpretable, and human-aligned decision-making partnerships.

B. Confidence and Uncertainty Displays

A prominent approach to improving trust calibration in human-AI interaction involves communicating the AI system's confidence or uncertainty levels. These displays aim to make the system's internal reasoning and limitations more transparent, allowing users to adjust their reliance on AI outputs according to perceived reliability. When well-designed, such indicators can foster calibrated trust, reduce automation bias, and help users recognize when human oversight is necessary. However, the effectiveness of confidence and uncertainty displays depends critically on users' ability to correctly interpret and integrate these signals into their decision-making processes.

Prior work has shown that presenting confidence alone is insufficient if users lack the contextual or cognitive tools to make sense of probabilistic information. For instance, Zhang and Xu [11] demonstrate in the maritime domain that multimodal indicators, such as uncertainty bars, linguistic cues, and system status indicators, are more effective than confidence scores alone in promoting trust calibration and preventing overreliance or disuse. These findings highlight the importance of designing interfaces that help users develop accurate mental models of AI decision boundaries.

Similarly, byasa and Rahmania [12] emphasize the value of explanation-assisted confidence displays in medical imaging. Their approach integrates visual saliency explanations with model confidence in 3D brain tumor segmentation tasks. This combination improved clinician understanding of when to trust or question AI outputs, suggesting that confidence information is most effective when paired with interpretable explanations.

Taken together, these insights emphasize that uncertainty communication is as much a matter of human-centered design as it is of algorithmic transparency. Effective confidence displays must balance informativeness and interpretability, tailoring the presentation of uncertainty to users' cognitive and contextual constraints. As a result, ongoing work in this area increasingly integrates research from explainable AI, human–computer interaction, and cognitive psychology to develop uncertainty representations that genuinely support trust calibration.

C. Confidence Alignment in Human–AI Collaboration

Effective trust calibration in human-AI collaboration requires a bidirectional approach: AI systems must communicate confidence that accurately reflects their underlying uncertainty, while human users must be supported in correctly interpreting and responding to these cues. Achieving alignment between human and AI confidence is not merely a technical issue of probabilistic calibration, but also a human-centered challenge involving perception, communication, and adaptive interface design. When either side of this alignment fails, when the AI misrepresents its certainty or when humans misread it, the partnership risks degradation through underutilization, overreliance, or unsafe decision-making.

In dynamic settings such as maritime navigation, Zhang and Xu [11] emphasize the importance of adaptive user interfaces that integrate explainable AI (XAI) components. They find that calibrated confidence and compliance indicators support user understanding of automation, fostering more consistent trust judgments under uncertainty. Their work highlights how interface-level interventions can prevent automation bias and encourage proper human oversight.

Reinforcing this view, von Reeken, Salous, and Abdenebaoui [13] demonstrate that subtle interface variations in conversational AI systems can significantly affect how users align their trust with system recommendations. Their study shows that users benefit from interface cues that signal confidence calibration quality, especially in retrieval-augmented generation systems. When these cues are absent or misaligned, trust can diverge from actual system reliability, leading to overtrust or disuse.

Finally, Marusich et al. [14] underscore the necessity of designing for trust calibration in time-sensitive, high-stakes applications. They advocate for adaptive confidence visualizations and user training strategies that evolve with changing task difficulty and user experience. Their findings suggest that integrating behavioral modeling into the interface design, such as adjusting explanation granularity based on user trust metrics, can prevent cascading decision errors and improve joint performance.

Taken together, these studies affirm that trust calibration is best achieved through a combination of calibrated AI outputs and adaptive, user-sensitive interface design. Future systems should be designed not just to communicate confidence but to help users meaningfully act on it.

D. Confidence-Based Delegation Policies

Confidence-based delegation represents a structured mechanism for managing trust and control within human-AI collaboration. In such frameworks, decision authority dynamically shifts between the human and the AI system according to confidence thresholds, when the AI's confidence surpasses a predefined level, the system autonomously executes a decision; when confidence falls below that level, control is transferred to

the human operator. This approach formalizes trust calibration by operationalizing it into quantifiable and adaptive decision policies, thereby aligning task allocation with system reliability and uncertainty.

This paradigm offers several benefits. It allows for efficient division of labor, ensuring that AI systems handle routine or high-certainty cases while humans intervene in ambiguous or high-risk situations. By doing so, it mitigates both over-reliance and under-reliance on automation, promoting a balanced collaborative dynamic. However, the success of confidence-based delegation hinges on how well the confidence thresholds are defined, validated, and communicated. Misaligned thresholds can either overwhelm human operators with unnecessary interventions or, conversely, lead to excessive automation that undermines human oversight and accountability.

Recent work by Le Denmat, Desender, and Verguts [15] underscores the importance of aligning system confidence with real-time human decision dynamics. Their study shows that agents can learn optimal confidence thresholds through experience, adjusting delegation based on trial-level feedback about decision accuracy. This learning-based approach allows human-AI systems to optimize collaboration patterns dynamically and avoid rigid reliance on static thresholds. This work builds on this by examining how performance varies across different threshold settings and demonstrating that fine-tuned delegation improves joint outcomes significantly. Such insights are crucial for deploying human-AI systems in dynamic, high-stakes environments where uncertainty varies widely across tasks.

III. Methodology

A trust calibration strategy was investigated for a human-AI team performing repeated binary classification tasks, such as diagnosing medical images or identifying fraudulent financial transactions. The team consisted of two agents: an AI model and a simulated human decision-maker. Both agents produced a class prediction and an associated confidence score for each decision instance. A simple confidence-based delegation policy was introduced, wherein the AI's confidence determined which agent's decision was adopted.

A. Confidence-Based Delegation Policy

Formally, the delegation policy was defined by a threshold parameter $\tau \in [0.5, 1.0]$. For each instance, the AI produced a class prediction and a confidence score $C_{\text{AI}} \in [0.5, 1.0]$. The confidence was restricted to be at least 0.5 since probabilities below this value would imply a different predicted class. The policy operated as follows:

- If $C_{\text{AI}} \geq \tau$, the AI's prediction was selected.
- If $C_{\text{AI}} < \tau$, the human's prediction was selected.

This threshold-based policy enabled dynamic delegation: the AI was trusted when sufficiently confident, while decisions were deferred to the human otherwise. Lower thresholds led to increased AI usage, whereas higher thresholds resulted in greater reliance on the human agent. It was hypothesized that an intermediate threshold could yield optimal overall accuracy by balancing the complementary strengths of both agents.

B. Simulation Framework

The decision-making process of the human-AI team was simulated to evaluate the proposed strategy.

a) AI Model: The AI was modeled as a binary classifier with fixed accuracy and calibrated confidence scores. Specifically, an AI accuracy of 77.7% across decision instances was simulated. The AI's confidence C_{AI} was sampled uniformly from the interval [0.5, 1.0]. The correctness of each prediction was determined probabilistically to ensure the specified overall accuracy.

b) Human Model: The human agent was modeled with imperfect confidence calibration. For each decision, a confidence value $c \in [0, 1]$ was reported. The probability of correctness given the confidence was defined as:

$$p_h(c) = 0.95 - 0.3c$$

This formulation captured typical miscalibration patterns, such as overconfidence at high confidence levels and underconfidence at low ones. For instance, when $c = 1.0$, the actual accuracy was 65%; when $c = 0.2$, accuracy increased to 89%. Confidence values were drawn from a distribution yielding an overall accuracy of 71.9%.

c) Independence Assumption: For analytical tractability, statistical independence between the AI and human confidences and correctness outcomes was assumed. Although correlated errors may occur in practice, this assumption allowed isolation of the effects of the delegation policy.

C. Decision and Evaluation Procedure

For each simulated decision instance, the following procedure was executed:

1) An AI confidence score C_{AI} was sampled, and correctness of the AI prediction was determined.
2) A human confidence score c was sampled, and correctness was determined based on $p_h(c)$.
3) The threshold policy was applied to select either the AI or human prediction.
4) The correctness of the chosen prediction was recorded.

Over many instances, two key metrics were computed:

- Team Accuracy: The proportion of correct final decisions.
- AI Usage Rate: The proportion of instances where $C_{\text{AI}} \geq \tau$.

By varying τ from 0.50 to 0.99, the effects on performance were examined. At the extremes, $\tau = 0.50$ corresponded to complete reliance on the AI (team accuracy = 77.7%), while $\tau = 0.99$ corresponded to near-exclusive human decision-making (team accuracy = 71.9%). Optimal team performance was expected at intermediate thresholds, where complementarities between AI and human decision-making were maximized.

D. Experimental Setup

Simulations were conducted at thresholds $\tau \in \{0.50, 0.60, 0.70, 0.80, 0.90, 0.95, 0.99\}$, with tens of thousands of instances sampled per setting to ensure statistical robustness. For each threshold:

- AI confidence C_{AI} was sampled uniformly from [0.5, 1.0].
- AI correctness was probabilistically determined to ensure a 77.7% overall accuracy.
- Human confidence c was sampled to yield a 71.9% accuracy based on $p_h(c)$.
- The delegation rule was applied, and the correctness of the selected agent's decision was recorded.

This simulation framework enabled systematic evaluation of how the delegation threshold influenced both decision accuracy and the division of labor between the human and AI agents.

IV. Results

A. Team Performance vs. Threshold

Table I summarizes team accuracy and AI usage rates across different confidence threshold values. As the threshold τ increased from 0.50 to 0.99, team accuracy followed an inverted U-shaped curve. At $\tau = 0.50$, where the AI always makes the decision, team accuracy matched the AI's standalone performance of 77.7%. Increasing the threshold to $\tau = 0.60$ boosted team accuracy to 82.0%, and a further increase to $\tau = 0.70$ yielded the highest observed accuracy of **84.1%**.

At this optimal threshold, the AI handled approximately 75% of the instances, while the human handled the remaining 25%. Beyond $\tau = 0.70$, accuracy began to decline: at $\tau = 0.80$, it dropped to 83.0%; at $\tau = 0.90$, to 79.0%; and by $\tau = 0.99$, to 72.0%, only marginally above the human-alone baseline of 71.9%. AI usage rates decreased accordingly: from 100% at $\tau = 0.50$ down to approximately 3% at $\tau = 0.99$.

Table I demonstrate a clear "sweet spot" at $\tau = 0.70$, where team accuracy is maximized. The gain is substantial: a 6.4 percentage point improvement over the AI alone (77.7%) and a 12.2 point gain over the human alone (71.9%). These results validate the hypothesis that confidence-based delegation can yield performance gains by exploiting complementary strengths.

B. AI Usage vs. Threshold

As shown in the AI usage column of Table I, increasing the confidence threshold gradually reduces the frequency with which the AI's prediction is used. From full usage at $\tau = 0.50$, AI involvement drops to 75% at $\tau = 0.70$, then falls steeply to 50% at $\tau = 0.80$, 25% at $\tau = 0.90$, and near-zero at $\tau = 0.99$. This shift implies increasing reliance on the human as the threshold rises, and team performance decreases accordingly when the human is responsible for too many decisions.

Interestingly, the best accuracy occurs when the AI is used about 75% of the time, aligning with its higher individual accuracy compared to the human. In scenarios where the human were more accurate than the AI, we would expect the optimal threshold to shift accordingly.

C. Interpretation of Results

The results demonstrate that confidence-based delegation is a viable and effective strategy for trust calibration in human-AI teams. The optimal threshold reflects a division of labor that exploits each agent's strengths. At $\tau = 0.70$, the AI handles the decisions where it is relatively confident, while the human steps in where the AI is uncertain. This allocation improves the team's collective performance.

To understand why this threshold works, consider that when the AI is less than 70% confident, it is often wrong on those predictions. Our human model, while less accurate overall, is calibrated to sometimes outperform the AI on low-confidence cases. Conversely, when the AI is highly confident (e.g., $C_{\text{AI}} \geq 0.90$), it tends to be right, and deferring to it yields better results than relying on the human.

Thus, the delegation policy implicitly partitions the decision space: confident, likely-correct decisions go to the AI, and ambiguous, error-prone cases go to the human. Provided the AI's confidence is reasonably well-calibrated, this partitioning enhances team accuracy and supports appropriate reliance.

In summary, this experiment demonstrates that appropriately calibrated confidence thresholds can yield significant performance gains in human–AI collaboration, validating the utility of confidence as a trust calibration mechanism.

V. Discussion

The effectiveness of confidence-based delegation as a mechanism for trust calibration in human-AI collaboration was demonstrated. By using the AI's own confidence scores to determine reliance, decision-making was dynamically allocated to the most appropriate agent, achieving outcomes superior to either agent alone. The implications, necessary conditions, and design considerations for applying this strategy in practice are discussed below.

A. The Value of Calibrated Delegation

The threshold-based policy examined captures a key principle of appropriate reliance: deference to the AI when high confidence is expressed, and reliance on human judgment when uncertainty is greater. This simple policy significantly improved team performance, mitigating both over-reliance on incorrect AI outputs and disuse of valuable AI recommendations. At the optimal threshold $\tau = 0.70$, many of the AI's confident and unconfident mistakes were avoided through intelligent decision allocation.

This outcome aligns with theoretical work suggesting that automation should be applied when AI confidence is high and human input should be sought otherwise. The observed performance gain, from 77.7% to 84.1%, represents a 29% reduction in error. In real-world domains such as medical diagnostics or fraud detection, such improvements could have meaningful impacts.

These benefits, however, depend on human-AI complementarity: each agent must be capable of correcting the other's

TABLE I. TEAM DECISION ACCURACY AND AI USAGE RATE AT DIFFERENT CONFIDENCE THRESHOLDS

Confidence Threshold τ	Team Accuracy (%)	AI Usage Rate (%)
0.50 (Always AI)	77.7	100
0.60	82.0	90
0.70	**84.1**	75
0.80	83.0	50
0.90	79.0	25
0.95	76.0	10
0.99 (Rarely AI)	72.0	3

errors. In the simulation, this complementarity was modeled by allowing the human to outperform the AI in low-confidence cases. When error overlap is substantial, confidence-based delegation may offer limited advantage.

B. Dependence on AI Confidence Calibration

A foundational assumption is that the AI's confidence is reasonably well-calibrated. In practice, confidence miscalibration, manifesting as overconfidence or underconfidence, can severely undermine delegation policies. Overconfident models may mislead users into trusting erroneous outputs, whereas underconfident models may lead to missed opportunities for automation.

Calibration techniques such as Platt scaling, isotonic regression, and temperature scaling can improve the reliability of confidence scores. Alternatively, "learning to defer" approaches explicitly optimize the decision of when to abstain and defer to a human, effectively learning an optimal threshold τ directly from data.

C. Human Factors and Policy Compliance

Strict adherence to the delegation policy was assumed in the simulation. However, real users may deviate due to cognitive biases, trust propensities, or interface design. For example, a clinician might override a confident AI due to recent negative experiences or accept low-confidence AI suggestions due to overtrust.

Compliance can be improved through design interventions. Visual cues indicating whether a confidence threshold has been met could nudge users toward intended behavior. Training and feedback mechanisms may further support trust calibration by displaying statistics on when AI advice was followed or overridden, along with the corresponding outcomes.

Thresholds may also be personalized. Overtrusting users may benefit from higher thresholds that enforce engagement, while distrustful users may begin with lower thresholds that increase over time as trust builds. Adaptive systems that monitor user behavior and adjust τ dynamically may enhance collaboration.

D. Integration with Explanations and Interpretability

Although confidence was the primary trust signal considered, AI systems increasingly provide explanations such as saliency maps and rationales. These can either support or interfere with trust calibration. An explanation aligning with user expectations can reinforce high-confidence decisions, whereas poor explanations may lead to unjustified distrust.

Combining confidence with selective explanations presents a promising direction. Explanations could be shown for low-confidence cases to assist human judgment, and withheld for high-confidence cases to reduce cognitive load. Future empirical research should evaluate such hybrid strategies.

E. Complementarity and Task Structure

The efficacy of threshold-based delegation depends on complementary error patterns between human and AI agents. When failures occur on different instances, confidence-based delegation yields the greatest gains. Task design can enhance complementarity by training AI models on instances difficult for humans or by employing disagreement-based sampling.

Task difficulty distribution also plays a critical role. Confidence-based delegation performs best when there is a broad range of instance difficulties. In tasks that are uniformly easy or uniformly hard, the confidence spectrum may collapse, limiting the utility of threshold-based strategies.

Moreover, error cost asymmetry should inform threshold selection. In high-risk applications, thresholds might be set conservatively to ensure human oversight. While this study optimized for accuracy, practical deployments may need to optimize precision, recall, or cost-sensitive metrics.

F. Implications for Human-Centered AI Design

Confidence thresholds offer a transparent and tunable mechanism for managing human-AI collaboration. They can be adapted to task domain, risk level, and user behavior, making system behavior predictable and auditable to aid accountability.

Effective implementation requires careful attention to interface design, user training, performance monitoring, and explanation integration. The delegation policy should be visible, justifiable, and adaptable.

The findings support a central tenet of human-centered AI: the objective is not to replace humans, but to design systems in which humans and AI complement each other. Confidence-based trust calibration provides a concrete, interpretable, and effective strategy for achieving such synergy.

VI. CONCLUSION

A simulation-based investigation of confidence-based trust calibration in human-AI teams was presented, focusing on a threshold delegation strategy in which the AI's confidence score determined whether its prediction was used or deferred to the human. It was found that selecting an appropriate confidence threshold could significantly enhance team performance: in the examined scenario, team accuracy peaked at 84.1%,

surpassing both the AI-alone baseline (77.7%) and human-alone performance (71.9%). This improvement highlights the value of calibrated reliance, whereby each agent contributes most effectively in contexts that align with their respective strengths.

These findings are consistent with prior research emphasizing the importance of trust calibration in human-AI interaction. Confidence-based delegation policies provide a transparent and operationalizable mechanism for achieving such calibration, assuming that the AI's confidence scores are well-calibrated and that human decision-makers are appropriately guided to interpret and act on those scores.

For designers of human-centric AI systems, the results suggest that implementing confidence-threshold strategies constitutes a practical and beneficial design approach. Rather than positioning human and AI agents as parallel or redundant decision-makers, a coordinated policy can systematically leverage their complementary capabilities. Nevertheless, the realization of these benefits in applied settings is contingent on factors such as user education, interface design, and the reliability of the AI's uncertainty estimates.

Future research is encouraged to investigate adaptive threshold strategies that adjust dynamically based on user behavior, task context, or evolving trust calibration. Empirical user studies are also needed to assess how individuals interact with confidence-based delegation interfaces, the extent to which prescribed policies are followed, and how interventions, such as visual cues or feedback mechanisms, may enhance compliance and comprehension.

Ultimately, confidence-based trust calibration exemplifies the goals of human-centered AI: systems designed not only for accuracy but also to support and align with human decision-making processes. By enabling reliance on AI systems to the extent that their predictions are trustworthy, progress is made toward the development of AI tools that are both effective and accountable. The approach described herein demonstrates that even a simple, interpretable rule anchored in confidence can yield meaningful improvements in team performance. With ongoing advancements in calibration techniques and human-AI interface design, trust calibration strategies are expected to occupy a central role in the next generation of decision-support systems.

REFERENCES

[1] B. Ebenso, E. Namisango, I. Abejirinde, and M. J. Allsop, "The scale-up and sustainability of digital health interventions in low-and middle-income settings," p. 1634223, 2025.

[2] B. P. SAMEERKUMAR, "Ethical considerations in ai design and deployment," *WORLD*, vol. 25, no. 1, pp. 2166–2173, 2025.

[3] C. Happer, "Ai-enabled signal detection in pharmacovigilance," 2025.

[4] J. Kornowicz, "Human integration in ai: Calibrating trust and improving performance in decision support systems."

[5] F. Ghaffar, "Understanding human decision variability and the effects of ai system data modality on trust and acceptance in human–ai collaboration," Ph.D. dissertation, University of Waterloo, 2025.

[6] J. Joseph, "Designing for dignity: Ethics of ai surveillance in elderly care," *Frontiers in Digital Health*, vol. 7, p. 1643238, 2025.

[7] G. Faisal, "Understanding human decision variability and the effects of ai system data modality on trust and acceptance in human–ai collaboration: A human-centred approach to designing ai systems in healthcare contexts," Ph.D. dissertation, 2025.

[8] M. Tyrovolas, "Advanced methods for explainable artificial intelligence based on fuzzy cognitive maps," Ph.D. dissertation, Πανεπιστήμιο Ιωαννίνων. Σχολή Πληροφορικής και Τηλεπικοινωνιών. Τμήμα ..., 2025.

[9] M. Kneer, M. Loi, and M. Christen, "Trust and responsibility in human-ai interaction," *Available at SSRN 5731431*, 2025.

[10] A. Kulal, "Cognitive risks of ai: Literacy, trust, and critical thinking," *Journal of Computer Information Systems*, pp. 1–13, 2025.

[11] Z. Zhang and H. Xu, "Explainable ai for maritime autonomous surface ships (mass): Adaptive interfaces and trustworthy human-ai collaboration," *arXiv preprint arXiv:2509.15959*, 2025.

[12] J. Abyasa and R. Rahmania, "Axons-3: An xai-augmented approach for advancing trust and transparency in 3d brain tumor segmentation," in *2025 IEEE Conference on Cognitive and Computational Aspects of Situation Management (CogSIMA)*. IEEE, 2025, pp. 64–71.

[13] T. von Reeken, M. Salous, and L. Abdenebaoui, "Un-trusting the chat: Designing for calibrated trust in retrieval-augmented conversations," in *Proceedings of the 7th ACM Conference on Conversational User Interfaces*, 2025, pp. 1–10.

[14] L. R. Marusich, B. T. Files, M. Bancilhon, J. C. Rawal, and A. Raglin, "Trust calibration for joint human/ai decision-making in dynamic and uncertain contexts," in *International Conference on Human-Computer Interaction*. Springer, 2025, pp. 106–120.

[15] P. Le Denmat, K. Desender, and T. Verguts, "Learning to be confident: How agents learn confidence based on prediction errors," 2025.

AI-Based Framework for Automated Cell Cleavage Detection and Timing in Embryo Time-Lapse Videos

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***Abstract*—In vitro fertilization (IVF) has become a primary therapeutic intervention for couples worldwide addressing infertility challenges. IVF success depends critically on embryo quality assessment, where cell cleavage timing serves as a key developmental parameter. Traditional morphological evaluation methods suffer from inter-observer variability and labor-intensive manual analysis. This study presents an automated AI-based framework for cleavage stage detection and cleavage onset timing estimation from Time-Lapse Microscopy (TLM) videos to assist embryologists in embryo selection. The proposed YOLO-based approach addresses significant class imbalance through selective data augmentation and random undersampling strategies. To ensure precise temporal data, an OCR (Optical Character Recognition) library was integrated to automatically read and record the Hours Post-Insemination (HPI) timestamps from the video frames. The proposed framework accurately identifies cell division stages up to the seven-cell stage with 1-2 hours mean timing delay post-insemination. The framework achieves an overall Accuracy of 86.61% , F1-score of 86.24% ,and precision of 86.24% in cleavage stage classification, demonstrating significant improvements over existing methods, particularly in intermediate and later stages (4-cell to 8-cell transitions) where previous research have demonstrated challenges in accurately detecting them. Automated extraction of morphokinetic parameters enables objective embryo assessment, reducing subjectivity in clinical decision-making. The proposed framework demonstrated significant improvements over previous research, which frequently has trouble accurately classifying beyond early cleavage stages. This has implications in improving the selection of good-quality embryos, and thus to help improve the success rate of IVF. This work contributes to advancing assisted reproductive technology by providing reliable, automated embryo quality assessment tools.**

Keywords*—In vitro fertilization; Time-Lapse Microscopy (TLM) videos; AI-based framework; cleavage stage; cleavage onset timing; optical character recognition; Hours Post-Insemination (HPI)

I. Introduction

Infertility affects approximately 17. 5% of adults worldwide each year, and 1 in 6 people are affected by infertility in their lifetime [1]. Serious consequences can negatively affect the lives of infertile couples in terms of physical and psychological well-being, social life, and finances [2]. Among assisted reproductive technology (ART), in vitro fertilization (IVF) is the most popular treatment for infertility since the first successful IVF birth in the UK in 1978. In a typical IVF cycle, the ovaries are stimulated hormonally, mature oocytes are surgically removed, fertilization takes place in a lab, and the embryo is then transferred to the uterus. Currently, there are 35 ART centers in Saudi Arabia that perform more than 20,000 IVF treatment a year [3]. However, the success rates of these treatments are still low. In general, only 20-30% of the transferred embryos result in implant [4] and less than half of the implanted embryos survive to live birth. Thus, selecting the best quality embryo is crucial to ensure the success of the IVF process. Embryologists categorize each embryo based on different morphological criteria and morphokinetic parameters that have been linked to successful embryo development ,including the examination of cell division dynamics [5]. In addition, irregular timings have been associated with genetic abnormalities, implantation failure, and miscarriage that normally manifest during the 8-cell stage [6], [7]. The number of embryonic cells and their subsequent cell division define a cell cleavage stage. It has been demonstrated that the time of cell divisions in human IVF embryos correlates with embryonic viability [6], [8]. Time-lapse studies showed that embryos that cleave in middle time periods have a higher probability of implantation compared to those that develop faster or slower [9], [10]. To assess timing features, embryologists manually annotate the cleavage occurrences of each embryo. Annotating a single embryo usually takes less than two minutes [11], but when examining many embryos (e.g., 5-10), the total time needed can increase significantly - up to 20 minutes [12]. Although manual annotation of embryo morphokinetics is considered efficient, this process is often tiresome and prone to subjectivity or human error. When counting cells in the early stages of embryonic development, cell overlap presents a significant challenge. It becomes harder to identify individual cells as they multiply because they are more densely packed, especially in the stage of 7-8 cells. This overlap makes accurate counting and monitoring more difficult. With rapid technological advancements, artificial intelligence (AI) offers a promising solution to these challenges. AI can help embryologists overcome these obstacles by automating routine tasks such as counting cells, tracking video clips,

and keeping track of division times. The use of artificial intelligence, particularly deep learning models such as convolutional neural networks (CNNs), has expanded significantly in embryo evaluation. These models are capable of automating tasks such as object detection, image segmentation, and optical character recognition (OCR), which contribute to faster and more consistent assessments of embryo development [13]–[16]. In particular, time-lapse imaging combined with AI methods has shown promise in analyzing human embryo development, enabling continuous monitoring of cell division dynamics [17]. Manual annotation of time-lapse microscopy (TLM) videos in embryology is a significant challenge, as it is a time-consuming task and subject to human variation and bias. With the increasing number of cases requiring embryological assessment, the burden on embryologists is increasing. This research develops an AI-based solution to fully automate the annotation of embryo development in TLM videos. The goals include cell detection and counting, cleavage time estimation, and enhancement of precision, productivity, and the reliability of embryo assessment. Achieving these automation objectives will help embryologists in their workflows by facilitating real-time, evidence-based decision-making, thus enhancing the practice of reproductive medicine.

The remainder of this paper is structured as follows. Section II reviews related work. Section III describes the proposed framework in detail. Section IV presents the experimental results, and Section V offers a discussion and analysis of these findings. Finally, Section VI concludes the paper and outlines potential directions for future research.

II. Related Work

Recent decades have witnessed a significant transformation in the medical scene due to technological advancements, with AI emerging as a pivotal factor in transforming healthcare [18]. The incorporation of the two fields has revolutionized various aspects of medical practice, including accurate diagnosis [19], early disease detection [20], [21], and the reading and maintenance of medical records [22]. Medical imaging has benefited greatly from AI, especially deep learning, which can identify intricate patterns and characteristics that the human eye misses [23] By offering fresh viewpoints on pertinent image attributes, these technologies not only improve diagnostic precision but also aid in clinical decision-making. In the context of assisted reproductive technologies (ART), several studies have investigated the potential of employing AI at various stages of the reproductive process. Supervised learning models have been used to evaluate embryo motility [24], assess the cost-effectiveness of egg freezing [25], and classify sperm cells [26]. Artificial neural networks (ANNs), including deep learning models, have also been widely utilized in embryo image segmentation [27], blastocyst assessment [28], and prediction of implantation outcomes, thereby enhancing consistency and scalability in clinical decision-making. Building on these broader applications, recent research has shown increasing interest in exploiting AI, particularly object detection models, to analyze embryo development using TLM. This trend has opened up unprecedented opportunities to automate the detection of critical embryonic developmental stages, such as cell divisions and stage transitions, which are essential criteria for embryo evaluation and selection in the context of assisted reproductive treatments. Studies have varied in their approaches, with an increasing number using AI-based approaches, ranging from probabilistic models to deep learning frameworks.

Among the early efforts that used probabilistic models to automate cleavage detection were [29] proposed a conditional random field (CRF) framework that combines tracking- based and tracking-free elements within a data-driven approach. The model leverages a rich set of discriminative image and geometric features, along with their spatiotemporal context, to enhance the detection of cleavage stages. Using time-lapse embryo microscopy image showed an increased accuracy in identifying mitotic events. Upon assessment of 275 clinical sequences, the suggested model demonstrated an enhanced accuracy of 24.2% compared to traditional tracking-based techniques and 35.7% over tracking-free approaches in measuring division events within the initial 48 hours of development.

Building upon this concept, [30]. extended the use of CRF to automate monitoring for human embryonic cells beyond the 4-cell stage using TLM images. Instead of segmenting or tracking individual cells, their method used a conditional random field framework to predict the number of cells in each frame. This gets around the drawbacks of earlier techniques that were limited to 4-cell analysis. The CRF model incorporates temporal dependencies between frames as well as a wide range of discriminative frame-based and cell evolution features. To further enhance predictions, authors also suggested incorporating learned probabilities of cell transitions. Their approach outperformed alternative models, achieving over 92.4% accuracy in counting cells up to 5 or more when tested on a dataset of 33 embryo sequences.

In a subsequent work [31], the same authors introduced a hybrid model that integrates CNN with CRF to automatically count cells in TLM images of human embryos. Cell counting was formulated as a classification problem, and an end-to-end convolutional neural network trained directly on raw microscopy images were utilized, with the only annotation needed being the total cell count. Their deep CNN method significantly outperformed manual feature-based counting techniques by generating hierarchical visual representations from massive amounts of data. It achieved 92.18% accuracy in predicting cell numbers up to the 5-cell stage. Using a conditional random field to model the growth of embryos over time, they introduced temporal constraints and further improved performance. Despite obstacles from cell overlaps, noise, and image variability, evaluation on a dataset of 265 embryo sequences showed that their deep learning framework could count cells in early embryonic development with reliability. The findings indicate the potential of deep learning techniques to automate cell counting in TLM images without performing segmentation steps.

While earlier methods primarily used probabilistic models and hand-crafted features, more recent research utilizes deep learning techniques to automate feature learning straight from raw images. For instance, Malmsten et al. [32] suggested an automated approach employing a CNN to identify and classify cell divisions directly from raw TLM images, with the goal of reducing the subjectivity and manual effort normally associated with embryonic assessment. Two datasets were used to test their approach: a private human embryo dataset (up to the 8-cell stage) and a public mouse embryo dataset (up to the 4-cell

stage). In 93.9% of cases, the model detected human cleavage stage transitions within a five-frame margin, while it attained nearly 100% accuracy for mouse embryos. This work showed how CNN-based systems can improve annotation uniformity and facilitate automated evaluation of embryo viability in IVF situations.

Contributing to this line of research, Sharma et al. [17] used a YOLO-based detection framework instead of traditional CNN classifiers, which enabled the extraction of accurate timing metrics, which can be used to which can be used to make predictions of embryo viability and the real-time detection of cell divisions. Their approach used YOLOv5 to detect embryonic cells and Pytesseract to extract timestamps from TLM videos. Focusing on embryos up to the five-cell stage, the system achieved an average temporal deviation of only 2–3 hours post-insemination. The model effectively detected important features like blastocysts and morulae and separated cells from detritus, despite performance declining in later stages due to increased cell overlap. Their study further emphasizes the expanding significance of automated, data-driven analysis in improving consistency and efficiency in IVF operations by demonstrating the ability to annotate videos at a rate of roughly one minute apiece.

Despite significant advances in automated embryo monitoring using deep learning and computer vision, existing methods continue to have critical limitations in accurately detecting and tracking cleavage events, especially in complex scenarios involving rapid cell divisions, high overlap, and fragmentation. Many previous studies used CRF or CNN for cell counting and stage classification. Still these methods often lack direct cleavage stage detection or rely on suboptimal OCR methods, such as Pytesseract, to extract hpi, leading to reduced accuracy in time annotation. Additionally, the majority of studies have concentrated on human embryos, but our research utilizes mouse embryo datasets, which have distinct morphological traits and developmental dynamics. An AI-based automated framework is proposed to fill these gaps by utilizing YOLOv11 for accurate cell detection and a more sophisticated OCR library tailored for TLM conditions, which guarantees reliable and accurate hpi extraction.

III. Methodology

This research proposes an AI-based automated annotation framework that predicts cell cleavage onset and cell stage from TLM videos. The pipeline is composed of three main components:

1) Object Detection Model: This uses a deep learning approach to localize and count blastomere cells in TLM embryo frames, supporting fast and accurate cleavage detection even in the presence of overlapping cells or fragments.
2) Cleavage Stage Transition Detection: It monitors changes in the number of detected cells and captures the first frame where a new cell count appears, as this corresponds to the earliest moment of morphological transition that indicates cell cleavage. reflecting the onset of a cleavage stage. Biologically, this is consistent with embryologists' approach of identifying the beginning point of cleavage as the key developmental indicator. The primary output of this step is an organized list of key frames that mark the beginning of each cell division stage, with one frame assigned to each stage. This list forms a valuable basis for the subsequent step in analyzing embryonic development.
3) Time Extraction: It uses OCR to read the hpi from each selected frame. When OCR fails due to low contrast or visual artifacts, the timing is estimated using the video's frame rate and fertilization start time.

For object detection, YOLO (You Only Look Once) is used because of its real-time detection capabilities and track record of accuracy in biomedical image analysis [33]. YOLOv11 was selected despite the consideration of competing models because it strikes a compromise between speed, accuracy, and ease of integration with video-based pipelines. For hpi extraction, Three OCR tools—PyTesseract, EasyOCR, and PaddleOCR— are evaluated and compared chosen for their various underlying technology and relevance to TLM video conditions. While PyTesseract is a typical rule-based image processing OCR engine, EasyOCR and PaddleOCR use deep learning-based designs, which provide more robustness when dealing with noisy, low-contrast, or irregular timestamps. Fig. 1 illustrates the workflow of the methodology. The proposed framework produces two primary outputs: 1) annotated frames enriched with relevant metadata, and 2) an Excel file containing cleavage timing data. As shown in the methodology flowchart, the system identifies the cleavage time points t2–t8, where tn represents the hpi time at which the embryo reaches n cells. The reported temporal outputs correspond to sequential inter-cleavage durations between consecutive developmental stages (e.g., t3 - t2, t4 - t3, t5 - t4). This structured output enables embryologists to systematically analyze early embryo developmental dynamics.

A. Dataset Description

Due to ethical considerations and privacy issues, it is challenging to obtain human embryo dataset. Thus, a dataset of mouse embryos was used instead. According to the National Institutes of Health, mice are a model organism with benefits, including genetic homogeneity, affordability, and simplicity of access [34]. Moreover, the limited availability of publicly accessible resources of human embryos emphasizes the importance of using mouse embryos to enhance this field of study. The study utilizes a TLM dataset that has been previously developed and documented in [35]. The dataset consists of video sequences recorded during the development of approximately 100 mouse embryos, taken from the 2-cell stage through to the blastocyst stage. The videos record cell divisions and dynamic changes in embryo morphology throughout important stages of preimplantation development (e.g. 2-8 cell stage, morula, blastocyst). The dataset was captured using EmbryoScope™ (Vitrolife), a specialized culture device designed with 12 individual wells per slide to allow parallel monitoring of multiple embryos under identical conditions. The dataset consisted of 18 videos, each containing 12 embryos, along with an additional video containing 8 embryos, resulting in a total of 224 individual mice embryo development sequences. These videos were recorded under controlled laboratory conditions [35] and include various cleavage events from the 2-cell stage

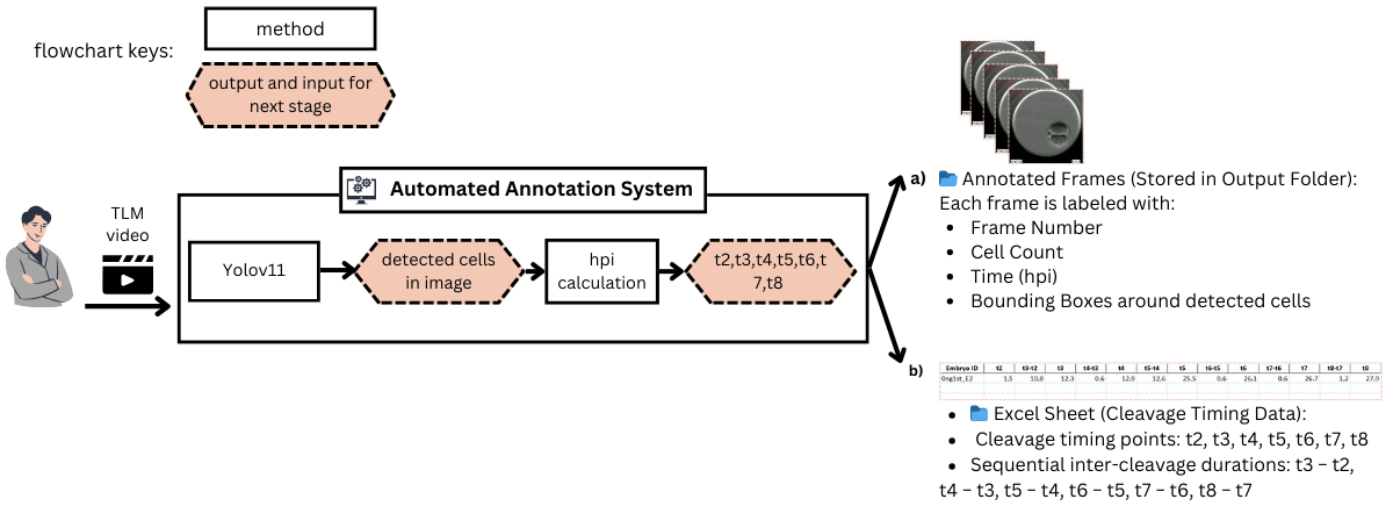


Fig. 1. AI-based automated framework for predicting cell cleavage stages and timing from Time-Lapse Microscopy videos.

to later stages, such as 8-cell or blastocyst formation. All of the videos were saved in AVI format and were captured at a constant 5 frames per second (FPS). The videos also contained time information that was embedded and crucial to our study: the elapsed time since fertilization in hpi is indicated by a visible timestamp in the bottom-right corner of each frame, which is shown as white digits on a black rectangular background.

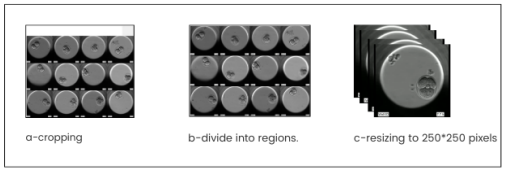


Fig. 2. Preprocessing steps for embryo isolation: (a) cropping of the original TLM field of view, (b) division into fixed regions corresponding to individual embryos, and (c) resizing of each isolated embryo sequence to 250 × 250 pixels.

B. Preprocessing Pipeline

As a first step, each TLM video undergoes basic preprocessing to ensure consistency in frame dimensions, format, and temporal alignment. Using Python and the OpenCV (cv2) package, the videos are cropped to remove unnecessary white space at the top, ensuring that the focus remains on the embryos. For every video, this results in a consistent resolution of 1000x752 pixels and contains 12 embryo wells arranged in a fixed 3-row by 4-column grid. To isolate individual embryos for independent analysis, the video frame is uniformly divided along both axes—width divided by 4 and height divided by 3 resulting in a consistent crop size of 250×250 pixels per well. This standardized resolution ensures that each embryo is spatially separated, uniformly scaled, and appropriately formatted for subsequent deep learning-based object detection and OCR-based timing analysis. As a result of this preprocessing stage, the framework extracts 224 individual embryo videos from the original dataset, each corresponding to a single embryo well and standardized at a resolution of 250×250 pixels. For each video, video frames are extracted at 5 FPS, matching the dataset's native recording rate. This uniform sampling ensured consistent data representation across recordings, supporting reliable analysis and classification of embryos at varying developmental stages. Fig. 2 illustrates the preprocessing steps used for spatial isolation of individual embryos.

C. Data Annotation

Annotation was conducted using 100 TLM videos to provide spatial and temporal oversight of the model development. An experienced embryologist from King Abdulaziz University Hospital was involved to ensure the accuracy of the labeled data and provide the biological "ground truth" needed to effectively train the AI model. First, a frame-level annotation file was created for each embryo video, recording three attributes for every frame: the frame number, the hours post-insemination (hpi), and the cell stage. The dataset included frames from the following cell stages: two-, three-, four -, five -, six -, seven-, and eight-cells. Bounding boxes were manually drawn around each individual blastomere(cell) using the Roboflow platform. Roboflow's annotation tool offers an easy-to-use interface for effective annotation, to ensure consistency and high-quality labeling throughout the dataset [36], [37]. This discrete object detection strategy was adopted over global embryo localization to provide the model with the high-resolution morphological data required to differentiate between consecutive cleavage states (e.g., 2-cell vs. 3-cell). By identifying each cell as an independent instance, the proposed framework calculates the developmental stage through the aggregate count of detected bounding boxes per frame, ensuring that subtle internal boundaries are recognized as primary features for classification .

D. Data Augmentation and Class Distribution Balancing

The dataset comprises frames capturing various stage of cell development, such as the 2-, 3-, 4-, 5-, 6-, 7-, and 8-cell stages. With earlier stages (like 2-cell and 4-cell) being over- represented and later stages (like 6-cell, 7-cell, and 8-cell) being relatively underrepresented, in Fig. 3 a thorough distribution analysis shows a notable imbalance across the stages. The observed imbalance in the number of frames across cleavage stages—characterized by a higher proportion of frames in earlier stages and fewer in later stages—can be attributed to two main factors. The first is **short Later Stage Duration**: Compared to earlier stages, later stages—like 6-cell and 7-cell—occur over significantly shorter time intervals, resulting in fewer frames being recorded. The second factor is **cell Overlap in Advanced Stages**: Individual cells spatially overlap as cell division advances, making precise cell differentiation more difficult. Both data collection and annotation are made more difficult by this phenomenon. All images were scaled to a consistent resolution of 416 x 416 pixels to ensure consistency throughout the dataset. To guarantee sufficient representation of every cell stage for model development and assessment, the dataset is divided into 70% for training, 20% for validation, and 10% for testing. Some of the dataset's original images showed blurring and focus issues, which are common problems with (TLM) generated images. These flaws can occur as a result of lens focus errors or image noise, which, if not addressed, can have a negative impact on the model's performance. The dataset was artificially expanded while maintaining biological relevance through the use of images augmentation. The changes consist of:

1) Flipping both horizontally and vertically: To take into consideration variations in imaging angles.
2) Brightness Adjustment (±8%): To improve resilience to changes in lighting, exposure changes are simulated.
3) Random Gaussian Blur (sigma = 1 px): To improve generalization and simulate noise, making the model more tolerant to minor image flaws and obstacles experienced in TLM imaging.

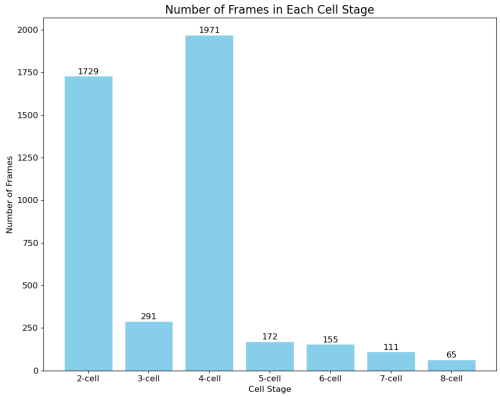


Fig. 3. Dataset distribution.

Undersampling was used to lessen the dominance of over-represented stages following augmentation. The goal was to maintain adequate representation for efficient training while achieving a more consistent distribution of 700 frames across all cell stages. Fig. 4 shows the distribution of the dataset for all cell stages after undersampling and augmentation.

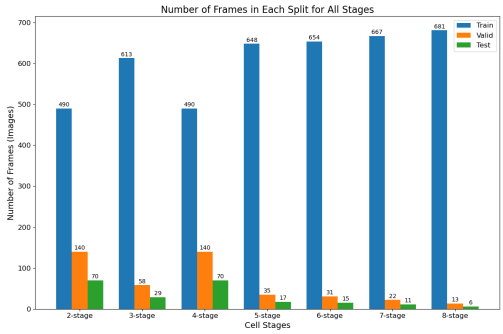


Fig. 4. Distribution of dataset frames for each cell stage: 70% for training, 20% for validation, and 10% for testing after handling class imbalance.

E. Cell Detection

Object Detection is one of the principal application areas in computer vision. The aim of object detection is to detect and localize objects in images through class labels and bounding boxes [38], [39]. There are two main types of detection methods: two-stage detectors like Faster R-CNN and Mask R-CNN that are guaranteed to produce an accurate answer, and one-stage detectors like YOLO and SSD that produce fast answers. There is a growing cadre of methods, including DETR and EfficientDet, that are focused on efficiency and scalability. Among these detection methods, YOLO is a prominent method for real-time detection. YOLO divides images into grids, predicting the bounding boxes and confidence scores for the object(s) contained in each of the grid cells. Using layers that are pre-trained among other bounding box layers, YOLO is able to produce good performance across a range of objects.

YOLOV11 is the most recent model in Ultralytics' YOLO series of real-time object detectors. it comes in a variety of model sizes, from nano to extra-large, making it suitable for a wide range of applications, from resource-limited edge devices to powerful computing systems. It adds new architectural features such as the C3k2 block, SPPF, and C2PSA, which improve its ability to extract and process features more efficiently. These enhancements enable YOLOv11 to better analyze and interpret complex visual data, potentially improving detection accuracy in a variety of scenarios. The integration of advanced spatial attention mechanisms, such as the C2PSA, is a significant improvement because it allows the model to focus on important regions of an image. YOLOV11 was selected for cell detection due to its ability to efficiently process large-scale time-lapse microscopy (TLM) datasets while maintaining reliable localization performance. Unlike two-stage object detectors, YOLO's single-stage architecture enables rapid frame-wise inference, which is essential for analyzing long TLM video sequences at high temporal resolution. Furthermore, the proposed framework uses YOLO exclusively for detecting individual cells rather than directly classifying cleavage stages. Developmental stages are subsequently inferred by counting detected cells across consecutive frames, thereby avoiding reliance on subtle morphological distinctions between stages and improving robustness under variable illumination and cell

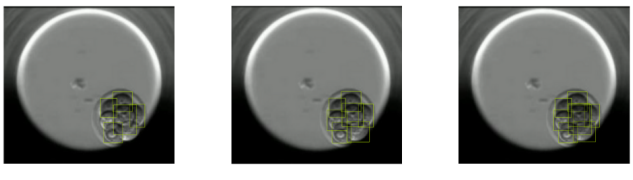


Fig. 5. Impact of IoU threshold on detection accuracy.

overlap conditions. Our proposed model operated as follows: Detection, Identifying and locating every instance of the "cell" class in the frame. Stage Assignment: The overall count of detected cells within a frame determines the cleavage stage label for that frame. For example, the existence of five unique cells signifies the 5-cell stage. The YOLOv11 model was set up on Ultralytics Hub [40]. To improve accuracy and shorten training time, a pre-trained model served as a foundation for the training process. The training procedure was set up with 100 epochs using 416×416 resized input images, a 100-epoch patience threshold to avoid overfitting. The batch size of 22 is determined by the AutoBatch mechanism, which automatically determines the maximum batch size that can be accommodated in the GPU memory during training to adjust to the available computational resources. The optimizer was configured with a momentum of 0.9 and a learning rate of 0.002. To train the YOLOv11 model efficiently, two NVIDIA T4 GPUs were used in a Kaggle environment.

YOLOv11 efficiently locates and categorizes overlapping objects, such as cells in our case, by employing anchor boxes to predict bounding boxes and their associated confidence scores in a single forward pass. During detection, many bounding boxes may be proposed for the same object. In order to overcome this, YOLO employs Non-Maximum Suppression (NMS), which selects the box with the highest confidence score after suppressing overlapping boxes based on their Intersection over Union (IoU) values. This ensures precise localization of individual cells, even when they significantly overlap, and sustains a high detection performance as indicated by measures like mean Average Precision (mAP). accuracy. Fig. 5 illustrates the impact of Intersection over Union (IoU) thresholds on detection accuracy. A higher IoU value (e.g., 0.70) facilitates more precise and reliable cell localization, whereas lower IoU values (e.g., 0.20 or 0.40) are associated with increased misdetections or overlapping prediction errors.

F. Cleavage Stage Identification and HPI Determination

Using a fixed confidence threshold of 0.55 across all cleavage stages, a YOLOv11 model is employed to detect individual cells within each frame. Additionally, an IoU threshold of 0.70 is applied by the model to provide precise bounding box predictions. The cell count is shown on the frame, and bounding boxes are drawn around any cells that are found. Only cleavage stages containing between 2 and 8 cells are considered in this analysis. A frame is saved to the output folder only when it corresponds to the initiation of a new cleavage stage, defined by the following criteria:

1) Uniqueness: if the number of detected cells is unique, meaning it hasn't been recorded before.
2) Progression: The current cell count is higher than the previous count that was noted.

Because of the inherent heterogeneity of embryo growth, certain division phases might not be captured in the video, necessitating this second requirement. For instance, the three-cell stage might not be apparent in the video, or some embryos might split straight from two to four cells without going through it. This criterion reduces the possibility of errors resulting from overlapping cells that could otherwise be misinterpreted for example, falsely recognizing three cells when only two are present by guaranteeing that only major stage transitions are recorded. Determining the corresponding hpi of the saved frames is the next step. Accurate hpi calculation is essential to monitor embryo development over time. OCR is a technology that transforms handwritten or printed text in images into digital formats that can be read by machines [41]. OCR is essential to biomedical research because it allows the extraction of quantitative data from medical images, including Medical Records [42], Ocular Biometry reports [43], text from figures in full-text biomedical articles [44], and experimental annotations. Numerous efficient Python libraries have been developed for OCR, including Tesseract, a popular open-source engine; Pytesseract [45], a Python wrapper for Tesseract; OpenCV, a flexible computer vision library; and EasyOCR [46], an open-source OCR tool based on deep learning. EasyOCR uses long short-term memory (LSTM) architectures and CNNs to detect and recognize text. PaddleOCR, deep learning-based OCR system created by the PaddlePaddle group. For high text detection and recognition accuracy, PaddleOCR utilizes CNNs, attention mechanisms, and sequence models like recurrent neural networks (RNNs) [47], [48]. Deep learning-based OCR tools were chosen for their robustness and ability to handle the complex imaging conditions common in biomedical TLM data, thus making sure that the annotations of hpi are accurately extracted.

The timestamp was extracted by cropping a fixed region of interest corresponding to the white rectangular overlay containing the hpi value, which appears at a consistent location across all time-lapse images. The cropping coordinates (x = 300, y = 350, width = 200, height = 200) were predefined and automatically applied to all frames, without manual intervention or sequence-specific adjustment, ensuring standardized OCR input across the dataset. To ensure the reliability of the extracted hpi values, a simple numerical validation step was applied to the OCR output. Since all embryos in the dataset fall within a biologically plausible range below 73 hours post-insemination, any extracted value exceeding 73 hpi was treated as an OCR artifact caused by an erroneous leading digit and was automatically corrected by removing the leading digit, restoring the expected temporal range. This lightweight validation step effectively filtered OCR misreads while preserving correct timestamps for downstream cleavage timing analysis. Due to variability in image brightness or quality, OCR is not always flawless and sometimes misreads numbers. Three OCR libraries—PyTesseract, EasyOCR, and PaddleOCR—were tested for performance. The hpi value is allocated to the frame if OCR is successful in extracting it. When OCR is unable to retrieve the timestamp. Several reasons can lead to OCR failures:

- creation of out-of-bound values, where valid times-

tamps (e.g., 69.9 h) are misinterpreted as wrong values like '4569,' which exceeds the system's maximum allowed hpi range (mice embryo typically reaches the 8-cell stage around 48 to 72 hpi).

- misrecognition of digits, where the algorithm finds or interprets numbers improperly.

An alternate approach has to be used. In these situations, our dataset of TLM videos' empirical observations of cleavage timing serve as the basis for this alternate approach. After examining several embryos, it was observed that the cleavage stages occurred at a comparatively constant interval of about 0.6 hpi each frame. Previous studies have employed a similar approach, in which, in the absence of precise hpi values, the time annotations for cleavage stages were obtained using frame rate and time-lapse system setups [17].

$$t_n = t_1 + 0.6 \times (F_n - 1)$$

where:

- t_1 – The hpi of the first frame.
- F_n – The frame number for which the time is being calculate.
- 0.6 – The frame interval.

IV. Results

This section presents the results of the proposed methodology on two major tasks: cell-cleavage stage detection and OCR evaluation that used for cleavage onset time prediction. For clarity, the findings are divided into two corresponding subsections.

A. Cell Stage Detection

This section presents a detailed evaluation of the YOLOv11 model in detecting embryo cell stages (two to eight cells), using a test set of 218 images sized (416x416 pixels). The YOLOv11 model achieved strong performance, with a precision of 0.9793, a recall of 0.9565, and an F1-score of 0.9678. The mAP@0.5 (mean Average Precision at an IoU threshold of 0.5) was 0.9767. This shows that our model successfully identified and localized most cells, achieving a strong alignment between the predicted and ground-truth bounding boxes. while mAP@0.5:0.95, which evaluates precision across various IoU thresholds from 0.5 to 0.95 in increments of 0.05, was measured at 0.74. was 0.7407. Fig. 6 shows the overall precision and recall, as well as the mean Average Precision (mAP) at thresholds 50 (mAP50) and 50-95 (mAP50-95), for the validation set throughout training epochs. Fig. 7 shows the confusion matrix for the model in detecting and classifying cell stages generally. For the majority of cell stages, the matrix shows high classification accuracy; this is especially true for the 2-cell and 4-cell stages, when most predictions match the actual labels. Compared to the earlier cleavage stages in the matrix, there were more incorrect classifications between the seven-cell stage and the nearby phases of five, six, and eight cells.

A set of key metrics was used to evaluate the model's performance: accuracy, precision, recall, F1-score, and specificity.

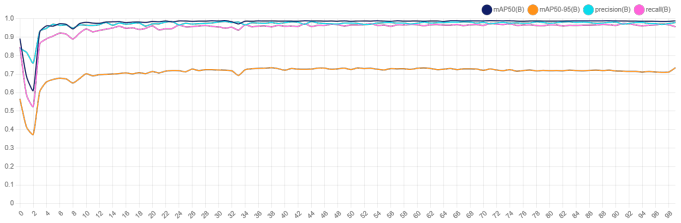


Fig. 6. Validation metrics over epochs.

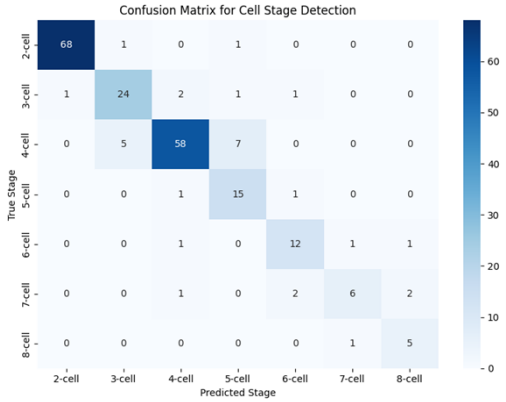


Fig. 7. Confusion matrix for automated cell stage detection. Rows: true stages (embryologist annotations); Columns: predicted stages (model output).

TABLE I. Evaluation Metrics for Every Cell Stage

Category	Precision	Recall	F1-Score	Specificity	Accuracy
2-cell	98.55%	97.14%	97.84%	99.32%	98.53%
3-cell	80%	82.76%	81.35%	96.83%	94.86%
4-cell	92.06%	82.86%	87.25%	96.62%	92.02%
5-cell	62.50%	88.24%	73.17%	95.52%	94.86%
6-cell	75%	80%	77.42%	98.03%	96.97%
7-cell	75%	54.55%	63.27%	99.04%	96.88%
8-cell	62.50%	83.33%	71.43%	98.60%	98.26%
Overall	**86.24%**	**86.24%**	**86.24%**	**97.71%**	**86.61%**

These metrics offer a thorough grasp of the model's capacity to accurately identify and categorize every cell stage based on the number of detected cells in the frame. Precision measures the percentage of all predicted cell stages correctly identified as instances of the target cell stage. Recall (also known as sensitivity) measures the ratio of true positives (correctly detected instances of the target stage) to the sum of true positives and false negatives (i.e., all frames that truly belong to that stage). The precision and recall weighted average is known as the F1-score. Specificity is calculated as the ratio of true negatives (i.e., frames that are correctly identified as not belonging to the target stage) to the total number of frames that truly do not represent that stage. It demonstrated the ability of the model to prevent misclassifications for non-target stages. The accuracy reflects the overall effectiveness of the model by measuring the proportion of correctly classified instances (both positives and negatives) out of all predictions made. Table I summarizes these metrics for each cell stage using input images of size (416x416 pixels).

Although the table presents the raw quantitative results,

the subsequent list presents a brief overview of the model's performance at each stage, emphasizing both its advantages and limitations:

- Two-cell stage: The model demonstrated strong efficacy in this category by classifying 2-cell stages with high precision 98.55%, recall 97.14% , and F1-score 97.84%. These results indicate robust and consistent detection of two-cell instances with a low misclassification rate.
- Three-cell and four-cell stages: With F1-scores of 81.35% and 87.25% , respectively, both stages demonstrated high performance, although with somewhat reduced precision and recall when compared to the 2-cell stage.
- Five-cell and Six-cell stages: The model's performance showed moderate accuracy. For the 5-cell stage, the F1-score of 73.17% reflects low precision 62.50% and high recall 88.24%, indicating frequent false positives despite successfully identifying most true cases. In contrast, the 6-cell stage achieved a more balanced outcome (F1-score 77.42%; precision 75%; recall 80%), suggesting that most instances were correctly classified with a moderate level of misclassification.
- seven-cell and eight-cell stages: The model struggled most with the 7-cell stage, hitting an F1-score of just 63% and recall at 55%. This happened mostly because there weren't many examples in the dataset, and the cells tended to overlap a lot, which led to confusion with the 6- or 8-cell stages. On the other hand, the 8-cell stage did better, landing an F1-score of 71% The recall was strong 83% so the model caught most of the real 8-cell stages. But the precision dropped to 63%, which means it also flagged quite a few that weren't actually 8-cell, so false positives were still a problem.
- Overall Performance: With an overall F1-score of 86.24% and specificity of 0.9771, demonstrating a strong ability to distinguish between target and non-target classes and consistent classification performance across all cell stages.

B. OCR Evaluation

Three OCR libraries were assessed to determine their performance in extracting HPI timestamps: PyTesseract, EasyOCR, and PaddleOCR. The objective text was a time stamp in the format xx.x h, placed in a small white rectangle with black numbers in the bottom right corner of each frame. Due to the large variation in contrast between the images in the dataset, no pre-processing was applied, rendering the generic enhancement techniques unreliable. Instead, each frame was cropped to the region of interest to isolate the timestamp and minimize noise. The performance of PyTesseract, EasyOCR, and PaddleOCR was evaluated using Manual Recognition Accuracy. To establish a ground truth, To perform this, a dataset of frames was randomly selected, and the timestamps visible in the images were manually annotated as ground truth. The output of each OCR engine was manually compared against the visual timestamp visible in the Time-Lapse Monitoring (TLM) images. An "Exact Match" criterion was utilized, where a detection was marked as correct only if it perfectly mirrored the visual data. The following list summarizes the OCR libraries' performance, highlighting the progression from less to more effective approaches depending on digit recognition under varying image conditions in terms of accuracy, dependability, and robustness.

- PyTesseract: Initially, PyTesseract was tested with various configurations but showed unsatisfactory results. The library had difficulties in accurately reading digits, either misreading them or failing to extract them at all. For example, "13.7" was incorrectly read as "3.7".
- EasyOCR: Next, EasyOCR was subsequently evaluated and demonstrated improved performance compared to PyTesseract.However, the library continued to have challenges in accurately recognizing some numbers. In particular, the library failed to read the tens place in some cases, such as reading "31.5" as "1.5", or completely ignoring the tens place and reading "1.5" as "5".
- PaddleOCR: PaddleOCR was evaluated last and demonstrated the highest accuracy. All values extracted by Paddle were accurately matched to the annotations provided by embryologists. Due to this consistent and reliable performance, Paddle was adopted as the preferred tool in our methodology for automating the hpi annotation process.

Table II summarizes the performance of the three OCR libraries in extracting hpi values, compared to the expert-annotated ground truth.

TABLE II. COMPARISON OF EXPERT-ANNOTATED HPI VALUES WITH PREDICTIONS FROM THREE OCR TOOLS

Expert (hpi)	PaddleOCR	EasyOCR	PyTesseract	Error Description
1.5	1.5	5	–	Misread digit (EasyOCR) ,Missing value (PyTesseract)
35.1	35.1	35.4	–	Misread digit (EasyOCR) ,Missing value (PyTesseract)
46.5	46.5	646.5	–	Extra digits (EasyOCR) ,Missing value (PyTesseract)

V. DISCUSSION

This study aimed to automate the process of tracking embryonic development by identifying cleavage stages and accurately determining the onset times of cell division. Deep learning and image processing techniques were used to analyze TLM videos. This was achieved by constructing an efficient methodology that annotates hpi of each cleavage stage while accurately locating cells within the corresponding stage images. This study showcases the power of deep learning and computer vision in automating the identification of crucial cleavage stages in embryo development. By providing precise, frame-by-frame predictions and organized data on cleavage timing, the proposed approach gives embryologists valuable developmental insights that exceed those gained from traditional manual observation. This level of accuracy in stage detection allows for more objective and consistent evaluations of embryos. Our methodology demonstrated the ability to accurately identify the onset of cell division stages up to the seven-cell stage, with an average time delay of 1–2 hpi. However, at the eight-cell stage, a significant time delay was observed compared to the embryologists' annotations. This disparity is explained by the more significant overlap between cell borders, which intensifies with increasing cell count. This

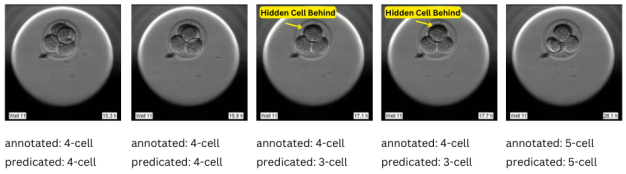


Fig. 8. Time-series of frames illustrating cell occlusion: A 4-cell stage can be seen in the first frame, but as the series goes on, one cell trails behind another, giving the impression that the stage contains only three cells. This illustrates how difficult it is to find overlapping cells.

overlap between cells was also observed in [14,17], and the inferiority of their methodology caused a delay of 2-3 hours in detecting the starting time of cell cleavage. The occurrence of overlapping cells and visual obstructions in certain frames, particularly during the later stages (after the six-cell stage), led to a decrease in detection accuracy. This was especially evident in the counting and differentiation of closely packed cells. This illustrates a challenge with the dataset, which contains overlaps that occur naturally in the later stages of cleavage. Adding a wider variety of overlapping cell configurations to the dataset could help overcome this restriction. Future enhancements, such as the integration of temporal context or refined segmentation techniques, could significantly bolster performance in these challenging scenarios. Our proposed methodology also faces challenges in detecting hidden cells: cells with dark shadows or those that are partially hidden behind other cells are not recognized. This problem is particularly important in the transition state between one stage and another, as shown in Fig. 8. More occluded cell samples should be included in the dataset in future studies so that the model can better learn and generalize these patterns.

The proposed model operated directly on raw TLM frames to ensure that the training data closely matched real-world scenarios. This design choice aims to enhance the robustness and generalizability of the method by avoiding transformations that may alter biologically relevant visual cues. Given the heterogeneous illumination conditions present in the TLM dataset, applying global image normalization or contrast enhancement could introduce inconsistencies across samples and potentially distort meaningful morphological information. As part of our research, the time differences between subsequent cleavage stages were calculated. This feature helps to improve the assessment of embryo quality by giving embryologists comprehensive data on developmental dynamics. Two complementary techniques were combined to address the dataset's class imbalance issue. Selective data augmentation was applied to increase the number of samples in minority classes. Then, random undersampling is used to decrease the number of samples in the majority classes. This combined strategy yielded satisfactory evaluation metrics, demonstrating its effectiveness in addressing class disparity. In order to put the performance of the proposed YOLOv1-based cell stage detection model into perspective, the obtained results are compared with those of earlier studies that used YOLOv5 for the detection of human embryo cell stage. Applying data augmentation techniques [17], the model performed well on early cleavage stages (e.g., F1-score of 95% for 1-cell and 88% for 2-cell), but performance significantly declined on later stages, with F1-scores falling to 0.32 for 3-cell, 0.36 for 5-cell, and 17% for 6-cell. Our method, on the other hand, produced consistently high overall F1-scores of 0.8624 and accuracy of 86.61% when applied to mouse embryo time-lapse videos. The F1-scores were relatively stable across stages, ranging from a minimum of 63.27% (7-cell) to a maximum of 97.84% (2-cell). Higher specificity (97.71% overall) and a better balance between sensitivity and precision at every stage further supported this performance. The superiority of the proposed framework is quantitatively validated through a comparative analysis with the recent study by Sharma et al. [17], as detailed in Table III. Furthermore, our approach corrects for class imbalance by undersampling and targeted data augmentation, which probably helped to improve minority-stage class detection. The framework demonstrates high adaptability to diverse clinical environments through a calibratable OCR pipeline. By utilizing coordinate-based ROI localization. The system can be seamlessly adjusted to different incubator display formats. Direct quantitative comparison with prior time-lapse embryo analysis studies is constrained by the absence of publicly available, standardized datasets and by differences in embryo species, imaging systems, and annotation protocols. This limitation is explicitly acknowledged in the present study. Accordingly, performance claims are restricted to improvements observed within the same experimental setting and under a consistent evaluation protocol. Where comparisons with related work are discussed, they are intended to illustrate relative gains in robustness and detection capability—particularly at later cleavage stages—rather than to assert absolute superiority across heterogeneous datasets. The comparative analysis highlights the generalizability and robustness of our deep learning pipeline, especially in managing class imbalance and handling transitional stages with greater stability, despite the differences in the dataset.

TABLE III. PERFORMANCE BENCHMARKING AND COMPARATIVE ANALYSIS: PROPOSED YOLOV11 FRAMEWORK VS. STATE-OF-THE-ART BASELINE OF SHARMA ET AL.[17] (YOLOV5)

Cell Stage	Sharma et al.[17] - yolov5 Accuracy (%)	Proposed Model Accuracy (%)
2-cell	85%	98%
3-cell	57%	94%
4-cell	55%	92%
5-cell	51%	94%
6-cell	39%	96%
7-cell	31%	96%
8-cell	47%	98%

VI. CONCLUSION

Given that the timing of cell cleavage is a critical parameter of embryo viability and developmental potential, it certainly plays a major role in embryo assessment. Detecting and extracting the onset of these cleavage events automatically can help embryologists Assess the quality of embryos and select candidates with better chances of implantation. In this work, YOLOv11 and OCR-based timing extraction are used to automatically annotate mouse embryos' cleavage stage and onset time. The suggested approach, despite the challenging class imbalance present in the dataset, achieves high performance in cleavage stage detection and cleavage onset timing extraction. Through the combination of selective data augmentation and random undersampling. The problem of class imbalance was

successfully addressed, which enhanced the model's robustness and evaluation metrics. Our methodology demonstrated the ability to accurately identify the onset of cell division stages up to the seven-cell stage, with an average time delay of 1–2 hpi, and showed excellent performance in differentiating between various developmental phases in mouse embryo TLM videos, achieving Accuracy of 86.61% , F1-score of 86.24% ,and precision of 86.24% in identifying and classifying cleavage stages. One of the key difficulties encountered in this work is the significant cell overlap, which affected the model's performance, particularly at the later stages of cleavage. As it influenced the accuracy of detection and caused minimal delays in determining the onset of division. In addition, the approach was having issues identifying cells that were occluded partially or overshadowed, particularly with fast changes in developmental phases. There are several promising avenues for future research in this field to overcome the present limitations. Accumulating larger and well-annotated TLM datasets is a crucial step to increase model robustness and promote more balanced learning across all cleavage stages. Future work could utilize 3D imaging techniques or incorporate temporal context using video-based models that analyze frame sequences rather than individual frames to address issues such as partially hidden and overlapping cells.

Data Availability

While the dataset is not publicly available due to clinical privacy and institutional ethical constraints, it can be shared upon reasonable request to support reproducibility, subject to applicable data governance protocols.

References

[1] World Health Organization. *Infertility Prevalence Estimates, 1990–2021*. Geneva: World Health Organization, 2023. Licence: CC BY-NC-SA 3.0 IGO

[2] Iqbal, I., Mustafa, G., and Ma, J. 2020. "Deep Learning-Based Morphological Classification of Human Sperm Heads." *Diagnostics* 10 (5): 325–332.

[3] Almaslami, F., Aljunid, S. M., and Ghailan, K. "Demographic Determinants and Outcome of In Vitro Fertilization (IVF) Services in Saudi Arabia." *Journal of International Medical Research* 46, no. 4 (April 2018): 1537-1544. https://doi.org/10.1177/0300060517749329.

[4] Lockhart, L. 2021. "Automating Assessment of Human Embryo Images and Time-Lapse Sequences for IVF Treatment." Master's thesis, Simon Fraser University.

[5] Meseguer, Maria, et al. "The Use of Morphokinetics as a Predictor of Embryo Implantation." *Human Reproduction* 26, no. 10 (2011): 2658–2671.

[6] Wong, Connie C., Kevin E. Loewke, Nancy L. Bossert, Barry Behr, Christopher J. De Jonge, Thomas M. Baer, and Renee A. Reijo Pera. 2010. "Non-invasive Imaging of Human Embryos Before Embryonic Genome Activation Predicts Development to the Blastocyst Stage." *Nature Biotechnology* 28 (10): 1115–1121. Nature Publishing Group US New York.

[7] Rai, R., and L. Regan. "Recurrent Miscarriage." *The Lancet* 368, no. 9535 (2006): 601–611.

[8] Wong, C., AA Chen, B. Behr, and S. Shen. 2013. "Time-lapse Microscopy and Image Analysis in Basic and Clinical Embryo Development Research." *Reproductive BioMedicine Online* 26 (2): 120–129. Elsevier.

[9] Hlinka, D., B. Kal'atová, I. Uhrinová, S. Dolinská, J. Rutarová, J. Řezáčová, S. Lazarovská, and M. Dudáš. 2012. "Time-Lapse Cleavage Rating Predicts Human Embryo Viability." *Physiological Research* 61 (5): 581–589.

[10] Cetinkaya, Murat, Caroline Pirkevi, Hakan Yelke, Yesim Kumtepe Colakoglu, Zafer Atayurt, and Semra Kahraman. 2015. "Relative Kinetic Expressions Defining Cleavage Synchronicity Are Better Predictors of Blastocyst Formation and Quality Than Absolute Time Points." *Journal of Assisted Reproduction and Genetics* 32: 27–35. Springer.

[11] Senechkin, I. V., L. V. Hilkevich, and M. A. Kurcer, "Cleavage of human embryos: Options and diversity," Acta Naturae, vol. 8, no. 3, pp. 88–96, 2016.

[12] Raudonis, Vidas, Agne Paulauskaite-Taraseviciene, Kristina Sutiene, and Domas Jonaitis. 2019. "Towards the Automation of Early-Stage Human Embryo Development Detection." *Biomedical Engineering Online* 18: 1–20. Springer.

[13] Nakaguchi, Victor Massaki, and Tofael Ahamed. 2022. "Development of an Early Embryo Detection Methodology for Quail Eggs Using a Thermal Micro Camera and the YOLO Deep Learning Algorithm." *Sensors* 22 (15): 5820. MDPI.

[14] Sharma, Akriti, Mette H. Stensen, Erwan Delbarre, Momin Siddiqui, Trine B. Haugen, Michael A. Riegler, and Hugo L. Hammer. 2022. "Detecting Human Embryo Cleavage Stages Using YOLO V5 Object Detection Algorithm." In *Symposium of the Norwegian AI Society*, 81–93. Springer International Publishing Cham.

[15] Jia, Nan, Bin Li, Yuliang Zhao, Shijie Fan, Jun Zhu, Haifeng Wang, and Wenwen Zhao. 2023. "Exploratory Study of Sex Identification for Chicken Embryos Based on Blood Vessel Images and Deep Learning." *Agriculture* 13 (8): 1480. MDPI.

[16] Yang, Ruixin, and Yingyan Yu. 2021. "Artificial Convolutional Neural Network in Object Detection and Semantic Segmentation for Medical Imaging Analysis." *Frontiers in Oncology* 11: 638182. Frontiers Media SA.

[17] Sharma, Akriti, Ayaz Z. Ansari, Radhika Kakulavarapu, Mette H. Stensen, Michael A. Riegler, and Hugo L. Hammer. 2023. "Predicting Cell Cleavage Timings from Time-Lapse Videos of Human Embryos." *Big Data and Cognitive Computing* 7 (2): 91. https://doi.org/10.3390/bdcc7020091.

[18] Pinto-Coelho, L. How Artificial Intelligence Is Shaping Medical Imaging Technology: A Survey of Innovations and Applications. Bioengineering 2023, 10, 1435. https://doi.org/10.3390/bioengineering10121435

[19] Ghaffar Nia, N.; Kaplanoglu, E.; Nasab, A. Evaluation of Artificial Intelligence Techniques in Disease Diagnosis and Prediction. Discov. Artif. Intell. 2023, 3, 5.

[20] Parmar, U.P.S.; Surico, P.L.; Singh, R.B.; Romano, F.; Salati, C.; Spadea, L.; Musa, M.; Gagliano, C.; Mori, T.; Zeppieri, M. Artificial Intelligence (AI) for Early Diagnosis of Retinal Diseases. Medicina 2024, 60, 527. https://doi.org/10.3390/medicina60040527

[21] Tanveer, Hassan, Muhammad Faheem, Arbaz Haider Khan, and Muhammad Ali Adam. "AI-Powered Diagnosis: A Machine Learning Approach to Early Detection of Breast Cancer." INTERNATIONAL JOURNAL OF ENGINEERING DEVELOPMENT AND RESEARCH 13, no. 2 (2025): 153-166.

[22] Bongurala, Archana Reddy, Dhaval Save, Ankit Virmani, and Rahul Kashyap. "Transforming health care with artificial intelligence: redefining medical documentation." Mayo Clinic Proceedings: Digital Health 2, no. 3 (2024): 342-347.

[23] Kumar, Y.; Koul, A.; Singla, R.; Ijaz, M.F. Artificial Intelligence in Disease Diagnosis: A Systematic Literature Review, Synthesizing Framework and Future Research Agenda. J. Ambient. Intell. Humaniz. Comput. 2023, 14, 8459–8486.

[24] VerMilyea, M.; Hall, J.M.M.; Diakiw, S.M.; Johnston, A.; Nguyen, T.; Perugini, D.; Miller, A.; Picou, A.; Murphy, A.P.; Perugini, M. Development of an artificial intelligence-based assessment model for prediction of embryo viability using static images captured by optical light microscopy during IVF. Hum. Reprod. 2020, 35, 770–784

[25] Kragh, M.F.; Karstoft, H. Embryo selection with artificial intelligence: How to evaluate and compare methods? J. Assist. Reprod. Genet. 2021, 38, 1675–1689.

[26] Chen, F.; Chen, Y.; Mai, Q. Multi-Omics Analysis and Machine Learning Prediction Model for Pregnancy Outcomes After Intracytoplasmic Sperm Injection–in vitro Fertilization. Front. Public Health 2022, 10, 924539.

[27] Zhao, M., Xu, M., Li, H., Alqawasmeh, O., Chung, J. P. W., Li, T. C., Lee, T. L., Tang, P. M., & Chan, D. Y. L. (2021). Application of convolutional neural network on early human embryo segmentation during in vitro fertilization. Journal of cellular and molecular medicine, 25(5), 2633–2644. https://doi.org/10.1111/jcmm.16288

[28] Rajendran, Suraj, Matthew Brendel, Josue Barnes, Qiansheng Zhan, Jonas E. Malmsten, Pantelis Zisimopoulos, Alexandros Sigaras et al. "Automatic ploidy prediction and quality assessment of human blastocysts using time-lapse imaging." Nature Communications 15, no. 1 (2024): 7756.

[29] Moussavi, Farshid, Yu Wang, Peter Lorenzen, Jonathan Oakley, D. Russakoff, and Stephen Gould. "A Unified Graphical Models Framework for Automated Human Embryo Tracking in Time-Lapse Microscopy." In *2014 IEEE 11th International Symposium on Biomedical Imaging (ISBI)*, 314–320. IEEE, 2014.

[30] Khan, Aisha, Stephen Gould, and Mathieu Salzmann. "Automated Monitoring of Human Embryonic Cells up to the 5-Cell Stage in Time-Lapse Microscopy Images." In *2015 IEEE 12th International Symposium on Biomedical Imaging (ISBI)*, 389–393. IEEE, 2015.

[31] Khan, Aisha, Stephen Gould, and Mathieu Salzmann. "Deep Convolutional Neural Networks for Human Embryonic Cell Counting." In *Computer Vision–ECCV 2016 Workshops: Amsterdam, The Netherlands, October 8-10 and 15-16, 2016, Proceedings, Part I 14*, 339–348. Springer, 2016.

[32] Malmsten, Jonas, Nikica Zaninovic, Qiansheng Zhan, Zev Rosenwaks, and Juan Shan. "Automated Cell Division Classification in Early Mouse and Human Embryos Using Convolutional Neural Networks." *Neural Computing and Applications* 33 (2021): 2217–2228. Springer.

[33] Ragab, Mohammed Gamal, Said Jadid Abdulkadir, Amgad Muneer, Alawi Alqushaibi, Ebrahim Hamid Sumiea, Rizwan Qureshi, Safwan Mahmood Al-Selwi, and Hitham Alhussian. "A comprehensive systematic review of YOLO for medical object detection (2018 to 2023)." IEEE Access 12 (2024): 57815-57836.

[34] Quinn, Patrick, and Frederick C. Horstman. "Is the Mouse a Good Model for the Human with Respect to the Development of the Preimplantation Embryo In Vitro?" *Human Reproduction* 13, no. suppl_4 (December 1998): 173–183. https://doi.org/10.1093/humrep/13.suppl_4.173.

[35] Sabhnani, Tanya V., Aisha Elaimi, Hanan Sultan, Adel Alduraihem, Paul Serhal, and Joyce C. Harper. "Increased Incidence of Mosaicism Detected by FISH in Murine Blastocyst Cultured In Vitro." *Reproductive BioMedicine Online* 22, no. 6 (2011): 621–631.

[36] Lebumfacil, Aaron Joaquin, and Patricia Angela Abu. "Traffic Sign Detection and Recognition Using YOLOv5 and Its Versions." In *2022 IEEE 1st International Conference on Cognitive Mobility (CogMob)*, 11–18. IEEE, 2022.

[37] Aydin, Burchan, and Subroto Singha. "Drone Detection Using YOLOv5." *Eng* 4, no. 1 (2023): 416–433. MDPI.

[38] Brownlee, Jason. 2019. "A Gentle Introduction to Object Recognition with Deep Learning." *Machine Learning Mastery*. May 2019. https://machinelearningmastery.com/object-recognition-with-deep-learning/.

[39] Soviany, Petru, and Radu Tudor Ionescu. 2018. "Optimizing the Trade-Off Between Single-Stage and Two-Stage Deep Object Detectors Using Image Difficulty Prediction." In *2018 20th International Symposium on Symbolic and Numeric Algorithms for Scientific Computing (SYNASC)*, 209–214. https://doi.org/10.1109/SYNASC.2018.00041.

[40] Ultralytics. *Ultralytics HUB*. Accessed April 8, 2025. https://hub.ultralytics.com/.

[41] Islam, Noman, Zeeshan Islam, and Nazia Noor. 2017. "A Survey on Optical Character Recognition System." *arXiv preprint* arXiv:1710.05703.

[42] Zaryab, M. A., and C. R. Ng. "Optical Character Recognition for Medical Records Digitization with Deep Learning." In *2023 IEEE International Conference on Image Processing (ICIP)*, 3260–3263. IEEE, October 2023.

[43] Salvi, A., L. Arnal, K. Ly, G. Ferreira, S. Y. Wang, C. Langlotz, V. Mahajan, and C. A. Ludwig. "Ocular Biometry OCR: A Machine Learning Algorithm Leveraging Optical Character Recognition to Extract Intraocular Lens Biometry Measurements." *Frontiers in Artificial Intelligence* 7 (2025): 1428716. https://doi.org/10.3389/frai.2024.1428716.

[44] Kim, D., and H. Yu. "Figure Text Extraction in Biomedical Literature." *PLOS ONE* 6, no. 1 (2011): e15338.

[45] madmaze. "GitHub - madmaze/pytesseract: A Python Wrapper for Google Tesseract." *GitHub*. Accessed March 2025. https://github.com/madmaze/pytesseract.

[46] JaidedAI. "GitHub - JaidedAI/EasyOCR: Ready-to-Use OCR with 80+ Supported Languages and All Popular Writing Scripts Including Latin, Chinese, Arabic, Devanagari, Cyrillic, and More." *GitHub*. Accessed March 2025. https://github.com/JaidedAI/EasyOCR.

[47] Qin, Hao, Jiajie Jin, Wei Sun, Yucheng Qian, Haigang Wang, and Zhi Wang. "An Analysis Method for Recognizing and Analyzing Multi-Type Documents in Electric Power Operation Site Based on PaddleOCR." In *2024 8th International Conference on Smart Grid and Smart Cities (ICSGSC)*, 363-367. 2024. https://doi.org/10.1109/ICSGSC62639.2024.10813769.

[48] Feng, Lei, Zongwu Ke, and Na Wu. "ModelsKG: A Design and Research on Knowledge Graph of Multimodal Curriculum Based on PaddleOCR and DeepKE." In *2022 14th International Conference on Advanced Computational Intelligence (ICACI)*, 186-192. 2022. https://doi.org/10.1109/ICACI55529.2022.9837529.

Fine-Tuning Language Models for Pedagogy-Aligned Lesson Plans in Cybersecurity Education

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***Abstract*—Lesson planning in cybersecurity is time-consuming and cognitively demanding, especially for less experienced instructors, and manual approaches often lack flexibility across courses and contexts. We present a framework for generating pedagogy-aligned lesson plans using a large language model, integrating measurable objectives (Revised Bloom's Taxonomy), explicit learning theories, and evidence-based teaching strategies. We constructed a domain-specific knowledge base for cybersecurity topics and organized it with sentence-level embeddings and KMeans clustering. A pretrained large language model (GPT-3.5) was then fine-tuned to produce lesson plans that follow this structure. On a held-out test set, the model achieved BLEU 73.5, ROUGE-1 82.2, ROUGE-L 78.2, and BERTScore F1 97.4, reflecting strong lexical and semantic fidelity to reference plans. Although the study is limited to a single academic program and relies primarily on automated metrics, the framework offers practical support for instructors by reducing preparation time, enhancing consistency, and ensuring alignment with pedagogical standards. Future work will expand the curricular scope and involve expert review and classroom validation to assess educational impact.**

***Keywords*—Fine-Tuning; large language models; lesson planning; cybersecurity**

I. Introduction

Lesson plans are essential instruments in education, providing teachers with a clear framework for delivering effective and organized instruction [1]. They outline learning objectives, teaching methods, classroom activities, instructional materials, and assessment strategies required to achieve educational goals [2], [3]. By establishing a structured approach, lesson plans enhance teaching effectiveness and ensure instructional consistency and clarity [3], [4]. Although their components may vary depending on curriculum, educational context, or teacher preference, the primary purpose of lesson plans remains the improvement of instructional quality and student outcomes [5], [1]. Aligning lesson plans with established learning theories, such as constructivism, cognitivism, and constructionism, further strengthens their effectiveness by grounding instruction in well-established principles of how learners acquire, process, and apply knowledge [6], [7]. In addition, the integration of contemporary teaching strategies, including project-based learning, problem-based learning, and flipped classrooms, promotes active engagement, collaboration, and deeper understanding [8], [9].

Within this broader educational context, cybersecurity presents distinctive challenges. As a discipline, it is concerned with safeguarding the confidentiality, integrity, and availability of digital systems [10]. Given its rapidly evolving nature, cybersecurity education must combine strong theoretical foundations with practical, hands-on learning experiences [7], [11]. Effective lesson plans in this domain must balance theory with application, incorporate up-to-date content, and prepare learners to respond to emerging threats [12]. However, lesson planning is often time-intensive and cognitively demanding, particularly for novice teachers with limited pedagogical experience [3], [5]. Traditional lesson planning methods, which rely heavily on manual preparation, can be inefficient and may lack the flexibility to meet diverse instructional needs [2].

Recent advances in large language models (LLMs) such as BERT [13], GPT-3/4 [14], [15], and LLaMA [16] have enabled high-quality, controllable text generation for educational applications [17]. Although pre-training on extensive text corpora provides broad language competence [18], [19], these models often show limited effectiveness in specialized domains. Fine-tuning addresses this limitation by adapting pre-trained models to domain-specific tasks, thereby improving contextual accuracy and alignment with specialized requirements [20], [21]. Such approaches have already been applied in areas such as legal rule classification [22], transportation safety [23], and language-specific text summarization [24].

The effectiveness of fine-tuned models is typically assessed using automatic evaluation metrics that capture different aspects of text quality. In this study, such metrics are employed to assess lexical overlap, structural similarity, and semantic alignment between generated and reference lesson plans, providing a reproducible basis for evaluating instructional content.

Despite recent progress, existing studies have not fully explored the use of fine-tuned large language models for generating structured lesson plans in technically specialized domains such as cybersecurity. This gap is particularly relevant given the growing demand for scalable, pedagogy-aligned, and domain-specific instructional resources. Rather than relying solely on prompt engineering or post-generation filtering, the present study adapts a pre-trained language model to generate cybersecurity lesson plans by embedding pedagogical structure within the data representation and model fine-tuning process. Accordingly, the study addresses the following research questions:

- RQ1. How accurately can a fine-tuned large language model generate structured lesson plans for cybersecurity education?
- RQ2. To what extent do the generated lesson plans align with established pedagogical standards and instructional design principles?

The contributions of this research are as follows:

1) This work designs and constructs a domain-specific lesson planning dataset for cybersecurity to support pedagogy-aware language model fine-tuning.
2) It proposes a structured framework that incorporates explicit pedagogical elements into the fine-tuning process of a large language model for lesson plan generation.
3) It provides an empirical evaluation demonstrating that pedagogy-aligned fine-tuning enables the generation of structurally consistent and instructionally valid lesson plans.

The remainder of this paper is organized as follows: Section II reviews related work, Section III describes the methodology, Section IV presents the results and discussion, and Section V concludes the paper.

II. Related Work

The rapid progress of large language models has generated significant interest in their role within teaching and learning. Recent surveys highlight both their potential to transform instructional practices and the challenges they introduce in terms of reliability, bias, and alignment with educational objectives [17], [20]. Kasneci et al. [17] emphasize the ability of these models to reduce teacher workload and broaden access to instructional resources, while also noting the importance of producing outputs that educators can trust and adapt. Similarly, Zhang et al. [20] report that instruction-tuned models show promising capabilities but remain highly sensitive to the design of adaptation strategies and evaluation protocols. Together, these studies provide valuable context for educational use of LLMs, while also indicating that effective deployment depends on careful consideration of pedagogical alignment rather than generic application alone.

Recent work has explored how large language models can support assessment and instructional content generation. Sridhar et al. [25] investigated the use of GPT-4 to generate learning objectives, demonstrating that model outputs can follow established instructional design frameworks such as Bloom's taxonomy when guided by structured prompts. Similarly, Scaria et al. [26] examined automated question generation across Bloom's taxonomy levels and validated the quality of exam-style questions through expert review. Latif and Zhai [27] applied a fine-tuned ChatGPT model to automated scoring, reporting performance comparable to human graders on large collections of student responses. Collectively, these studies highlight the effectiveness of LLMs in generating and evaluating individual instructional components. At the same time, they primarily focus on isolated elements such as objectives, questions, or assessment outcomes, and therefore provide limited insight into how these components can be coherently integrated into complete, pedagogy-aligned lesson plans.

Evaluating the quality of generated content requires reliable and reproducible measures, leading to the widespread adoption of automatic evaluation metrics in natural language processing. BLEU [28] remains a common standard for measuring precision-oriented n-gram overlap, while ROUGE [29] is frequently employed to capture recall-oriented coverage in summarization. More recently, BERTScore [30] has been introduced to provide a semantic perspective by comparing contextual embeddings, offering closer alignment with human judgments of similarity. Together, these metrics provide complementary views of lexical fidelity, content coverage, and semantic similarity, and their primary strength lies in enabling consistent and scalable evaluation of generated text. However, they implicitly assume that textual similarity is a sufficient proxy for instructional quality, which limits their ability to fully capture pedagogical effectiveness when used in isolation.

Beyond assessment and evaluation, prior research has examined lesson planning systems as a means of providing more direct support for teachers. Zheng et al. [1] proposed an automatic lesson plan generator that improves plan quality through iterative self-critique, while Hu et al. [2] evaluated GPT-4 generated teaching plans and reported benefits such as efficiency and creativity alongside limitations related to inconsistency and insufficient pedagogical grounding. Fan et al. [3] introduced *LessonPlanner*, an interactive system designed to help novice teachers structure lesson components more effectively. Earlier systems, including Strickroth's *Platon* [5] and retrieval-augmented planning approaches explored by Kloker et al. [31], further demonstrate the feasibility of digital tools for lesson organization. Collectively, these approaches highlight the potential of automated and interactive systems to support lesson planning; however, they are largely designed for general instructional contexts and provide limited support for domain-specific requirements, such as those found in cybersecurity education.

A growing body of research has examined model adaptation through fine-tuning as a means of producing more consistent and domain-sensitive outputs. Within educational contexts, Tsai et al. [32] fine-tuned BERT and GPT-2 for short-answer question generation and reported improvements in quality and diversity over template-based approaches. Jia et al. [33] embedded Gagné's nine events of instruction into a fine-tuned model to generate lesson plans grounded in established pedagogical theory, while Gharbi et al. [34] demonstrated the potential of fine-tuned models to support personalized learning at scale in MOOCs. Beyond education, fine-tuning has been successfully applied to legal rule classification [22], transportation safety [23], and domain-specific summarization [24], highlighting its versatility across application areas. While these studies confirm the effectiveness of fine-tuning for improving domain alignment, they largely address either isolated instructional tasks or general learning contexts, leaving limited exploration of fine-tuned systems that generate fully structured lesson plans for specialized domains such as cybersecurity, where alignment between theoretical concepts and practical application is essential.

III. Methodology

The study employed a four-phase methodology integrating pedagogical theory with computational modeling. The methodology was designed to incorporate pedagogical alignment through both dataset construction and model fine-tuning, ensuring that instructional structure and pedagogical constraints are embedded in the generation process rather than applied during subsequent evaluation. Phase 1 identified relevant learning theories and teaching strategies through a literature review

and expert validation. Phase 2 constructed the knowledge base through schema design, sample generation, and expert evaluation. Phase 3 refined the model through dataset clustering, balancing, and fine-tuning. Finally, Phase 4 evaluated model performance using established automatic metrics. The overall process is illustrated in Fig. 1.

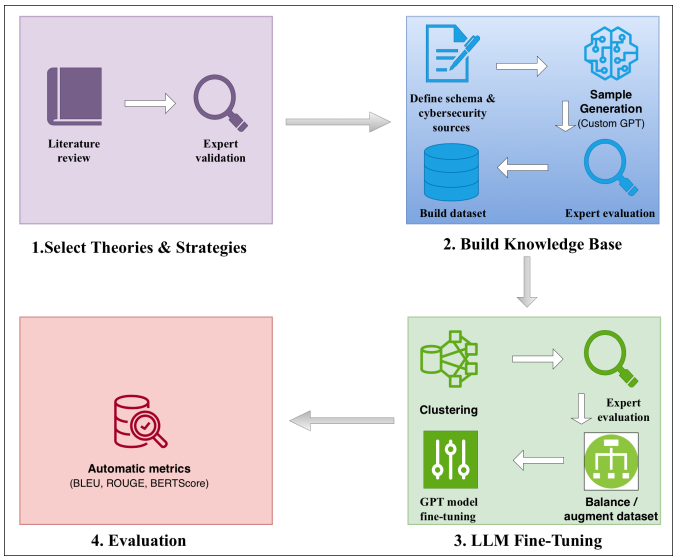


Fig. 1. Four-phase methodology pipeline.

A. Selection of Learning Theories and Teaching Strategies

This phase guided the design of lesson plans by identifying pedagogical foundations most relevant to cybersecurity education. A targeted review of pedagogical literature was conducted, complemented by consultations with an instructional design specialist. This process ensured that the selected learning theories and teaching strategies were both theoretically grounded and practically applicable to the demands of cybersecurity instruction, where adaptability and professional relevance are critical [7].

A range of learning theories were considered in shaping the instructional approach, with the following perspectives identified as particularly relevant.

Differential theories of learning transfer highlight that knowledge can only be successfully applied across contexts under specific conditions, such as having sufficient prior knowledge, possessing cognitive flexibility, and learning in environments similar to those of application [7]. Constructionist theories of learning emphasize creating tangible outcomes to build knowledge, promote creativity, encourage hands-on experimentation, and support iterative problem-solving [7]. The general cognitive science perspective emphasizes meta-cognitive control, analogical reasoning, and structured problem-solving as fundamental processes in learning; it supports instructional strategies that guide learners from basic comprehension to expert application through reflection and goal-oriented practice [7].

Cognitive-associationist theories focus on strengthening mental links between declarative, procedural, and conditional knowledge, with learning taking place incrementally through sequenced tasks that develop complex competencies [7]. Similarly, Cognitive-Constructivist theory emphasizes that learners actively build mental models through problem-solving, exploration, and reflection, integrating new knowledge with existing experience to produce higher-level cognitive schemas [7]. Coordinative transfer theory seeks to reduce negative transfer by improving learners' ability to determine when and how to apply existing knowledge [7].

More broadly, cognitive learning theories view learning as an active process of acquiring, organizing, and integrating knowledge, with a focus on internal mechanisms such as attention, memory encoding, and schema activation [35]. Experiential learning theory defines learning as a cyclical process involving concrete experience, reflective observation, abstract conceptualization, and active exploration [35]. Transformative learning theory emphasizes the importance of learners critically analyzing their preexisting assumptions and ideas in response to disorienting situations; through introspection and discussion, learners reframe their perspectives and develop more expansive and informed worldviews [35]. Finally, social learning theory affirms that people acquire skills and behaviors through social interaction, modeling, and observation, encompassing cooperation, peer review, and role modeling in education [35].

Building on these theories, a variety of teaching strategies were selected to translate abstract principles into practical methods that effectively support cybersecurity education, such as Problem-Based Learning (PBL), in which students collaborate to explore complex, real-world issues without predetermined answers. In this approach, teachers serve as facilitators, guiding students as they investigate, evaluate, and overcome obstacles [11], [9]. Similarly, Project-Based Learning (PrBL) involves students in long-term projects that apply cybersecurity concepts to real-world challenges. This strategy requires learners to create a tangible product or solution and promotes sustained engagement, teamwork, and iterative problem-solving [9].

Another approach is the use of practical exercises, which immerse students in real-world cybersecurity scenarios. Conducted in controlled physical or virtual environments, these sessions enable learners to develop technical competence, apply theoretical knowledge, and gain experience with industry-standard tools and protocols [36]. The Flipped Classroom model further complements this by requiring students to study core materials (e.g., videos, texts, or mini-lectures) before class, allowing in-class time to be dedicated to higher-order activities such as collaborative analysis, simulations, and practical problem-solving under instructor guidance. This method promotes self-paced study outside of class and deeper participation during class [9], [4].

Case-Based Learning extends this applied approach by using real-world cybersecurity cases to engage students in analyzing complex problems, comparing approaches, and proposing well-justified solutions. It encourages critical thinking and helps learners apply academic knowledge to practice [9]. Lecture-Based Learning also remains valuable for presenting fundamental cybersecurity concepts, where instructors can arrange content, provide expert framing, and establish conceptual baselines. When enriched with examples, questions,

and discussions, lectures can enhance engagement and comprehension, though they are most effective when combined with active learning techniques [9], [37].

To further enhance engagement, Role-Playing activities assign learners specific roles, immersing them in authentic cybersecurity scenarios. This approach improves empathy, decision-making, and communication, making it especially beneficial for developing soft skills and ethical reasoning in collaborative, high-pressure environments [38]. Finally, Simulation activities replicate real-world cybersecurity operations in secure, controlled environments, enabling students to practice technical skills, incident response, and decision-making under pressure [39].

Together, these learning theories and teaching strategies provide a solid foundation for designing cybersecurity instruction that is both grounded in established principles and responsive to real-world practice.

B. Build Knowledge Base

To fine-tune a large language model for generating cybersecurity lesson plans, a standardized structure was developed based on instructional design concepts. Each plan included five components: course title, topic, learning objectives (based on Revised Bloom's Taxonomy [40]), learning theory, and teaching strategy. Theories and strategies were taken from the previously presented curated lists, ensuring that they related to known educational frameworks. Because no existing dataset combined these features with cybersecurity content, a customized knowledge base was created using courses from the Diploma in Cybersecurity program at King Abdulaziz University (KAU), thereby ensuring both disciplinary relevance and educational validity.

1) Custom GPT for Knowledge Base Generation: To construct a pedagogically grounded knowledge base, OpenAI's Custom GPT was configured as a dedicated instance of ChatGPT. Custom GPT leverages prompt engineering and metadata settings to control tone, structure, and output format [41]. Within this setup, the model was instructed to generate structured instructional entries that could later serve as training data for fine-tuning a larger model specialized in lesson plan creation. For each course title and topic, the system consistently generated three elements: learning objectives, a learning theory, and a teaching strategy all defined according to established instructional design parameters. In particular, the Custom GPT created three measurable objectives for each topic based on Revised Bloom's Taxonomy [40]. Best practices for 60-90 minute sessions were followed to maintain focus and manage cognitive load [42].

2) Sample Generation and Expert Evaluation: To evaluate the instructional quality of the Custom GPT, a pilot dataset was created using one course from the cybersecurity diploma program. The course included nine topics, and for each, the model generated a structured lesson plan with three components: measurable learning objectives, an aligned learning theory, and a related teaching strategy. Eight professionals evaluated this dataset, including three curriculum and pedagogy specialists and five classroom-experienced cybersecurity instructors.

Each group received a tailored evaluation form with shared core criteria and role-specific emphasis. This ensured that the lesson plans were assessed for both educational quality and practical application. Educational experts examined eight criteria, including the clarity, measurability, alignment, and cognitive complexity of objectives; the appropriateness of the selected learning theory; the suitability of the teaching strategy; and the overall coherence of the topic, objectives, theory, and method. Cybersecurity instructors employed the same criteria, excluding the theoretical dimension.

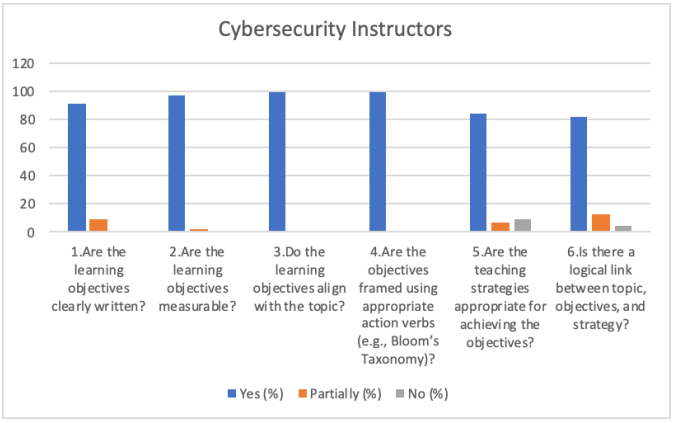


Fig. 2. Evaluation results from cybersecurity instructors across nine topics: percentage distribution of yes, partially, and no responses for six criteria.

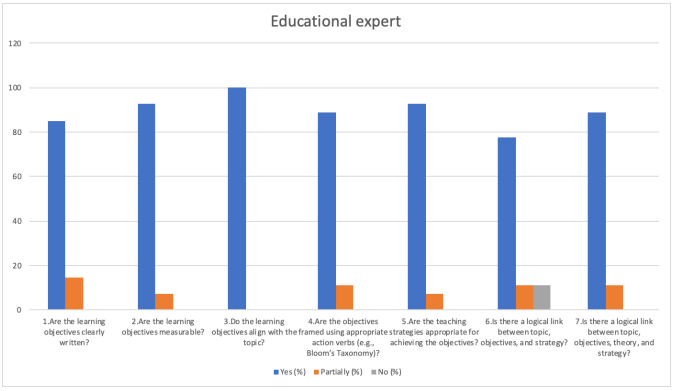


Fig. 3. Evaluation results from educational experts across nine topics: percentage distribution of yes, partially, and no responses for seven criteria.

Cybersecurity instructors reported high agreement on all rating criteria. Learning objectives were almost consistently rated as clear, measurable, well-aligned with the topic, and correctly framed with Bloom's verbs. Teaching strategies (84.4%) and the logical relationship between components (82.2%) also received strong ratings, indicating instructional coherence (see Fig. 2).

Educational experts similarly reported strong agreement across all criteria. Learning objectives were rated as clear (85.2%), measurable (92.6%), well-aligned with the topic (100%), and appropriately framed using Bloom's action verbs (88.9%). Teaching strategies (92.6%) and the logical relationship between topic, objectives, and strategy (77.8%) also scored highly, with the extended link to theory rated at 88.9%. These results highlight the instructional validity of the framework (see Fig. 3).

TABLE I. ELBOW METHOD AND SILHOUETTE SCORES FOR TF-IDF-BASED CLUSTERING

k	SSE	Silhouette Score
2	113.46	0.0123
3	111.95	0.0104
4	109.82	0.0126
5	108.32	0.0137
6	106.07	0.0193
7	104.25	0.0180
8	103.06	0.0179
9	101.17	0.0220
10	99.63	0.0241

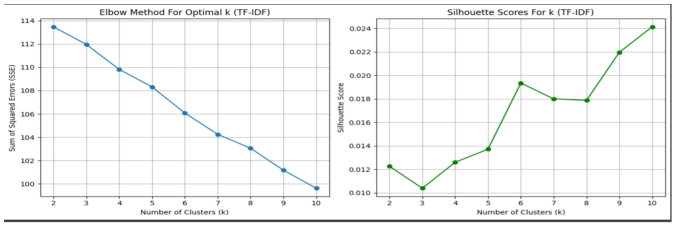


Fig. 4. Evaluation of TF-IDF clustering using the elbow method and silhouette scores.

TABLE II. NUMBER OF TOPICS BEFORE AND AFTER BALANCING USING TF-IDF-BASED CLUSTERING

Cluster	Original Samples	After Balancing
0	8	65
1	23	65
2	16	65
3	65	65[a]
4	7	65
Total Rows	119	325

[a] Unchanged during balancing.

TABLE III. ELBOW METHOD AND SILHOUETTE SCORES FOR SBERT-BASED CLUSTERING

k	SSE	Silhouette Score
2	42742.39	0.0635
3	40998.04	0.0470
4	39532.42	0.0599
5	38017.05	0.0649
6	36452.24	0.0651
7	35318.29	0.0726
8	35471.88	0.0617
9	34536.95	0.0649
10	33433.46	0.0646

After expert evaluation of the pilot course, the dataset was extended to cover the full diploma program, resulting in 119 structured entries across 14 courses. Topics were drawn directly from the official curriculum, while Custom GPT generated the corresponding objectives, theories, and strategies using the validated schema. The additional entries were generated automatically and were not subjected to further expert evaluation.

C. LLM Fine-Tuning

1) Dataset Preparation: To prepare the dataset for supervised fine-tuning, consistent and repeatable labels were required, since the Course Title and Topic fields alone did not provide enough overlap to enable generalization. To address this, an unsupervised clustering approach was used to introduce broader instructional categories. Specifically, the KMeans algorithm was used to group semantically related subjects, with each cluster assigned a pseudolabel representing a provisional instructional category [43]. For effective clustering, two feature extraction methods were tested on the Topic field: Term Frequency-Inverse Document Frequency (TF-IDF), which captures surface-level word relevance, and Sentence-BERT (SBERT), which generates dense semantic embeddings [44], [45]. Using both approaches enabled a comparison analysis to identify the representation most effective for structuring the dataset.

- TF-IDF: The first feature extraction approach converted topic phrases into numerical vectors using TfidfVectorizer with English stop-word removal. KMeans clustering was then applied to group related topics. The optimal number of clusters was determined using the Elbow Method [46] and Silhouette Score [47], with k=5 providing the best balance of compactness and interpretability (Table I, Fig. 4). The resulting clusters represented distinct instructional themes, which were assigned pseudo-labels for supervised fine-tuning. To address class imbalance (Table II), oversampling was applied, and lightweight data augmentation introduced paraphrased learning objectives (e.g., describe → explain) to enhance linguistic diversity. After balancing, the Silhouette Score for k=5 increased from 0.0137 to 0.1059, indicating stronger cohesion (Fig. 6b).
- SBERT: is a neural embedding approach built on a fine-tuned BERT architecture that captures sentence-level semantics using siamese and triplet networks [45]. Unlike TF-IDF, which relies on surface word frequencies, SBERT generates dense embeddings that encode contextual meaning, making it more effective for clustering short instructional topics. The pre-trained `all-MiniLM-L6-v2` model from the `sentence-transformers` library was used to encode topic entries, which were then clustered with KMeans. As with TF-IDF, the Elbow Method and Silhouette Score identified k=5 as the most interpretable solution (Table III, Fig. 5). The clusters represented coherent instructional themes and were assigned pseudo-labels for supervised fine-tuning.To address class imbalance (Table IV), oversampling and paraphrasing-based augmentation were applied. After balancing, the Silhouette Score for k=5 increased to 0.1150, reflecting stronger semantic cohesion (Fig. 6a).

To compare TF-IDF and SBERT, a mixed evaluation was performed. Internal metrics (Elbow, Silhouette) provided numerical validation, but six cybersecurity education experts reviewed representative clusters to assess semantic coherence, topic distinctiveness, and pedagogical relevance. While TF-IDF achieved slightly higher quantitative scores (Fig. 6b),

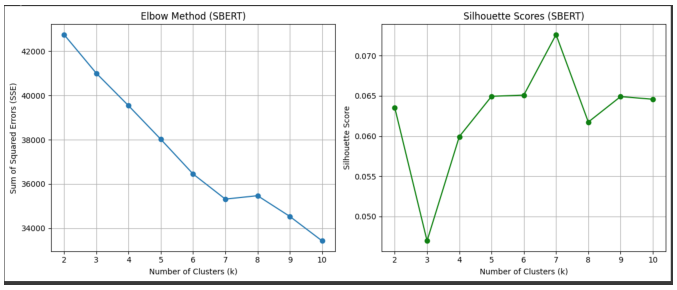
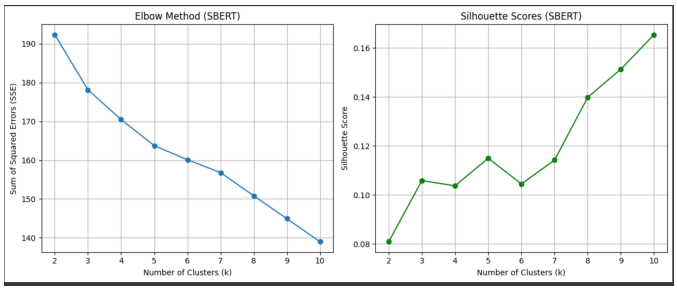


Fig. 5. Evaluation of SBERT clustering using the elbow method and silhouette scores.

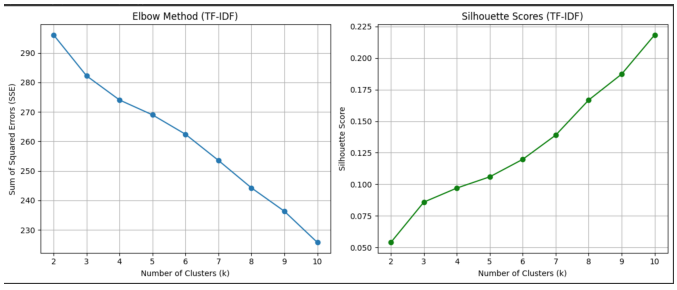
TABLE IV. NUMBER OF TOPICS BEFORE AND AFTER BALANCING USING SBERT-BASED CLUSTERING.

Cluster	Original Samples	After Balancing
0	30	53
1	53	53[a]
2	12	53
3	11	53
4	13	53
Total Rows	119	265

[a] Unchanged during balancing.



(a) SBERT-based clustering.



(b) TF-IDF-based clustering.

Fig. 6. Comparison of clustering evaluation between SBERT and TF-IDF (post-balancing).

experts consistently preferred SBERT-based groupings, citing clearer semantics and greater instructional utility. Consequently, SBERT was adopted for subsequent model development.

2) Fine-Tuning Process: The fine-tuning process was carried out using the OpenAI API, which provides access to state-of-the-art instruction-following language models.

- Base Model: The experiments used `gpt-3.5-turbo-1106`, recommended by OpenAI for instruction-oriented tasks [48]. GPT-3.5 Turbo is an efficient variant of the GPT-3.5 family optimized for conversational and structured text generation, making it well suited for producing lesson plans.
- Inputs: Fine-tuning data was formatted in `.jsonl`, with each entry structured as a dictionary. A chat-style prompt format was adopted with three roles:
  - System: standardized as "You assist instructors with designing effective lesson plans."
  - User: structured inputs (domain, course title, topic).
  - Assistant: instructional outputs (learning objectives, theoretical context, teaching strategy).

  The dataset was partitioned using stratified sampling to preserve instructional category proportions: 70% training, 15% validation, and 15% testing.
- Training: OpenAI's fine-tuning framework allows adjustment of three hyperparameters: `n_epochs`, `batch_size`, and `learning_rate_multiplier`. This study used the platform defaults: `n_epochs = 3`, `learning_rate_multiplier = 2`, and `batch_size = 1`.

D. Evaluation

We evaluated the fine-tuned model on a held-out test split comprising 15% of the dataset, which was excluded from both training and validation. This setup ensured that the assessment reflected the model's ability to generalize to unseen lesson plan inputs rather than relying on memorized exemplars. The use of a reserved test partition also provides a more reliable indication of performance when the model is applied to new instructional material. Performance was assessed using BLEU, ROUGE, and BERTScore, which together provide complementary perspectives on lexical fidelity, structural coverage, and semantic alignment with the reference dataset. Within this evaluation, the metrics serve as consistent indicators of the extent to which the generated lesson plans align with the intended instructional material.

IV. RESULTS AND DISCUSSION

This section presents the experimental results to assess the generated lesson plans in terms of lexical similarity, semantic alignment, and consistency with the intended instructional structure.

The evaluation of the fine-tuned model on the held-out test set (15%, $n = 40$) indicates strong lexical and semantic similarity between the generated lesson plans and the reference texts. The results are summarized in Table V. The BLEU score (73.54) reflects high n-gram precision, suggesting close surface-level correspondence in instructional vocabulary and phrasing. This result indicates that the model consistently reproduces domain-relevant instructional language, contributing to clarity and standardization in the generated pedagogical content.

TABLE V. AUTOMATED EVALUATION METRICS FOR THE FINE-TUNED MODEL

Metric	Score
BLEU	73.54
ROUGE-1	82.19
ROUGE-2	68.91
ROUGE-L	78.16
ROUGE-Lsum	81.28
BERTScore P	97.40
BERTScore R	97.46
BERTScore F1	97.43

TABLE VI. COMPARATIVE EVALUATION OF FINE-TUNED LLMS (SCORES ON A 0–100 SCALE)

Study	Model	BLEU	R-1	R-2	R-L	BERT-F1
This study	GPT-3.5	73.54	82.19	68.91	78.16	97.43
Russian Summ. [24]	GPT-3	23.10	11.40	1.40	10.00	89.00
LLMs Cyber Q&A [49]	LLaMA-3	96.70	76.20	–	76.20	–

ROUGE scores provide further evidence of lexical and structural correspondence between the generated lesson plans and the reference texts. ROUGE-1 (82.19) demonstrates strong unigram recall, ROUGE-2 (68.91) reflects solid bigram coverage despite the stricter matching requirement, and ROUGE-L (78.16) indicates that generated outputs preserve sequential coherence with reference lesson plans. Together, these values show that the model effectively captures key instructional concepts and maintains structural organization, which are essential for high-quality instructional content.

BERTScore results (Precision = 97.40; Recall = 97.46; F1 = 97.43) indicate very high semantic similarity between the generated lesson plans and the reference texts. These values suggest that, even when lexical variation occurs, the generated content preserves meaning and reflects the intended pedagogical intent. Moreover, the consistently high semantic scores indicate that the fine-tuned model reliably adheres to the required instructional structure (three learning objectives, one theoretical context, and one instructional strategy), supporting pedagogical consistency across generated outputs.

Overall, these findings indicate that the fine-tuned model performs reliably in generating structured educational content. Its ability to balance lexical fidelity with semantic adequacy, while consistently adhering to the intended instructional structure, underscores its potential for practical use in lesson plan generation where pedagogical relevance is essential. To contextualize these results, Table VI compares the proposed model against recent fine-tuning efforts in other domains, including Russian text summarization [24] and cybersecurity question answering [49]. Although these tasks differ in format lesson plan generation, abstractive summarization, and factual question answering they share the common challenge of producing outputs that are lexically precise, semantically coherent, and domain-specific.

As shown, the Russian summarization study reported lower n-gram and ROUGE values, with BLEU = 23.10, ROUGE-1 = 11.40, and ROUGE-L = 10.00, but achieved comparatively stronger semantic alignment (BERTScore F1 = 89.00) [24]. These outcomes are consistent with prior findings in abstractive summarization, where lexical overlap is often limited due to paraphrasing. In contrast, the cybersecurity Q&A study attained very high BLEU (96.70) and ROUGE-1/ROUGE-L (76.20) scores [49], reflecting the fact-oriented and terminologically constrained nature of short-answer tasks. Within this spectrum, the present study demonstrates a balanced profile, combining strong lexical correspondence (BLEU = 73.54; ROUGE-1 = 82.19; ROUGE-L = 78.16) with near-perfect semantic similarity (BERTScore F1 = 97.43). This suggests that structured instructional generation tasks benefit from maintaining both consistency in phrasing and preservation of pedagogical meaning.

V. CONCLUSION

This study addressed the challenge of generating structured, pedagogy-aligned lesson plans for cybersecurity, a discipline that requires both strong theoretical grounding and practical proficiency. By constructing a domain-specific dataset, integrating explicit learning objectives, learning theories, and evidence-based teaching strategies, and embedding these elements into the fine-tuning process, the study proposed a structured framework for lesson plan generation. The experimental results demonstrated strong lexical and semantic alignment between the generated and reference lesson plans, indicating that the framework effectively preserves instructional structure and pedagogical intent.

Despite these contributions, the study has limitations. The dataset was derived from a single academic program, which may not fully represent the diversity of cybersecurity curricula, and the evaluation relied primarily on automated similarity metrics that cannot capture all aspects of instructional effectiveness in real classroom settings. Future work should therefore expand the dataset to cover broader curricular contexts and incorporate expert review and classroom-based evaluations to assess instructional quality, adaptability, and learning impact more comprehensively.

More broadly, this work demonstrates that integrating pedagogical representations into the fine-tuning of large language models enables AI systems to function as pedagogy-aware instructional assistants rather than generic content generators. The proposed framework offers a practical and transferable approach to AI-assisted lesson planning, in which pedagogical design is embedded directly into the generation process. While this study focuses on cybersecurity education, the framework can be adapted to other domains by redefining the domain knowledge base and corresponding pedagogical mappings.

Within the scope of this study, the results indicate that pedagogy-aligned fine-tuning can effectively support the generation of structurally consistent and instructionally valid lesson plans in a specialized domain such as cybersecurity.

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REFERENCES

[1] Y. Zheng, X. Li, Y. Huang, Q. Liang, T. Guo, M. Hou, B. Gao, M. Tian, Z. Liu, and W. Luo, "Automatic lesson plan generation via large language models with self-critique prompting," in *Proceedings of the International Conference on Artificial Intelligence in Education*. Springer, 2024, pp. 163–178.

[2] B. Hu, L. Zheng, J. Zhu, L. Ding, Y. Wang, and X. Gu, "Teaching plan generation and evaluation with gpt-4: Unleashing the potential of llm in instructional design," *IEEE Transactions on Learning Technologies*, 2024.

[3] H. Fan, G. Chen, X. Wang, and Z. Peng, "Lessonplanner: Assisting novice teachers to prepare pedagogy-driven lesson plans with large language models," in *Proceedings of the 37th Annual ACM Symposium on User Interface Software and Technology*, 2024, pp. 1–20.

[4] S. Puranik, "Innovative teaching methods in higher education," *BSSS Journal of Education*, vol. 9, no. 1, pp. 67–75, 2020.

[5] S. Strickroth, "Platon: Developing a graphical lesson planning system for prospective teachers," *Education Sciences*, vol. 9, no. 4, p. 254, 2019.

[6] N. D. A. Lubis *et al.*, "Learning theory," OSF, 2021, [Online]. Available: https://osf.io. Accessed: Oct. 7, 2025.

[7] D. T. Hickey and R. J. Kantor, "Contrasting cognitive theories of learning transfer to advance cybersecurity instruction, assessment, and testing," *Journal of Cybersecurity Education, Research and Practice*, vol. 2024, no. 1, 2024.

[8] T. E. Dorgu, "Different teaching methods: A panacea for effective curriculum implementation in the classroom," *International Journal of Secondary Education*, vol. 3, no. 6, pp. 77–87, 2015.

[9] A. M. Alnajim, S. Habib, M. Islam, H. S. AlRawashdeh, and M. Wasim, "Exploring cybersecurity education and training techniques: a comprehensive review of traditional, virtual reality, and augmented reality approaches," *Symmetry*, vol. 15, no. 12, p. 2175, 2023.

[10] W. S. Admass, Y. Y. Munaye, and A. A. Diro, "Cyber security: State of the art, challenges and future directions," *Cyber Security and Applications*, vol. 2, p. 100031, 2024.

[11] M. Shivapurkar, S. Bhatia, and I. Ahmed, "Problem-based learning for cybersecurity education," *Journal of The Colloquium for Information Systems Security Education*, vol. 7, no. 1, pp. 6–6, 2020.

[12] M. Mukherjee, N. T. Le, Y.-W. Chow, and W. Susilo, "Strategic approaches to cybersecurity learning: A study of educational models and outcomes," *Information*, vol. 15, no. 2, p. 117, 2024.

[13] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "Bert: Pre-training of deep bidirectional transformers for language understanding," in *Proceedings of the 2019 conference of the North American chapter of the association for computational linguistics: human language technologies, volume 1 (long and short papers)*, 2019, pp. 4171–4186.

[14] T. Brown, B. Mann, N. Ryder, M. Subbiah, J. D. Kaplan, P. Dhariwal, A. Neelakantan, P. Shyam, G. Sastry, A. Askell *et al.*, "Language models are few-shot learners," *Advances in Neural Information Processing Systems*, vol. 33, pp. 1877–1901, 2020.

[15] J. Achiam, S. Adler, S. Agarwal, L. Ahmad, I. Akkaya, F. L. Aleman, D. Almeida, J. Altenschmidt, S. Altman, S. Anadkat *et al.*, "Gpt-4 technical report," *arXiv preprint arXiv:2303.08774*, 2023.

[16] H. Touvron, L. Martin, K. Stone, P. Albert, A. Almahairi, Y. Babaei, N. Bashlykov, S. Batra, P. Bhargava, S. Bhosale *et al.*, "Llama 2: Open foundation and fine-tuned chat models," *arXiv preprint arXiv:2307.09288*, 2023.

[17] E. Kasneci, K. Seßler, S. Küchemann, M. Bannert, D. Dementieva, F. Fischer, U. Gasser, G. Groh, S. Günnemann, E. Hüllermeier *et al.*, "Chatgpt for good? on opportunities and challenges of large language models for education," *Learning and Individual Differences*, vol. 103, p. 102274, 2023.

[18] M. Moradi, K. Yan, D. Colwell, M. Samwald, and R. Asgari, "Exploring the landscape of large language models: Foundations, techniques, and challenges," *arXiv preprint arXiv:2404.11973*, 2024.

[19] R. Patil and V. Gudivada, "A review of current trends, techniques, and challenges in large language models (llms)," *Applied Sciences*, vol. 14, no. 5, p. 2074, 2024.

[20] S. Zhang, L. Dong, X. Li, S. Zhang, X. Sun, S. Wang, J. Li, R. Hu, T. Zhang, G. Wang *et al.*, "Instruction tuning for large language models: A survey," *ACM Computing Surveys*, 2023.

[21] B. Weng, "Navigating the landscape of large language models: A comprehensive review and analysis of paradigms and fine-tuning strategies," *arXiv preprint arXiv:2404.09022*, 2024.

[22] D. Liga and L. Robaldo, "Fine-tuning gpt-3 for legal rule classification," *Computer Law & Security Review*, vol. 51, p. 105864, 2023.

[23] O. Zheng, M. Abdel-Aty, D. Wang, C. Wang, and S. Ding, "Trafficsafetygpt: Tuning a pre-trained large language model to a domain-specific expert in transportation safety," *arXiv preprint arXiv:2307.15311*, 2023.

[24] A. Nikolich, I. Osliakova, T. Kudinova, I. Kappusheva, and A. Puchkova, "Fine-tuning gpt-3 for russian text summarization," in *Computational Methods in Systems and Software*. Springer, 2021, pp. 748–757.

[25] P. Sridhar, A. Doyle, A. Agarwal, C. Bogart, J. Savelka, and M. Sakr, "Harnessing llms in curricular design: Using gpt-4 to support authoring of learning objectives," *arXiv preprint arXiv:2306.17459*, 2023.

[26] N. Scaria, S. Dharani Chenna, and D. Subramani, "Automated educational question generation at different bloom's skill levels using large language models: Strategies and evaluation," in *International Conference on Artificial Intelligence in Education*. Springer, 2024, pp. 165–179.

[27] E. Latif and X. Zhai, "Fine-tuning chatgpt for automatic scoring," *Computers and Education: Artificial Intelligence*, vol. 6, p. 100210, 2024.

[28] K. Papineni, S. Roukos, T. Ward, and W.-J. Zhu, "Bleu: a method for automatic evaluation of machine translation," in *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*, 2002, pp. 311–318.

[29] C.-Y. Lin, "Rouge: A package for automatic evaluation of summaries," in *Text Summarization Branches Out*, 2004, pp. 74–81.

[30] T. Zhang, V. Kishore, F. Wu, K. Q. Weinberger, and Y. Artzi, "Bertscore: Evaluating text generation with bert," *arXiv preprint arXiv:1904.09675*, 2019.

[31] S. Kloker, H. Bukoli, and T. Kateete, "New curriculum, new chance—retrieval augmented generation for lesson planning in ugandan secondary schools: Prototype quality evaluation," *arXiv preprint arXiv:2408.07542*, 2024.

[32] D. C. L. Tsai, W. J. W. Chang, and S. J. H. Yang, "Short answer questions generation by fine-tuning bert and gpt-2," in *Proceedings of the 29th International Conference on Computers in Education (ICCE)*, 2021, pp. 123–132.

[33] L. Jia, C. Qi, Y. Wei, H. Sun, and X. Yang, "Fine-tuning large language models for educational support: Leveraging gagne's nine events of instruction for lesson planning," *arXiv preprint arXiv:2503.09276*, 2025.

[34] M. Gharbi, M. T. Mohtadi, and A. F. Merkazi, "Revolutionizing moocs with fine-tuned chatgpt: Personalized learning at scale," *International Journal of Computing and Digital Systems*, vol. 16, no. 1, pp. 1–11, 2024.

[35] D. C. M. Taylor and H. Hamdy, "Adult learning theories: implications for learning and teaching in medical education: Amee guide no. 83," *Medical Teacher*, vol. 35, no. 11, pp. e1561–e1572, 2013.

[36] J. Vykopal, P. Seda, V. Švábenský, and P. Čeleda, "Smart environment for adaptive learning of cybersecurity skills," *IEEE Transactions on Learning Technologies*, vol. 16, no. 3, pp. 443–456, 2022.

[37] Z. Abulhul, "Teaching strategies for enhancing student's learning," *Journal of Practical Studies in Education*, vol. 2, no. 3, pp. 1–4, 2021.

[38] H. Rathore and H. Griffith, "Enhancing cybersecurity education through research-based role-playing," in *Proceedings of the IEEE Integrated STEM Education Conference (ISEC)*, 2025, pp. 1–6.

[39] H. Kavak, J. J. Padilla, D. Vernon-Bido, S. Y. Diallo, R. Gore, and S. Shetty, "Simulation for cybersecurity: state of the art and future directions," *Journal of Cybersecurity*, vol. 7, no. 1, p. tyab005, 2021.

[40] D. R. Krathwohl, "A revision of bloom's taxonomy: An overview," *Theory Into Practice*, vol. 41, no. 4, pp. 212–218, 2002.

[41] OpenAI, "Introducing gpts," https://openai.com/blog/introducing-gpts, 2023, accessed: Oct. 7, 2025.

[42] American College Health Association, "Guidance for designing successful learning objectives," https://www.acha.org/education-events/guidance-for-designing-successful-learning-objectives/, 2025, accessed: May 20, 2025.

[43] A. K. Jain, "Data clustering: 50 years beyond k-means," *Pattern Recognition Letters*, vol. 31, no. 8, pp. 651–666, 2010.

[44] J. Ramos, "Using tf-idf to determine word relevance in document queries," in *Proceedings of the 1st Instructional Conference on Machine Learning*, vol. 242, no. 1, New Jersey, USA, 2003, pp. 29–48.

[45] N. Reimers and I. Gurevych, "Sentence-bert: Sentence embeddings using siamese bert-networks," *arXiv preprint arXiv:1908.10084*, 2019.

[46] D. J. Ketchen and C. L. Shook, "The application of cluster analysis in strategic management research: An analysis and critique," *Strategic Management Journal*, vol. 17, no. 6, pp. 441–458, 1996.

[47] P. J. Rousseeuw, "Silhouettes: A graphical aid to the interpretation and validation of cluster analysis," *Journal of Computational and Applied Mathematics*, vol. 20, pp. 53–65, 1987.

[48] OpenAI, "Gpt-3.5 turbo," https://platform.openai.com/docs/models/gpt-3.5-turbo, 2023, accessed: Feb. 9, 2025.

[49] Y. Huang, "Fine-tuning of large language models for domain-specific cybersecurity knowledge," *arXiv preprint arXiv:2509.25241*, 2025.

Advanced Multi-Scale Enhanced U-Net for Efficient Land Cover Classification of Remote Sensing Images

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***Abstract*—For monitoring the environment, building cities, assessing crops, and studying the climate, it is very important to be able to accurately classify land cover from remote sensing images. Deep learning has made semantic segmentation work much better, especially with encoder-decoder designs like U-Net. Still, ordinary U-Net models have trouble capturing multi-scale contextual relationships, distinguishing narrow borders, and successfully emphasizing traits that are distinctive to an area. This work presents an Advanced Multi-Scale Enhanced U-Net (AMSE-U-Net) to address these difficulties. The AMSE-U-Net combines (i) multi-scale feature extraction, (ii) squeeze-and-excitation channel attention, and (iii) attention-gated skip connections. The model improves learning of both local and global features while getting rid of background noise that isn't useful. Tests done on common remote sensing datasets show big improvements in Intersection over Union (IoU), pixel precision, and boundary delineation when compared to standard U-Net and similar models. The suggested AMSE-U-Net works better for generalization with only a little amount of extra processing power, making it good for monitoring land cover and the environment.**

***Keywords*—Land cover classification; remote sensing; UNet; satellite images; AMSE-U-Net; multi-scale features; semantic segmentation**

I. Introduction

Remote sensing is a highly useful way to find out what sort of land cover is in many various regions. It is vitally crucial to classify land cover from satellite photos in order to discover forests area, manage resources, preserve the environment, anticipate the weather, and locate cities, etc. [1]. Land cover classification gives us a lot of information about how the ecosystem on Earth works by carefully sorting the Earth's surface into different categories of land. This creates a complete picture of the many types of land coverings. This makes it easier to comprehend and keep an eye on changes in our natural environment as a whole [3], [4]. This systematic classification makes it easier to comprehend and manage different ways that land is used. Remote sensing technology has changed the way traditional surveys work, like field surveys, aerial photography, map analysis, community engagement, and other early remote sensing techniques. These new methods can effectively collect and analyze land use and cover data, giving us high quality images and important information about vegetation cover, water bodies, and land use, building etc. [5].

There are two main types of traditional land use categorization methods: pixel-based and object-oriented. Deep learning methods have shown to be quite effective in automating mapping through semantic picture segmentation [6]. Recently, in semantic segmentation, particularly in land use and land cover segmentation, traditional machine learning (ML) methods have been declining in popularity. Penatti et al. shown that convolutional neural networks significantly surpass traditional machine learning approaches in land cover categorization [7]. DeepGlobe 2018 Satellite image understanding challenge [8], all the top list were predominantly led by deep neural networks (DNNs) techniques [9]–[11].

Land cover looks different in different areas, therefore data from one location may not be useful for mapping other areas. Also, satellite images may be taken in many different spectral bands [12]. It is very important to make a model that accurately predicts different types of land cover so that we can find aquatic and urban areas on the Earth's surface. This is important for keeping track of changes in the environment and the growth of human settlements. Semantic segmentation is figuring out how to get from broad to specific parts of a scenario. The first step is categorization, which makes a guess about the input. Deep learning, particularly fully convolutional neural networks (FCNs) [13], has transformed semantic segmentation. U-Net has become a very popular model in remote sensing because of its symmetric encoder-decoder construction and skip links [14]. Even though UNet has shown proven to be one of the best approach of semantic segmentation, but it has its own set of drawbacks as listed out below:

- Weak multi-scale representation: Land cover classes vary drastically in scale and texture.
- Limited global context: Standard convolutions capture restricted receptive fields.
- Generalization issues: Satellite imagery differs across countries, sensors, and acquisition conditions.
- Detail loss: Downsampling operations often remove crucial fine boundary features.

To overcome the the above said limitations of UNet model we proposed a Advanced Multi-Scale Enhanced U-Net (AMSE-UNet), which includes the modifications as listed below:

1) Atrous Multi-Scale Enhancement Module (AMEM)
2) Hybrid Channel–Spatial Attention Block (HCSAB)
3) Cross-Level Context Fusion (CLCF)

With the above said modification the proposed model is used for the classification of remote sensing images into the distinct regions showing land cover and land use segments within the image.

II. Literature Review

Land use and land cover mapping was examined by Lilay and Taye through the use of high-resolution Sentinel-2 images and a collection of deep learning models, which included CNN-RF, CNN-SVM, and LinkNet-ResNet34 [15]. The strategy that they took was successful in achieving an accuracy of 88.2%, which demonstrates the advantages of combining comprehensive satellite data with powerful neural networks. In the study, persisting issues such as misunderstanding among visually similar land cover categories and insufficient training samples are highlighted. Additionally, the study suggests that future work should make use of deeper spectral information and extend datasets.

SA-SC U-Net is an improved form of U-Net that Khan and Jung developed [16]. It contains self-attention mechanisms and separable convolutions, and it was called after the enhanced U-Net variant. When the model was evaluated using aerial images from Dubai, it achieved a 91 percent accuracy rate, highlighting its capacity to extract comprehensive spatial context for the purpose of land cover research.

Hybrid approach that integrates a dynamic arithmetic edge-detection technique with a BiLSTM-U-Net architecture to delineate land use and land cover elements from hyperspectral pictures was proposed by Yele. The suggested model demonstrated outstanding performance on the DeepGlobe dataset, with 98% accuracy, 99% recall, and a 99% F1-score, surpassing most current approaches in managing high-dimensional remote sensing data [17].

Tzepkenlis et al. [18] used the U-TAE (U-Net with Temporal Attention Encoder) architecture, initially developed by Sainte Fare Garnot and Landrieu, to facilitate land cover mapping using satellite image time series. Their methodology streamlines preprocessing through the utilization of temporal median composites and enhances performance by using multi-sensor data from Sentinel-1, Sentinel-2, and ALOS, in conjunction with channel attention modules. The enhanced model surpasses methods such as random forest, U-Net, and SegFormer while utilizing less trainable parameters. Additional efforts are scheduled for temporal change modeling and object-based segmentation.

A dual-velocity ensemble classification method was presented by Horry et al., this method combines the advantages of a Vision Transformer and a fast-training CNN [19], [20]. Their staged training pipeline demonstrated its potential for scalable remote sensing applications by achieving a level of accuracy of 65 percent on the So2Sat LCZ42 dataset. A hybrid model of HRNet and PSPNet was utilized by Sun and Zheng in order to enhance the pixel wise segmentation of high resolution aerial and satellite images [21]. Their approach makes use of multiband analysis and adaptive frequency band selection in order to categorize nine different types of terrain, hence achieving significant increases in the quality of segmentation performance. The authors emphasize the importance of conducting further research on multimodal fusion and change-detection-oriented segmentation, as stated in the literature.

According to their findings, the Res UNet system that is fitted with a ResNet 50 encoder provides the optimal balance between the level of accuracy and the level of architectural complexity. The authors also highlight the significance of efficient preprocessing and highlight the limitations of standard U-Net models in terms of their ability to capture a wider range of contextual information. Chueprasert et. al. carried out this investigation into the comparative evaluation of deep learning methods for the extraction of buildings from satellite imagery [22].

The study emphasizes the necessity of merging government datasets with unlabeled satellite imagery to enhance agricultural monitoring. The classification framework proposed by Payani et al. [23] was implemented using Deep Feed Forward Neural Networks (DFNN) and 1D Convolutional Neural Networks. This framework was based on spectral indices and used data from Landsat. The DFNN model they built using the KAPLCU dataset had a test accuracy of 99.57%, which was higher than the accuracy of the 1D CNN. the accuracy achieved by the 1D CNN.

The MST DeepLabv3+ model was presented by Wang et al involved the integration of SENet and MobileNetV2 with transfer learning in order to provide semantic segmentation that was both efficient and accurate [24]. A MIoU of 82.47% and an OA of 92.13% were achieved by the model on the ISPRS dataset. These results demonstrate the model's ability to handle high-resolution remote sensing scenes while still maintaining a lightweight design.

Dataset for Indian research was made by Rengma and Yadav with their investigation into the creation of a medium-scale land use and land cover [25]. More specifically, they examined and evaluated both conventional machine learning techniques and contemporary deep learning methods. Machine learning and deep learning models are shown to have comparable levels of accuracy in their experiments, highlighting the fact that the selection of an algorithm ought to be determined by the computational resources that are available. In their recommendation, they suggest extending evaluations across multiple states in India by utilizing imagery with a higher resolution.

Behera et al. [26] examined the integration of Object-Based Image Analysis (OBIA) with machine learning classifiers for LULC mapping using LISS IV imagery.The study highlights challenges in segment boundary definition and computational demand while demonstrating the value of OBIA for context-aware land cover mapping. The best accuracy, 75.2%, was achieved using the CART classifier.

Wang et al. [27] suggested DeepG-DLE, a lightweight semantic segmentation model that improves DeeplabV3+ by using GhostNet and depthwise separable convolutions. The model performs well in a wide range of situations, such as when there are shadows or when the class distributions are not balanced. The Fuyang Remote Sensing Image Dataset (FRSID) was created to help with benchmarking. Azedou et al. said that combining spectral indices with Deep Neural Networks (DNNs) can classify land cover from Sentinel-2 data with 94.5% accuracy [28]. Random Search, Hyperband, and Bayesian optimization are some of the optimization methods that made the model work better. Their results show that deep learning in the cloud can be useful for keeping an eye on natural resource.

Albarakati et al. [29] proposed a fused self-attention-based deep learning model for LULC classification using IBNR-

65 and DenseNet-64 feature extractors. The incorporation of Quantum Hyperparameter Optimization significantly reduced computation time while improving classification accuracy to 98.2% on the SIRI-WHU dataset. Amer et al. reviewed state of art methods and concluded that deep learning—particularly CNN-based and hybrid multi-scale models—remains the most effective strategy for remote sensing image classification [30]. Boonpook et al. [31] introduced LoopNet, a novel CNN architecture tailored for semantic segmentation of LULC classes in Landsat-8 imagery. LoopNet effectively captures complex land cover patterns and outperforms traditional models, though it faces difficulties in differentiating urban and miscellaneous classes. The study reaffirms the growing importance of deep learning for accurate LULC mapping.

III. Related Work

Over the past 20 years, the way we classify land cover has changed a lot. It has evolved from basic pixel-based techniques to sophisticated deep learning architectures capable of modeling both spatial and contextual information. This section gives a general idea of these changes and points out the problems that led to the design of the proposed AMSE-U-Net architecture [32], [33]. The introduction of U-Net was a big step forward for remote sensing's ability to make dense predictions. You can mix fine spatial details from the early layers with deep semantic information from the deeper layers thanks to the encoder-decoder structure and skip connections. This hierarchical feature fusion has worked well to separate things with complicated edges, such as roads, rivers, and built-up areas [34].

A number of variants have tried to make the original U-Net better. UNet++ added nested, densely connected skip pathways to make the semantic gap between the encoder and decoder feature maps smaller. Pay attention U-Net used spatial attention gates to get rid of irrelevant activations and bring out important features. Residual U-Net and Dense U-Net made it even easier to reuse features and keep gradients stable by using residual and dense connectivity [35].

Even with these improvements, classical U-Net architectures still have problems when used for remote sensing. Images from remote sensing often show objects that are very different in size and texture, which means that fixed-size convolutional kernels can't capture all of the spatial patterns [35]. U-Net also doesn't have clear ways to model global context, which is important for telling apart land cover types that have similar spectral characteristics. These constraints have spurred growing research interest in hybrid architectures that integrate U-Net's structural advantages with multi-scale and attention-based improvements [36].

A. Motivation for the Proposed Architecture

The ideas behind multi-scale processing, attention modeling, and hierarchical feature fusion have led to the creation of hybrid architectures designed for remote sensing. But a lot of the models that are already out there only look at one thing, like multi-scale extraction, channel attention, or spatial refinement, and they don't put them all together into one framework. Remote sensing segmentation, which is hard because of the wide range of scales, textures, and spectral complexities, works best with an architecture that includes multi-scale features, channel recalibration, and attention-guided skip fusion all at once. The proposed AMSE-U-Net combines these ideas by adding Multi-Scale Blocks (MSBs), Squeeze-and-Excitation (SE) modules, and Attention Gates (AGs) to a U-Net backbone. This unified design captures fine spatial details, enhances global context, and improves feature relevance, resulting in a more robust and generalizable segmentation framework for land cover classification.

B. AMSE Unet

The proposed Advanced Multi-Scale Enhanced U-Net (AMSE-U-Net) aims to address the issues encountered by standard U-Net and its variants when applied to intricate remote sensing images. Satellite images with high resolution show objects in a wide range of sizes, shapes, and textures. Long-range dependencies and semantic inconsistencies between deep encoder features and shallow decoder features also make it harder to get the right segmentation. To fix these problems, AMSE-U-Net adds three modules: the Atrous Multi-Scale Enhancement Module (AMEM), the Hybrid Channel–Spatial Attention Block (HCSAB), and the Cross-Level Context Fusion (CLCF) unit. All of these parts work together to improve contextual modeling, refine features, and make sure that everything in the network is the same across all scales.

AMSE UNet is based on the classic UNet design, but instead of using standard convolutional blocks, it uses modules that are more flexible and aware of the situation. The encoder uses AMEM blocks to mix multi-scale context with atrous convolutions that have different dilation rates. This gives it features that are organized in a hierarchy. HCSAB modules make the feature maps better at both the encoder and decoder stages by showing off useful channels and areas of space. Lastly, the CLCF module makes sure that the encoder and decoder's features work well together. This makes skip connections better and helps the decoder make more accurate land cover boundaries.

The three core models of the architecture are shown below:

- Atrous Multiscale Enhancement Module (AMEM): captures multiscale contextual features and long-range spatial dependencies through dilated convolutions.
- Hybrid Channel–Spatial Attention Block (HCSAB): enhances discriminative feature learning by combining channel attention and spatial attention.
- Cross-Level Context Fusion (CLCF): reduces the semantic gap between encoder and decoder layers through adaptive cross-scale feature alignment.

This modular design ensures that both local and global contextual cues are efficiently preserved, enabling robust segmentation of heterogeneous land cover types.

C. Atrous Multi-Scale Enhancement Module (AMEM)

The AMEM module is made easier to collect contextual information at different scales without making the calculations harder. Standard convolutions have small receptive fields, which makes it hard for them to capture big structures like

fields, bodies of water, or areas of vegetation. Atrous convolutions help with this problem by adding dilation factors that make the receptive field bigger.

The input feature map X, AMEM applies four parallel atrous convolutions with dilation rates $\{1, 2, 4, 8\}$:

$$F_d = \text{Conv}_d(X), \quad d \in \{1, 2, 4, 8\}. \tag{1}$$

These multi-scale features are concatenated as shown below:

$$F_{\text{concat}} = [F_1, F_2, F_4, F_8], \tag{2}$$

and fused through a 1×1 convolution to reduce dimensionality and enhance feature compactness:

$$F_{\text{AMEM}} = \text{Conv}_{1\times1}(F_{\text{concat}}). \tag{3}$$

This module provides richer context at each layer of the encoder, enabling better recognition of objects with varying scales and shapes.

D. Hybrid Channel–Spatial Attention Block (HCSAB)

Not all of the features that AMEM extracts are equally useful for segmentation, even though it adds depth to the context. AMSE-U-Net uses HCSAB, which combines channel attention and spatial attention to fully recalibrate features, to selectively improve relevant information.

Channel attention: Channel attention identifies the relative importance of each channel by applying a squeeze-and-excitation operation:

$$M_c = \sigma(\text{MLP}(\text{GAP}(X))), \tag{4}$$

where, GAP denotes Global Average Pooling and σ is the sigmoid activation. This mechanism captures channel-wise dependencies, allowing the network to strengthen informative channels while suppressing irrelevant ones.

Spatial attention: Spatial attention emphasizes important spatial regions by applying average pooling and max pooling across the channel dimension:

$$M_s = \sigma(\text{Conv}_{7\times7}([X_{\text{avg}}, X_{\text{max}}])). \tag{5}$$

Here, X_{avg} and X_{max} represent average-pooled and max-pooled feature maps, respectively. The 7×7 convolution captures spatial relationships over a wide receptive field.

Combined attention output: The recalibrated feature map is obtained by sequentially applying channel and spatial attention:

$$X' = X \odot M_c \odot M_s, \tag{6}$$

where, $\odot$ denotes element-wise multiplication. HCSAB thus enhances feature representations and improves the segmentation of boundaries, small objects, and spectrally similar land cover classes.

E. Cross-Level Context Fusion (CLCF)

Skip connections in classical U-Net simply concatenate encoder and decoder features, despite their semantic disparity. Encoder features tend to capture high-level semantic information at low resolution, whereas decoder features contain fine-grained spatial details. This mismatch often hampers segmentation performance.

To address this, the CLCF module aligns encoder and decoder features before fusion. Given encoder feature map F_{enc} and decoder feature map F_{dec}, CLCF applies transformation functions $\phi(\cdot)$ and $\psi(\cdot)$ to match channel dimensions and semantics:

$$F_{\text{CLCF}} = \phi(F_{\text{enc}}) + \psi(F_{\text{dec}}). \tag{7}$$

This operation ensures consistent representation across network levels, allowing the decoder to more accurately reconstruct object boundaries and spatial details. By mitigating semantic discrepancies, CLCF significantly enhances the effectiveness of skip connections.

IV. Proposed Method: AMSE UNet

A. Architecture Overview of the AMSE UNet

The Advanced Multi-Scale Enhanced UNet (AMSE UNet) is a new type of encoder-decoder architecture that was made to do very precise semantic segmentation of remote sensing images. It improves the classic U-Net by adding three major new features: 1) modules for extracting features at multiple scales, 2) recalibrating squeeze and excitation (SE) channels, and 3) skip connections guided by attention. These parts let the network pick up on small spatial structures while keeping track of global context, which makes it great for mapping complex land cover. Fig. 1 shows the block diagram of the proposed architecture.

B. Encoder: Multi-Scale Feature Extraction

The encoder is composed of a sequence of Multi-Scale Blocks (MSBs) designed to extract hierarchical and spatially rich feature representations. Each MSB processes the input using multiple convolutional branches:

- a standard 3×3 convolution,
- a dilated 5×5 convolution to enlarge the receptive field,
- a 1×1 convolution for channel mixing and dimensionality control.

The outputs of these parallel convolutions are concatenated to form a multi-scale feature map, followed by batch normalization and ReLU activation. Max-pooling operations at each stage downsample spatial dimensions while preserving feature richness. This design enables the encoder to capture both high-frequency details (e.g., edges, boundaries) and low-frequency patterns (e.g., vegetation texture, water bodies).

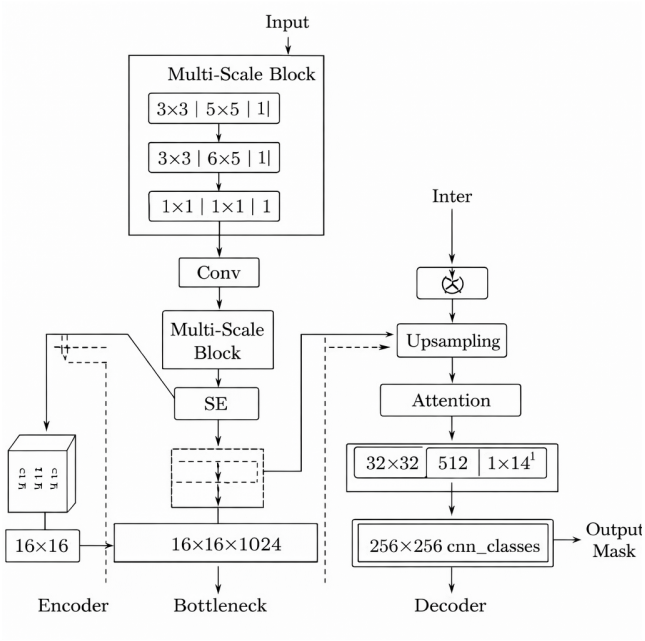


Fig. 1. Block diagram of the proposed AMSE-U-Net architecture.

C. Bottleneck: Contextual Enhancement with Squeeze-and-Excitation

At the network's deepest layer, the bottleneck consists of a Multi-Scale Block followed by a Squeeze-and-Excitation (SE) module. The SE block performs channel-wise attention:

1) Squeeze: Global average pooling aggregates spatial information into a channel descriptor.
2) Excitation: A gating mechanism with sigmoid activation learns per-channel importance.
3) Recalibration: Channels are reweighted to emphasize informative features and suppress noise.

This mechanism strengthens discriminative features, improves robustness against illumination and texture variations, and optimizes the information flow into the decoder.

D. Decoder: Attention-Guided Feature Reconstruction

The decoder reconstructs pixel-level predictions through upsampling and feature fusion. At each scale, feature maps are passed through:

- upsampling via transposed convolution,
- an Attention Gate (AG) applied to the corresponding encoder skip connection,
- a Multi-Scale Block to refine fused information.

Attention Gates suppress irrelevant encoder activations and retain only spatially consistent, task-relevant regions. This significantly improves segmentation quality along complex boundaries such as rivers, roads, and urban edges.

E. Output Layer

The final segmentation map is generated using a 1×1 convolution that maps decoder features to pixel-wise class probabilities. A sigmoid activation is used for binary segmentation, whereas softmax is applied for multi-class land-cover mapping. The output resolution matches the input resolution, maintaining precise localization.

F. Key Advantages of AMSE-U-Net

- Multi-scale feature extraction enhances the model's ability to detect objects of varying sizes.
- SE channel attention selectively amplifies informative channels.
- Attention-based skip connections reduce irrelevant spatial noise.
- Dilated convolutions extend receptive fields without increasing the parameter count.
- Improved boundary precision through deep decoder refinement.

Overall, AMSE-U-Net provides a strong and generalizable framework for remote sensing semantic segmentation, outperforming traditional U-Net variants in capturing fine details while maintaining contextual coherence.

V. Results

To evaluate the efficacy of the proposed AMSE-UNet Semantic Segmentation, tests were conducted on DeepGlobe dataset as shown in the Fig. 2. From the dataset 4 sample test images are taken and their obtained masks are shown along with the true masks. With the proposed algorithm the output masks perfectly lock into the different land cover regions of the remote sensing images

A. Experimental Setup

1) Dataset: The dataset used to get the results is called DeepGlobe Land Cover. It has 50 cm satellite images and 7 classes. The DeepGlobe Land Cover Classification dataset is a large-scale benchmark that includes high-resolution satellite images that have been carefully chosen for research on semantic segmentation [2]. The dataset was released as part of the 2018 DeepGlobe Challenge. It has RGB image tiles that are 2448 × 2448 pixels in size and have a ground sampling distance of about 50–60 cm. This makes it possible to do detailed analysis of different landscapes [8]. Each scene is manually labeled with seven land cover types: urban, agriculture, rangeland, forest, water, barren, and unknown. This gives dense pixel-level supervision that is good for training deep learning models. The dataset was gathered from a wide range of locations, so it has a lot of variation in scene structure, object size, and land cover patterns. This makes it a great resource for testing the robustness and generalization of segmentation architectures like U-Net, DeepLabv3+, and transformer-based models. DeepGlobe is one of the most popular benchmarks for remote sensing land cover classification because of its size, the quality of its annotations, and the variety of its classes.

2) Preprocessing: Images were normalized, resized to 512×512, and augmented using flipping, rotation, color jitter, and Gaussian noise.

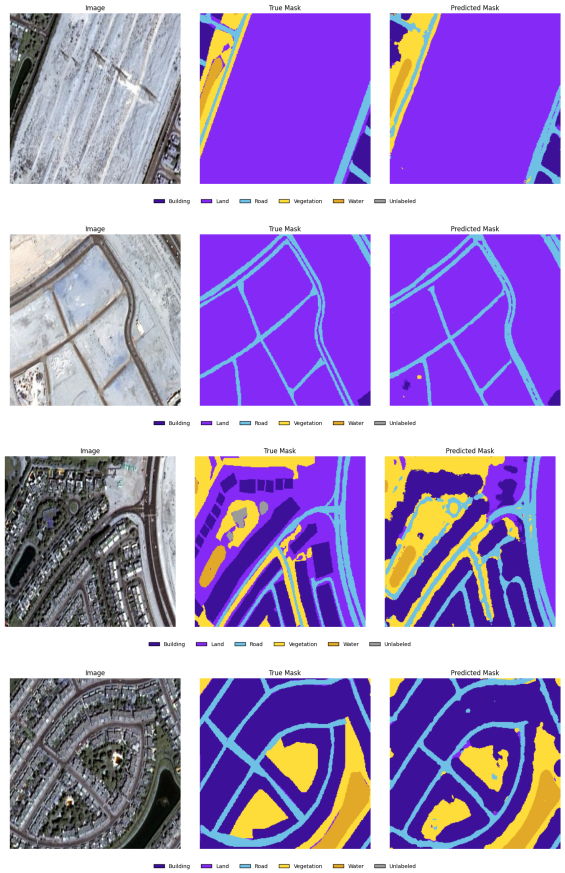


Fig. 2. Columns (i) & (iv) are input images, (ii) & (v) are ground truths, and (iii) & (vi) are predicted masks.

3) Training details: Training of the model done using:

- Optimizer: AdamW
- Learning rate: 10^{-4}
- Batch size: 8
- Loss: BCE + Dice loss
- Epochs: 100

4) System configuration and other settings: The CPU is Huawei-made Intel(R) Core(TM) i3 processor with 2.10GHz speed. The operating system is Windows11 (64-bit operating system), and the development environment is python .For the DeepGlobe dataset, testing images were selected randomly from the dataset. For each of the original images the model predicts the segmentation. The comarative analysis of our approach with other deep learning algorithms is shown in the Table I.

TABLE I. MIOU ON DEEPGLOBE

Model	mIoU (%)
U-Net	61.0
UNet++	63.4
DeepLabv3+	65.8
HRNet-Seg	66.1
AMSE-U-Net (proposed)	**69.3**

VI. CONCLUSION

In this work, an expanded U-Net-based architecture known as AMSE-U-Net was presented. The purpose of this architecture was to overcome the drawbacks of standard segmentation models in terms of managing the multi-scale complexity of land cover representations. By incorporating the Atrous Multi-Scale Enhancement Module (AMEM), the Hybrid Channel–Spatial Attention Block (HCSAB), and the Cross-Level Context Fusion (CLCF), the proposed model is able to effectively capture a wide variety of contextual information, improve feature discrimination, and enhance semantic alignment across all levels of the network.According to the findings of the experiments, AMSE-U-Net performs significantly better than standard U-Net systems when it comes to segmenting and locating borders. It has the capability of employing multi-scale context and attention-driven refinement in order to produce classifications of various forms of land cover that are more accurate. AMSE-U-Net is a formidable and adaptable framework for the segmentation of remote sensing data that has the potential to be utilized in the fields of environmental monitoring, urban planning, and geospatial analysis.

REFERENCES

[1] Fayaz, Muhammad, Junyoung Nam, L. Minh Dang, Hyoung-Kyu Song, and Hyeonjoon Moon. 2024. "Land-Cover Classification Using Deep Learning with High-Resolution Remote-Sensing Imagery" Applied Sciences 14, no. 5: 1844. https://doi.org/10.3390/app14051844.

[2] Burcu Amirgan, Arzu Erener,"Semantic segmentation of satellite images with different building types using deep learning methods", Remote Sensing Applications: Society and Environment, Volume 34,2024,101176, ISSN 2352-9385, https://doi.org/10.1016/j.rsase.2024.101176.

[3] K. S. Kalaivani et al., "Land Cover Segmentation in Satellite Images Using Transfer Learning," in Proc. ICoICI, Coimbatore, India, 2024, pp. 714–724.

[4] L. Thomas Ramos and A. D. Sappa, "Multispectral Semantic Segmentation for Land Cover Classification: An Overview," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 17, pp. 14295-14336, 2024.

[5] A. Shreehari, P. R. Chandan, P. V. Vinod and R. Hebbar, "Land Use Land Cover Classification using Deep Learning Techniques: A Comparative Study," 2024 11th International Conference on Signal Processing and Integrated Networks (SPIN), Noida, India, 2024, pp. 7-11, doi: 10.1109/SPIN60856.2024.10511460.

[6] N. Bengana and J. Heikkilä, "Improving Land Cover Segmentation Across Satellites Using Domain Adaptation," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 14, pp. 1399-1410, 2021, doi: 10.1109/JSTARS.2020.3042887.

[7] O. A. B. Penatti, K. Nogueira and J. A. dos Santos, "Do deep features generalize from everyday objects to remote sensing and aerial scenes domains?," 2015 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Boston, MA, USA, 2015, pp. 44-51, doi: 10.1109/CVPRW.2015.7301382.

[8] I. Demir et al., "DeepGlobe 2018: A Challenge to Parse the Earth through Satellite Images," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Salt Lake City, UT, USA, 2018, pp. 172-17209, doi: 10.1109/CVPRW.2018.00031.

[9] C. Tian, C. Li and J. Shi, "Dense Fusion Classmate Network for Land Cover Classification," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Salt Lake City, UT, USA, 2018, pp. 262-2624, doi: 10.1109/CVPRW.2018.00049.

[10] G. Huang, Z. Liu, L. Van Der Maaten and K. Q. Weinberger, "Densely Connected Convolutional Networks," 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, USA, 2017, pp. 2261-2269, doi: 10.1109/CVPR.2017.243.

[11] T. -S. Kuo, K. -S. Tseng, J. -W. Yan, Y. -C. Liu and Y. -C. F. Wang, "Deep Aggregation Net for Land Cover Classification," 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Salt Lake City, UT, USA, 2018, pp. 247-2474, doi: 10.1109/CVPRW.2018.00046.

[12] A. Yehia, H. Elhifnawy and M. Safy, "Effect of Different Spatial Resolutions of Multi-temporal Satellite Images Change Detection Application," 2019 International Conference on Innovative Trends in Computer Engineering (ITCE), Aswan, Egypt, 2019, pp. 41-46, doi: 10.1109/ITCE.2019.8646510.

[13] Q. Zhu and X. Zu, "Fully Convolutional Neural Network Structure and Its Loss Function for Image Classification," in IEEE Access, vol. 10, pp. 35541-35549, 2022, doi: 10.1109/ACCESS.2022.3163849.

[14] A. Kumar and T. Singh, "U-NET Architecture for Liver Segmentation using Multi Model Scans," 2022 IEEE 19th India Council International Conference (INDICON), Kochi, India, 2022, pp. 1-6, doi: 10.1109/INDICON56171.2022.10039786.

[15] M. Y. Lilay and G. D. Taye, "Semantic Segmentation Model for Land Cover Classification from Satellite Images in Gambella National Park, Ethiopia," SN Applied Sciences, vol. 5, p. 76, 2023.

[16] B. A. Khan and J.-W. Jung, "Semantic Segmentation of Aerial Imagery Using U-Net with Self-Attention and Separable Convolutions," Applied Sciences, vol. 14, no. 9, p. 3712, 2024.

[17] V. P. Yele, R. R. Sedamkar, and S. Alegavi, "Systematic Analysis of Effective Segmentation and Classification for Land Use Land Cover in Hyperspectral Image using Deep Learning Methods," in Proc. 20th CSI Int. Symp. Artificial Intelligence and Signal Processing (AISP), Babol, Iran, 2024, pp. 1–8.

[18] A. Tzepkenlis, K. Marthoglou, and N. Grammalidis, "Efficient Deep Semantic Segmentation for Land Cover Classification Using Sentinel Imagery," Remote Sensing, vol. 15, no. 8, p. 2027, 2023.

[19] V. S. F. Garnot and L. Landrieu, "Panoptic segmentation of satellite image time series with convolutional temporal attention networks," in Proc. IEEE/CVF Int. Conf. Computer Vision, 2021, pp. 4872–4881.

[20] M. J. Horry, S. Chakraborty, B. Pradhan, et al., "Two-Speed Deep-Learning Ensemble for Classification of Incremental Land-Cover Satellite Image Patches," Earth Syst. Environ., vol. 7, pp. 525–540, 2023.

[21] Y. Sun and W. Zheng, "HRNet- and PSPNet-based multiband semantic segmentation of remote sensing images," Neural Comput. Appl., vol. 35, pp. 8667–8675, 2023.

[22] T. Chueprasert, A. Udomchaiporn, and S. Intagosum, "Comparative Analysis of Deep Learning Models for Building Extraction from High-resolution Satellite Imagery," Current Applied Science and Technology, vol. 25, no. 1, 2024.

[23] C. A. Payani, C. Gupta, and A. K. M., "Spectral Indices based Land Cover Classification using Deep Learning," in Proc. ICRAIS, Manipal, India, 2024, pp. 166–171.

[24] Y. Wang, L. Yang, X. Liu, and P. Yan, "An Improved Semantic Segmentation Algorithm for High-Resolution Remote Sensing Images Based on DeepLabv3+," Scientific Reports, vol. 14, p. 9716, 2024.

[25] N. S. Rengma and M. Yadav, "Generation and Classification of Patch-Based Land Use and Land Cover Dataset in Diverse Indian Landscapes," Environmental Monitoring and Assessment, vol. 196, no. 6, p. 568, 2024.

[26] D. K. Behera, G. S. Pujar, R. Kumar, and S. K. Singh, "A comprehensive approach towards enhancing land use land cover classification through machine learning and object-based image analysis," Journal of the Indian Society of Remote Sensing, vol. 53, no. 3, pp. 731–749, 2025.

[27] G. Wang, J. Chen, L. Mo, P. Wu, and X. Yi, "Lightweight Land Cover Classification via Semantic Segmentation of Remote Sensing Imagery and Analysis of Influencing Factors," Frontiers in Environmental Science, vol. 12, p. 1329517, 2024.

[28] A. Azedou et al., "Enhancing Land Cover/Land Use (LCLU) Classification through a Comparative Analysis of Hyperparameters Optimization Approaches for Deep Neural Network (DNN)," Ecological Informatics, vol. 78, p. 102333, 2023.

[29] H. M. Albarakati et al., "A Novel Deep Learning Architecture for Agriculture Land Cover and Land Use Classification from Remote Sensing Images Based on Network-Level Fusion of Self-Attention Architecture," IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens., vol. 17, pp. 6338–6353, 2024.

[30] I. Amer, K. Rahouma, and A. Shahin, "Remote sensing image processing, deep learning classification algorithms survey and review," Journal of Advanced Engineering Trends, vol. 43, no. 1, pp. 239–267, 2024.

[31] W. Boonpook et al., "Deep Learning Semantic Segmentation for Land Use and Land Cover Types Using Landsat 8 Imagery," ISPRS Int. J. Geo-Inf., vol. 12, no. 1, p. 14, 2023.

[32] T. Lu, L. Wan, S. Qi, and M. Gao, "Land Cover Classification of UAV Remote Sensing Based on Transformer–CNN Hybrid Architecture," Sensors, vol. 23, no. 11, p. 5288, 2023.

[33] Irfan, Ayesha, Yu Li, Xinhua E, and Guangmin Sun. 2025. "Land Use and Land Cover Classification with Deep Learning-Based Fusion of SAR and Optical Data" Remote Sensing 17, no. 7: 1298. https://doi.org/10.3390/rs17071298

[34] Li, Zan, Hong Zhang, Zhengzhen Li, and Zuyue Ren. 2022. "Residual Attention UNet++: A Nested Residual-Attention U-Net for Medical Image Segmentation" Applied Sciences 12, no. 14: 7149. https://doi.org/10.3390/app12147149

[35] Zhu, Zhifu, Xiping Yuan, Shu Gan, Raobo Li, Weidong Luo, Rui Bi, and Cheng Chen. 2025. "Texture and Structure Interaction Guided Generative Adversarial Network for Multimodal Remote Sensing Image Change Detection." GIScience & Remote Sensing 62 (1). doi:10.1080/15481603.2025.2565866.

[36] Punn, N.S., Agarwal, S. Modality specific U-Net variants for biomedical image segmentation: a survey. Artif Intell Rev 55, 5845–5889 (2022). https://doi.org/10.1007/s10462-022-10152-1

A Fuzzy Petri Net Approach with Automated ANFIS Rule Learning for Modelling Real-Time Systems

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***Abstract*—In this paper, we propose a modelling approach for real-time intelligent systems using Fuzzy Petri Nets (FPNs), a formalism that generates dynamic fuzzy rules, supports uncertainty, and enables concurrent reasoning. FPNs offer a well-defined tool for dynamically evaluating Fuzzy Production Rules (FPRs), Certainty Factors (CFs), and truth degrees, and for making real-time decisions. To reduce the complexity of manually constructed or probabilistically modelled fuzzy rules, we extend the modelling toolkit with the Adaptive Neuro-Fuzzy Inference System (ANFIS). ANFIS learns membership functions and Sugeno-type rules from numeric datasets through a feature. This results in a richer and more accurate set of rules. At the novelty level, we propose a rule-integrating scheme that maps Sugeno rules learned by ANFIS into FPN transitions to obtain more clearly explained reasoning and traceable rule execution within a neuro-fuzzy Petri net. Based on these learned rules, FPN executes them within a two-layer real-time (prediction and decision) while maintaining concurrent inference and real-time execution. The hybrid methodology is verified by fitting a real-time expert system for solar collector cleaning. Results from the experiments demonstrate that, in terms of predictive performance, ANFIS-induced rules drastically boost accuracy (from 85% to 93%) and reduce Root Mean Square Error (RMSE) from 4.82 to 2.57 relative to those generated by a single probabilistic FPN model. These results indicate that using neural learning combined with an FPN-based expert system makes real-time decision-making much more accurate and reliable.**

Keywords*—*Fuzzy petri net; adaptive neuro-fuzzy inference system; expert systems; fuzzy logic; real-time system; artificial intelligence

I. Introduction

Expert systems support decision-making in uncertain and dynamic environments. Classical fuzzy expert systems rely on expert-defined linguistic rules, CFs, and membership functions, which makes them interpretable but labour-intensive, subjective, and challenging to scale to real-time or highly nonlinear settings [1], [2]. These limits are exacerbated when reasoning must continuously adapt to streaming data. FPNs have recently been proposed as a novel approach to handling expert systems because of their ability to represent FPRs and to support real-time reasoning through concurrency, formal semantics, and structural transparency [1], [3]. In many present-day FPN-based expert systems, the rule base is written offline. It depends on probabilistic derivation, which extracts CF and Thresholds (TH) from conditional probabilities [4]. While the aforementioned rule-generation methods are generally valid in many applications, they do not evolve over time and sometimes fail to describe real-time behaviour, such as that of dynamically changing systems. Alternatively, data-driven neuro-fuzzy learning combines the learning capabilities of neural networks and the interpretability of Fuzzy logic (FL) to offer a new approach [5], [6].

This work proposes a unified real-time modelling methodology. This strategy merges a new rule-based preparation technique that integrates Sugeno-type fuzzy inference representation with ANFIS learning with a new FPN model and execution infrastructure. The new concept is that the rule base is not treated as a static thing but as a dynamic model. A dynamic rule base was created using ANFIS, trained on data, and then integrated into an FPN-based inference and decision process. As well as explicating the whole procedure (rule preparation, mapping, modelling semantics, and real-time implementation), we present a controlled validation under a real-time case study, an expert system for solar collector Cleaning Decision-making (CD), a real-time validation of the proposed solution in the same experiment and comparison with other rule generation and decision-making strategies. This proves that the novelty is not merely a hybrid solution of two existing tools but a consistent modelling paradigm for real-time expert systems that connects data-driven rule learning with interpretable FPN execution. The main contributions of this work are as follows:

- Real-time unified model and execution of FPN: We introduce a unified FPN modelling and execution architecture for real-time expert systems, enabling concurrent reasoning and transparent rule-based inference within a single formal tool.
- Two-layer real-time modelling pattern: We develop a two-layer FPN decision model that separates a predictive layer (system-state estimation from streaming inputs) from a decision layer (action selection under real-time constraints), explicitly linking prediction outputs to decision transitions.
- Novel data-driven rule construction: We propose a rule-base preparation method that uses Sugeno-type fuzzy representation and ANFIS learning to generate a data-driven fuzzy rule base from numerical datasets for interpretable real-time execution.
- Expert-system rule integration pipeline: We define a systematic pipeline that converts ANFIS-learned Sugeno rules into FPRs and embeds them as executable FPN transitions, including explicit modelling of CF and TH for faithful truth propagation and firing behaviour.

- Real-time dynamic rule and model update: We support dynamic learning and dynamic modelling by updating the FPN structure during operation.
- Controlled comparison and real-time validation: We evaluate the proposed approach on real-time solar-collector CD-making and compare it fairly against a probabilistic rule-extraction baseline under identical execution conditions, demonstrating improved predictive accuracy and reduced RMSE using the ANFIS-learned rule base.

To complete the introduction and provide a clear reading guide, the remainder of this paper is organised as follows. Section II reviews representative FPN-, fuzzy-logic-, and ANFIS-based methods and highlights the gap addressed by our work. Section III summarises our unified real-time methodology, comprising a two-layer FPN architecture for prediction and decision-making, a probabilistic baseline, and a Sugeno-ANFIS rule-learning and rule-integration pipeline that explicitly handles CF/TH. Section IV provides an overview of the experimental setup and presents results on solar-collector CD-making regarding accuracy and RMSE under consistent conditions. Section V investigates the implications of the results, justifying the enhancement of ANFIS performance, the trade-off between rule-base size and real-time execution, and the proposed modelling paradigm's propensity to generalise. Finally, Section VI presents the concluding results and future research directions.

II. Related Works

Research on intelligent decision-making systems has long focused on how to represent uncertainty, model dynamic environments, and formalise knowledge-based reasoning. Within this context, FPN have emerged as an influential modelling formalism, capable of representing fuzzy rules, degrees of truth, and causal relationships while supporting concurrency and interpretability. Foundational work by Chen [1], [3] showed how FPNs can encode FPRs and provide transparent mechanisms for both reasoning and verification. Building on these foundations, later studies extended FPNs to applications such as fault diagnosis, production rescheduling, exception handling, and complex rule-based automation [7], [9], [10]. Further contributions introduced reversed reasoning for diagnostic analysis [11], invariant-based structural control [12], and learning-enabled FPN architectures [13], [14], improving the adaptability of Petri Net-based reasoning in uncertain environments. In contrast, our work targets three missing elements that make prior hybrid solutions difficult to compare: 1) an explicit rule-integration pipeline that converts ANFIS-learned Sugeno rules into FPRs and embeds them as FPN transitions with CF/TH handling, 2) a two-layer real-time modelling pattern within one FPN execution engine (prediction of reflectivity followed by decision-making), and 3) a controlled comparison between probabilistic rule extraction and ANFIS learning under identical execution conditions. Table I summarises these distinctions against representative FPN, probabilistic, and ANFIS-based approaches.

Verifying and validating fuzzy rule systems is essential to ensure their accuracy. For instance, Kouzehgar et al. [15] developed a method that gathers insights from experts through questionnaires to create rule bases. They then transform these into hierarchical fuzzy rules and connect them to FPN models. To identify semantic errors, they use reachability graphs, demonstrating how FPNs can serve as practical tools for reasoning and verification. Beyond this, Petri nets have been applied in various fields, such as modelling the behaviour of neural networks [16], optimising business processes [17], analysing power consumption in wireless sensor networks [18], and managing evolving workflows in healthcare [19]. FL remains a vital approach for addressing uncertainty across a range of applications, including diabetes detection [20], educational assessments [21], intelligent traffic control [22], and renewable energy management [23]. These studies highlight the importance of developing data-driven fuzzy systems to reduce our reliance on manually constructed rules. To overcome these limitations, ANFIS proposes a model that automatically optimises membership functions and rule parameters, combining neural learning with Sugeno-type fuzzy inference [6], [24], which was presented by Jang [5]. ANFIS has been used for nonlinear, interpretable modelling in various fields [25], [26], [27], [28] and is effective for predicting and managing renewable energy [29], [30], [31]. ANFIS has thus demonstrated a method that can provide data-driven fuzzy rules while also retaining interpretability. Reflectors/heliostats of solar energy systems are very sensitive to soiling, as reported reflectivity losses of up to 35% within weeks in dusty environments [32], [33], [34]. Thus, cleaning strategies and predictive maintenance have been investigated, including effective restoration methods [35] and learning-based reflectivity prediction [36], but black-box models pose explainability issues [37], [38]. Others have employed state-space methods in CSP plants [39], [40] and studied soiling and cleaning economics in a PV/Saharan area [41], [42], [43]. However, there is still a potential gap between interpretable fuzzy rule systems such as FPNs and adaptive neuro-fuzzy models such as ANFIS: FPNs represent precise causal semantics and have manual rule bases, whereas ANFIS recognises nonlinear behaviour but lacks a real-time, concurrent execution tool for decision support. There are, however, relatively few studies on hybrid neuro-fuzzy Petri Nets [13], [14]. In addition, probabilistic FPNs construct CF as conditional probabilities [44], [45], [46], and more recent work has assessed confidence values from errors in ANFIS training to optimise rules based on data-derived evidence.

Motivated by these observations, the present study integrates ANFIS-generated fuzzy rules into a formal FPN reasoning tool. This hybridisation combines the adaptability of neuro-fuzzy learning with the interpretability, concurrency, and structural rigour of Petri Nets. In doing so, it supports the construction of a real-time expert system capable of predicting solar reflectivity and determining optimal CDs under rapidly changing environmental conditions.

III. Methodology for Modelling Real-Time Expert Systems Using ANFIS and Probabilistic Methods Integrated within a Fuzzy Petri Net Approach

This section presents the methodological tool used to model a real-time intelligent decision system with the FPN formalism. FPNs provide a transparent, interpretable, and concurrent reasoning mechanism that can represent fuzzy knowledge, handle uncertainty, and dynamically propagate degrees of truth. To

TABLE I. RELATED WORK COMPARISON (MULTI-LAYER REFERS TO THE DECISION PIPELINE, NOT THE INTERNAL LAYERS OF ANFIS)

Paper / Approach	Rule learning (how rules are obtained)	How rules are embedded in FPN	Real-time evaluation	Multi-layer	What our work adds beyond it
FPN decision-making [2]	Manual fuzzy rules, certainty values attached to propositions/tokens	Rules encoded as places/transitions with fuzzy truth tokens	Not evaluated	No	Adds data-driven rule learning + explicit CF/TH handling + prediction→decision
FPN knowledge representation [1], [3]	Manual FPR (expert-defined rules)	FPR encoded in FPN structure (places/transitions)	Not evaluated	No	Adds learned-rule generation (ANFIS) + systematic rule-to-transition integration pipeline
Learning on FPN [7]	Supervised learning by adapting transition thresholds in a layered FPN	Learning changes FPN parameters (thresholds/weights)	Not evaluated	No	Adds explicit Sugeno-rule extraction (ANFIS) + rule-to-FPN transition embedding + controlled baseline comparison
Probabilistic FPN (reflectivity prediction) [4]	Rule base extracted by an expert system (association rules), CF/TH derived from conditional probability	Extracted rules mapped to FPN transitions with CF/TH	Yes (real-time prediction stated)	Yes (prediction only)	Adds ANFIS-learned rules + richer rule boundaries + full prediction→decision pipeline under the same execution tool
Probabilistic FPN (prediction + cleaning decision) [8]	Probabilistic / expert-system rule preparation (no neuro-fuzzy learning)	Rules mapped to two FPN expert systems (prediction and decision)	Yes (real-time cleaning decision setting)	Yes (two-stage pipeline)	Adds ANFIS(Sugeno) learning, automatic rule derivation, and dynamic enrichment by adding new transitions when rules are learned
ANFIS / Sugeno neuro-fuzzy [5], [6]	ANFIS learns Sugeno-type rule parameters and membership functions (hybrid learning), supports online updates in principle	Not FPN-based (standalone inference model)	Not evaluated as a real-time execution framework	No	Adds formal FPN execution + CF/TH semantics + concurrent rule execution + prediction→decision
Our approach (Sugeno–ANFIS + FPN)	**ANFIS learning + probabilistic baseline**	**ANFIS rules → FPR → FPN transitions (with CF/TH)**	**Yes**	**Yes**	**Unified comparative tool, learned-rule embedding/execution, supports online enrichment by adding transitions as new rules are learned**

validate the proposed approach, we model a complete real-time decision-making system that integrates expert reasoning, dynamic data streams, and multi-layer fuzzy inference. The modelling process relies on two distinct expert systems: 1) a probabilistic expert system based on conditional probabilities, and 2) a neuro-fuzzy expert system based on the ANFIS. Both expert systems generate fuzzy rules, expressed as FPR, which are then embedded into a unified multi-layer FPN architecture for real-time execution. This shared tool enables a direct, rigorous comparison of manually engineered probabilistic rules and automatically learned ANFIS rules under identical operating conditions.

Fig. 1 summarises the overall modelling workflow of the real-time intelligent decision system. The diagram shows how raw environmental data are progressively transformed into actionable CDs by coupling the probabilistic and ANFIS-based expert systems within a multi-layer FPN tool. The workflow commences with continuous meteorological data from sensors (direct normal irradiance (DNI), temperature, humidity, precipitation, and wind speed). The measurements are kept in an active database. The noise reduction module removes inaccurate readings and reconstructs missing values, producing consistent, accurate data. In addition to this cleaned dataset, a Markov Chain-based prediction block generates short-term predictions for key environmental variables, enabling the system to predict reflectivity degradation rather than simply responding to it. Then, numerical sensor measurements and predicted values are altered into linguistic variables via a fuzzification step by using trapezoidal membership functions. This creates the fuzzy input space needed by both expert systems. Herefrom, two paths running together for rule generation are established:

- In the probabilistic pathway, fuzzy rules are also introduced by abstracting away conditional probability distributions and subjected to human evaluations. Every rule will have a CF and a TH. To maintain interpretability and consistency, only rules with CF ≥ 0.5 and TH ≥ 0.3 are kept.
- In the ANFIS pathway, we use Least Squares Estimation and Gradient Descent as hybrid learning algorithms to automatically learn fuzzy IF–THEN rules, membership functions, and associated parameters from historical meteorological and reflectivity data. Every ANFIS rule has a confidence level defined by its RMSE, and only high-confidence rules are exported for reintegration.

All probabilistic and ANFIS rules are first written as FPR and then encoded in the FPN. Places represent fuzzy propositions with truth degrees (α), while transitions represent rules parameterised by CF and TH. Tokens carry truth values through the net: a transition fires when antecedent places satisfy TH constraints, and consequent places are updated. This mechanism ensures transparent inference and consistent uncertainty propagation. The decision system is implemented as a two-layer FPN. Layer 1 predicts reflector reflectivity in real time from meteorological inputs using rules generated by the two expert methods. Layer 2 combines the predicted reflectivity with real-time sensor data to infer the CD using a separate rule set. Token propagation across both layers supports dynamic tracking of reflectivity and estimation of appropriate cleaning time. Overall, the methodology unifies interpretable probabilistic rules with scalable ANFIS learning within an executable FPN tool for real-time operation, and is validated on an intelligent solar-collector CD system.

A. Data Preparation and Fuzzification

The data used in this study originates from five years of meteorological observations collected at one-hour intervals

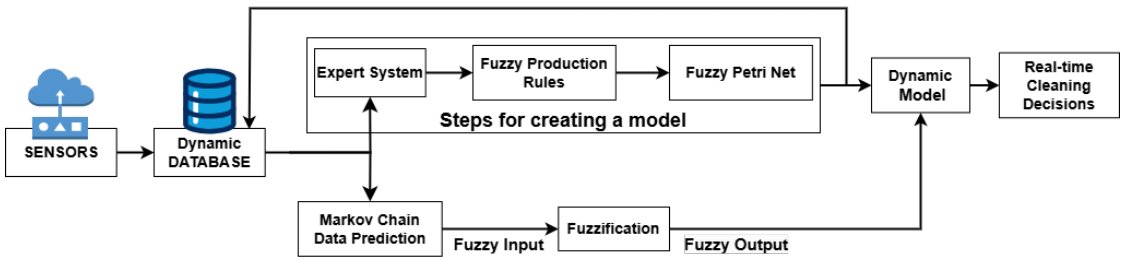


Fig. 1. Crafting and deploying our real-time decision model: step-by-step guidance for seamless implementation.

from a solar power plant in Morocco. The dataset includes five key environmental parameters-Direct Normal Irradiation (DNI), Temperature (T), Humidity (H), Wind Speed (WS), and Precipitation (P)-and one performance variable, Reflectivity (R). To prepare the data:

1) Data Cleaning: Outliers and erroneous readings (e.g., negative irradiance or reflectivity) are removed.
2) Normalisation : Each parameter is normalised into the range [0,1] to standardise the learning process.
3) Fuzzification: Quantitative data are transformed into linguistic variables (e.g., "Low," "Medium," "High") using trapezoidal membership functions. Each input variable is divided into fuzzy intervals defined by TH (a, b, c, d) describing the shape of each fuzzy set.

The trapezoidal membership function is defined mathematically as:

$$\alpha_A(x) = \begin{cases} 0, & x \le a, \\ \frac{x-a}{b-a}, & a < x \le b, \\ 1, & b < x \le c, \\ \frac{d-x}{d-c}, & c < x \le d, \\ 0, & x > d. \end{cases} \quad (1)$$

where $\alpha_A(x)$ is the membership degree of element x in the fuzzy set A.

The linguistic representation of variables ensures interpretability and forms the foundation of the FPR used in both expert systems.

B. Expert System Based on Conditional Probability

In the probabilistic expert system, fuzzy rules are generated based on conditional probability relationships between input and output variables. The probability of an event A given B is expressed as:

$$P(A|B) = \frac{P(A \cap B)}{P(B)}. \quad (2)$$

Using this concept, the CF for each rule is derived as:

$$CF_i = \frac{P(R|d_j)}{\max(P(R))}. \quad (3)$$

The TH is set based on the frequency or confidence level required for the rule to be considered valid:

$$TH_i = \frac{N_{valid}}{N_{total}}, \quad (4)$$

where N_{valid} is the number of successful occurrences satisfying the rule condition.

The resulting fuzzy rules are then represented in FPR format and encoded into the FPN. This approach ensures interpretability and transparency but lacks dynamic learning, requiring manual updates as conditions change.

C. Expert System Based on ANFIS

ANFIS, introduced by Jang [5] and based on the Sugeno-type model [6], merges the clarity of FL (interpretable IF-THEN rules) with the adaptation of neural networks. This system is crucial for generating rule-based, interpretable insights in data-heavy, real-time environments, automatically tuning both membership functions and rule parameters.

ANFIS employs a five-layer structure (see Fig. 2) based on the first-order Sugeno fuzzy model.

A first-order Sugeno fuzzy rule is defined as: [31], [5]

$$\text{If } x \text{ is } A_i \text{ and } y \text{ is } B_i, \text{ then } f_i = p_i x + q_i y + r_i \quad (5)$$

Where: x, y are inputs, A_i, B_i are fuzzy sets, and p_i, q_i, r_i are consequent parameters.

Each layer (see Fig. 2) performs a specific inference step [31], [5], [6]:

1) Layer 1: Fuzzification (Antecedent Parameters) Calculates the membership degree $\mu_{A_i}(x)$ for input x in fuzzy set A_i. Trapezoidal functions, defined by parameters a, b, c, d, are common [see Fig. 2]:
$$\mathcal{O}_{1,i} = \mu_{A_i}(x) \quad (6)$$
$$\mu(x, a, b, c, d) = \max\left(0, \min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right)\right) \quad (7)$$
2) Layer 2: Rule Firing Strength Computes the strength ω_i of the rule using the product operator:
$$\mathcal{O}_{2,i} = \omega_i = \mu_{A_i}(x) \cdot \mu_{B_i}(y) \quad (8)$$
3) Layer 3: Normalization Normalizes the firing strength to ensure proportional rule contribution ($\sum \bar{\omega}_k = 1$):
$$\mathcal{O}_{3,i} = \bar{\omega}_i = \frac{\omega_i}{\sum_{k=1}^{N} \omega_k} \quad (9)$$
4) Layer 4: Defuzzification (Partial Output) Calculates the weighted output of each rule using the normalised strength $\bar{\omega}_i$ and the Sugeno function f_i:
$$\mathcal{O}_{4,i} = \bar{\omega}_i f_i = \bar{\omega}_i (p_i x + q_i y + r_i) \quad (10)$$

The linear output can be expressed as:

$$f_i = \mathbf{C}_i \cdot \mathbf{Z} \tag{11}$$

where $\mathbf{C}_i = [p_i, q_i, r_i]$ and $\mathbf{Z} = [x, y, 1]$.

5) Layer 5: Aggregation (Final Output) Sums all weighted outputs to produce the final crisp system output $\mathcal{O}$:

$$\mathcal{O}_{5,i} = \mathcal{O} = \sum_{i=1}^{N} \bar{\omega}_i f_i \tag{12}$$

ANFIS training relies on a **hybrid algorithm** combining LSE and Gradient Descent [47]. The objective is to minimize the total error E between the predicted output $\mathcal{O}$ and the actual target $\mathcal{T}$.

The total squared error across M data points is:

$$E = \frac{1}{2} \sum_{k=1}^{M} (\mathcal{T}_k - \mathcal{O}_k)^2 \tag{13}$$

The hybrid training algorithm has two primary phases:

- Forward Pass (LSE): Input propagates forward. $\mathbf{C}_i$ (consequent, linear parameters) are optimized using Least Squares Estimation to minimize error.
- Backward Pass (Gradient Descent): Error propagates backward. a, b, c, d (premise, nonlinear parameters) are optimized using the Gradient Descent method to reduce the error gradient.

This parallel approach ensures efficiency and scalability, managing large datasets effectively [48].

The structured process for building an ANFIS expert system involves:

1) Data Collection and Preprocessing: Compile high-quality, preprocessed data.
2) ANFIS Design: Establish input-output associations and select appropriate membership functions.
3) Training ANFIS: Execute the hybrid algorithm to optimise all parameters.
4) Rule Extraction: Generate and prune fuzzy rules from the converged model [49]. Example rule:
   If Speed is Medium and Load is Normal, then Fuel Consumption
$$f = 0.6x + 0.4y + 1.2 \tag{14}$$
5) System Implementation: Integrate rules into the inference engine. Validate performance using metrics like **RMSE**.

D. FPN Representation of FPR in Knowledge Base Construction

The fuzzy knowledge base is represented through FPR, which encode expert knowledge or learned relationships between input and output variables. Each rule follows the general structure:

$$R_i : \text{IF } d_{j_1} \wedge d_{j_2} \wedge \ldots \wedge d_{j_m} \text{ THEN } d_k \, (CF = \mu_i, \, TH = \lambda_i), \tag{15}$$

where:

- $d_{j_1}, \ldots, d_{j_m}$ are fuzzy antecedent propositions (inputs),
- d_k is the fuzzy consequent proposition (output),
- $CF = \mu_i$ is the CF of the rule, representing its reliability,
- $TH = \lambda_i$ is the activation TH required for the rule to fire.

The firing condition for each rule is defined by:

$$y_k = \begin{cases} \min(y_{j_1}, \ldots, y_{j_m}) \times \mu_i, & \text{if } \min(y_{j_1}, \ldots, y_{j_m}) \geq \lambda_i, \\ 0, & \text{otherwise.} \end{cases} \tag{16}$$

The complete fuzzy rule base $\mathcal{R}$ is therefore a collection of all valid rules:

$$\mathcal{R} = \{R_1, R_2, \ldots, R_n\} \tag{17}$$

E. Formal Definition of Fuzzy Petri Net

An FPN is a bipartite-directed graph with two types of nodes: places and transitions. Circles represent places, and bars represent transitions (see Fig. 3). A token with a truth value between zero and one may or may not be present in each place in an FPN. A CF value between zero and one is assigned to each transition in an FPN. Directed arcs represent the relationships between places and transitions in an FPN. A collection of eight tuples can define a generalised FPN [1] structure

$$Fuzzy\ Petri\ Net = (P,\ T,\ D,\ I,\ O,\ f,\ \alpha,\ \beta) \tag{18}$$

Where

$P = \{p_1, \ p_2, \ \ldots, \ p_n\}$ denotes a finite set of places, represented by circles and corresponding to the propositions of FPR (see Fig. 3). $T = \{t_1, \ t_2, \ \ldots, \ t_m\}$ denotes a finite set of transitions, represented by bars and corresponding to the execution of FPR (see Fig. 3). $D = \{d_1, \ d_2, \ldots, \ d_n\}$ denotes a finite set of propositions of FPR which may contain some fuzzy linguistic variables such as "high," "low," "hot," etc. I: $T \longrightarrow P^{\propto}$ is the input function, a mapping from transitions to bags of places, represented by arcs directed from proposition (P) to rules (T). O: $T \longrightarrow P^{\propto}$ is the output function, a mapping from transitions to bags of places, represented by arcs directed from the rule (T) to propositions (P). $f : T \longrightarrow$ [0, 1] is an association function, a mapping from transitions to real values between zero and one, $f = \mu_1, \mu_2, ..., \mu_i$ where $\mu_i \in [0, 1]$ denotes (CF = μ_i) of rules R_i,$\alpha = \alpha_1, \alpha_2, ..., \alpha_n$. $\alpha : P \longrightarrow$ [0, 1] is an association function, a mapping from places to real values between zero and one, $\alpha = \alpha_1, \alpha_2, ..., \alpha_n$ where $\alpha_i \in [0, 1]$ denotes the degree of truth of propositions represented by the token in a place. β: $P \longrightarrow D$ is an association function, a bijective mapping from places to a set of propositions.

In an FPN, if $p_j \in I(t_i)$, a directed arc a_{ji} exists from the place p_j to the transition t_i. If $p_k \in O(t_i)$, there exists a directed arc a_{ik} from the transition t_i to the place p_k.The CF is a real value μ_i of a rule associated with its corresponding transition if $f(t_i) = \mu_i$ where $\mu_i \in [0, 1]$.The place p is said to be related to the proposition d if $\beta(p_i) = d_i$, where $d_i \in D$.

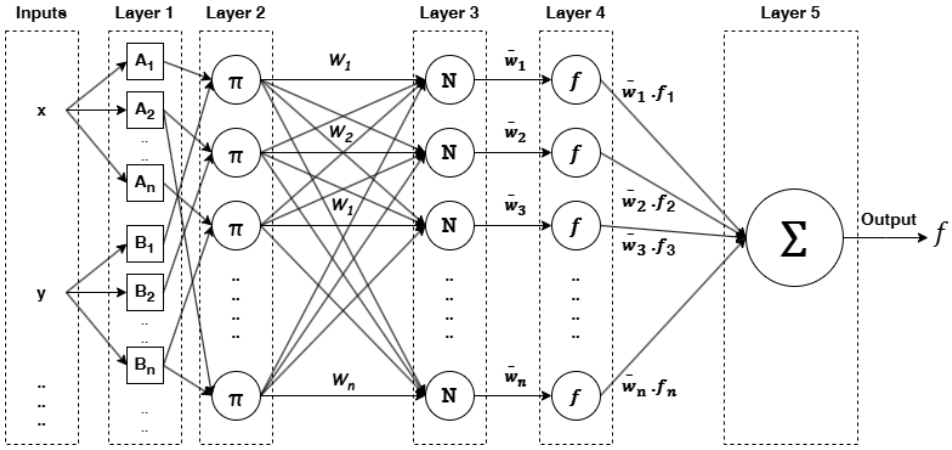


Fig. 2. Overall workflow of ANFIS-based expert systems integrated into a multi-layer FPN.

A marked FPN (see Fig. 1) is one in which a labeled dot represents some tokens in some places, a labeled dot represents the token in place p_i, and the token value in a place $p_i \in P$, is denoted by $\alpha(p_i)$, where $\alpha(p_i) \in [0,1]$. if $\alpha(p_i) = y_i$, where $y_i \in [0,1]$ and $\beta(p_i) = d_i$, then we can see that proposition d_i has a degree of truth of y_i. To reinforce the evolution capacity of our model, we can improve it by including a function $Th = \lambda_1, \lambda_2, ...\lambda_n$ where $\lambda_n \in [0,1]$ denotes the TH of transitions. When the values of tokens $\alpha(p_j)$ in all input places $p_j \in I(t_i)$ of the transition are greater than the TH $\alpha(p_j) \geq \lambda$, the transition t_i is enabled and can be fired.

F. A Multi-layer Approach to Dynamic Prediction and Decision-making

When $\alpha(p_i) \geq TH$, the transition is active, revealing a procedural adherence, identified adequately in our manuscript's Section III-D, where we present a hierarchical structure of the functionality of our system, emphasising the need for maintaining temporal constraints to prevent both computational and system-wide failures. FPN was selected because it comprises a rule-based component and readily supports simulation of real-time system dynamics. The truth-degree tokens are calibrated using data from a model's fuzzification system, with the twofold dependence on CF for concurrent FL and PN calculation for real-time prediction highlighted. This feature of our system, further illustrated with a real-life example in a conference publication [4], [8], demonstrates our approach's ability to forecast R, an important variable in renewable energy applications. In the construction of our two-layer predictive CD system, rigorous validation has been implemented to ensure that the model is robust and effective. As is often the case with machine learning model validation, 30% of the input is used to validate that the system's predictions and decisions stem from a reliable empirical base. This phase of validation is conducted on the remaining 70% of the initial dataset to ensure the dataset is valid and deployable for the model. In a post-validation version of the algorithm, based on the model's successful validation, specific data-collection and analysis intervals are determined. We adopt a Markov Chain probability model to predict new value-generating statistics to derive information for hourly CD-making (see Fig. 1). This methodology maintains a rigorous system to facilitate the execution of the entire model, from initial data processing to final decision-making and the visualisation of outputs in a structured manner. At this stage, every hour, a system performs a detailed computational analysis. The first step is to compute the average of each CD fuzzy interval, since the goal is to find the interval with the highest mean. The system's method approaches its goal by defining the interval's mean, which is then selected as the end case. For example, once the system has been running for a specific period and has been assessing data, like 24 hours, it makes one of its last adjustments to ensure that at least that interval has the highest average. This approach is heavily conditioned by predictive analytics. It means predicting forecasts at a scheduled time frame - typically 24 to 48 hours ahead to keep them in tip-top condition, such as maintaining mirrors well-kept after cleaning jobs. So, the system aims to forecast outcomes a day or two in advance, with a final decision within two days. It will allow experts to make rational, timely, and practical decisions based on this predictive process, leveraging insights from the entire system and its comprehensive analyses and forecasting. One of the aspects that sets our model apart is its ability to automatically extract outputs and present them, enabling real-time performance measurement with dynamic feedback.

G. Algorithmic Workflow

Algorithm 1 summarises the real-time inference process implemented by the FPN expert system. The system operates continuously, starting with the provision of real-time meteorological data (DNI, T, H, WS, P), which is immediately fuzzified to update the α degrees of truth at the FPN input locations. This step directly connects the current environmental conditions to the underlying fuzzy rule base. Central to this is the FPN's iterative firing cycle. The system scans for transitions t_i in every cycle and selects transitions whose input places in question have fuzzy markings α at least as large as their respective TH. Transitions are designated as enabled when they are executed. When an enabled switch fires, the output truth degree (y_{out}) is determined by applying the $\min$ operator to the input truth degrees and multiplying by the rule's CF. The value achieved is then propagated to the output points by the $\max$ operator to capture the contribution from multiple rules, and the confidence of each conclusion is updated at each

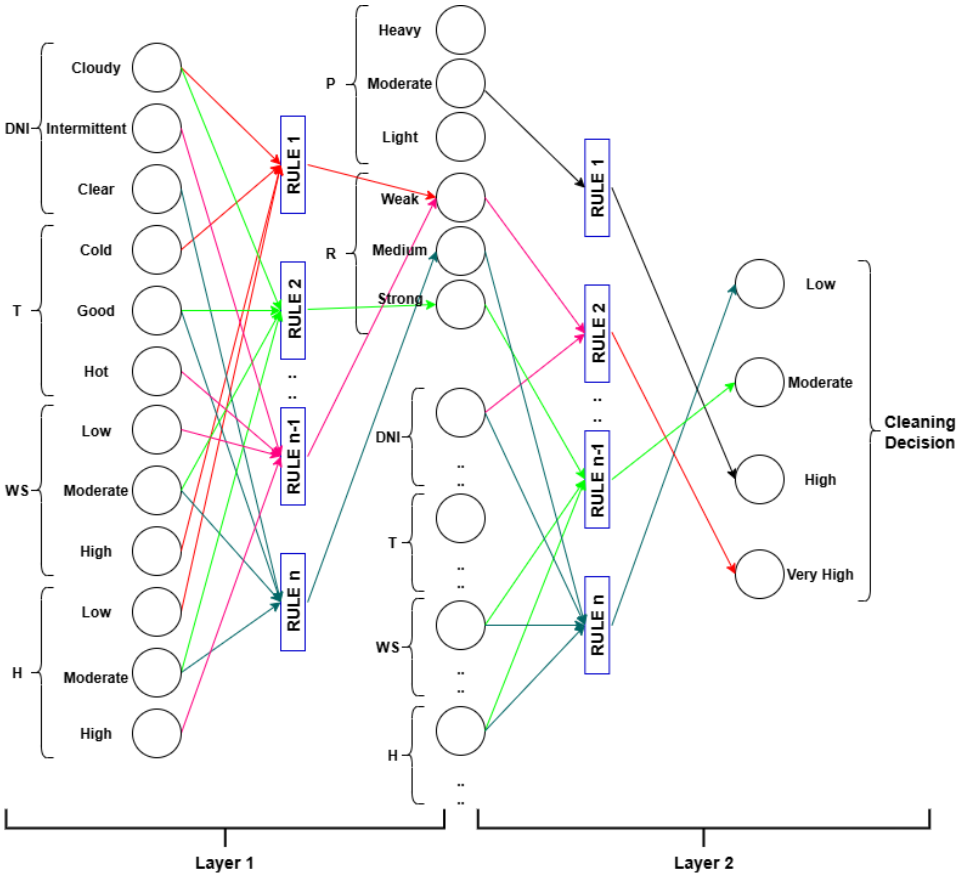


Fig. 3. A model of a solar collector's cleaning system using FPN grids to provide real-time CDs.

moment. After that, no further transitions can be tried. At the final steps of each cycle of this mechanism, the fuzzy marking of the relevant output places is derived from this number to obtain the CD. In this way, when the crisp control signal is needed to trigger or delay a cleaning action, the fuzzy output is defuzzified to reflect the situation. The resulting decision can be logged, and the process resumes with the next wave of real-time data. The FPN expert system's decision-making model is dynamic and adaptive, responding to fluctuating environmental conditions as they change.

IV. Results

In this section, the experimental validation of our proposed hybrid expert system is presented, along with an assessment of the potential value of the ANFIS-based fuzzy rule generation methodology compared with conventional probabilistic FL. We aim to demonstrate the superiority of the ANFIS-augmented model in terms of prediction accuracy, rule generation capabilities, and real-time inference efficiency. All simulations were performed with five years of real meteorological data from a solar power plant in Morocco. The data was split into 70% for training and 30% for validation. To ensure system responsiveness in real-time operation, the model was developed using a multithreaded architecture. Every fuzzy rule, such as one formed by probabilistic estimation or ANFIS training, is passed through an independent thread to the FPN engine. This architecture allows rules to be executed concurrently and also speeds up the inference phase, which is very important when dealing with large rule sets, such as those generated by ANFIS. Simulations were created to mimic natural operational scenarios comprising severe weather variability (temperature, wind speed, humidity), variable soiling conditions, and erratic sensor noise. Two expert system configurations were tested and benchmarked:

- Probabilistic FPN (Baseline): A rule base consisting of 43 FPR, derived from expert knowledge and conditional probability. Rules are associated with ($CF \geq 0.5$) and ($TH \geq 0.3$).
- ANFIS-Enhanced Fuzzy Expert System (Proposed): A data-driven expert system based on the ANFIS. ANFIS was trained on historical input-output data pairs to automatically generate 125 rules. Each rule is formulated in the Sugeno-style and converted into an FPN-compatible FPR. CFs are calculated based on RMSE: $CF = \frac{1}{1+\text{RMSE}}$.

The comparison was made over two system layers: reflectivity prediction and final CD generation.

A. Performance of Reflectivity Prediction Models

Table II compares three models: probabilistic FPN, classical FL, and ANFIS-based fuzzy inference, based on prediction accuracy and RMSE for solar reflectivity.

Algorithm 1 Real-Time Inference with FPN-based Expert System

Input: Real-time meteorological data (DNI, T, H, WS, P)
Initialize: Fuzzy rule base $\mathcal{R}$, FPN structure $(P, T, D, I, O, f, \alpha, \beta)$
while System active **do**
  Acquire and preprocess data
  Fuzzify inputs $\rightarrow$ update $\alpha(p_i)$ for all input places
  repeat
    Identify enabled transitions $\{t_i \mid \forall p_j \in I(t_i), \alpha(p_j) \geq TH_i\}$
    for each enabled t_i **do**
      Compute $y_{out} = \min(\alpha(p_j)) \times CF_i$
      Update output places: $\alpha(p_k) = \max(\alpha(p_k), y_{out})$
    end for
  until No transition can fire
  Aggregate outputs at Layer 2 $\rightarrow$ compute CD
  Defuzzify output if crisp value is required
  Log and display results
end while

TABLE II. COMPARISON OF REFLECTIVITY PREDICTION MODELS (LAYER 1)

Model	Rule Count	Validation Accuracy (%)	RMSE
Probabilistic FPN	43	85	4.82
Classical FL	30	60	6.15
ANFIS-Based FL	125	**93**	**2.57**

The ANFIS-based model clearly outperformed the others, achieving the highest accuracy and the lowest RMSE. This result validates the effectiveness of ANFIS in learning complex, nonlinear dependencies between environmental conditions (temperature, wind speed, humidity, and DNI) and reflectivity levels. The reduction in RMSE indicates a more precise reflectivity estimate, which is critical for determining the optimal timing for solar panel cleaning.

B. Cleaning Decision Validation (Layer 2)

The second layer of the system uses this to infer the best cleaning solution based on real-time sensor output and the predicted reflectivity of Layer 1. Evaluation results for the CD layer are summarised in Table III, which include precision, recall, F1-score, and RMSE. The ANFIS-enhanced classification model achieves significant gains across all metrics. Precision and recall scores show that the model can distinguish between fuzzy categories (Low, Moderate, High, Very High cleaning priority). In addition, the lower RMSE indicates that ANFIS-based decision-making yields results closer to the ground truth.

V. DISCUSSION

The results indicated that the ANFIS model can better fit the nonlinear relationship between meteorological variables and reflectivity, achieving higher accuracy and lower RMSE. Improvements to the CDs made at Layer 1, based on reflectivity predictions, enable cleaner cleaning at Layer 2 with greater reliability and less uncertainty about when and how the changes were applied. ANFIS has a cleaner, more adaptive decision boundary, as it learned all membership functions and Sugeno-type rules from the data, compared to manually decided or probabilistic ones. While the system is data-driven, it is interpretable: ANFIS produces well-defined IF–THEN rules. In contrast, the rules of the FPN remain interpretable by explicitly stating what information is accurate and which firing transition instructions to execute. This enables real-time responsiveness through concurrent execution and parallel rule evaluation, but requires more computation for larger rule bases.

The main comparative observations are as follows:

- Rule Base Expansion: A larger ANFIS produced finer-grained decision boundaries (125 rule-base vs. 43 rule-base), allowing us to consider more context-sensitive cleaning strategies.
- Higher Prediction Accuracy: The RMSE for the reflectivity prediction was reduced by almost 50%, and cleaner choices were more secure and resources allocated effectively.
- Scalability and Automation: In contrast to the static and expert-centric probabilistic rule base, the ANFIS model automatically learns new data through retraining to scale up effectively in evolving environments.
- Transparency and Interpretability: FPN architecture enables traceability of reasoning paths, while ANFIS supports flexibility, representing a complementary hybrid approach that provides a good balance of an interpretable and learned model.
- Real-Time Efficiency: The implementation of a multithreaded approach to generate the rules will help us optimise response times, even for a massive rule base, as this is an absolute necessity for a deployed system.

Therefore, pruning, merging, or prioritising may be required to prevent latencies. A hybrid approach that finds a balance between interpretability, scalability, and learning ability. Such rules are transparent, and the ANFIS is agile, providing better predictive capabilities. Such an approach could be extended to other real-time expert solutions, where transparency and adaptability are crucial, such as fault diagnosis or predictive maintenance. The need, however, arises for more validation through various datasets and operating conditions. Further work on explicit latency benchmarking,

TABLE III. VALIDATION METRICS FOR CLEANING DECISION OUTPUT

Model	Accuracy (%)	Precision Avg. (%)	Recall Avg. (%)	F1 Score (%)	RMSE
Probabilistic FPN	85	83	84	83	4.51
ANFIS-Fuzzy System	**93**	**90**	**91**	**90**	**2.57**

scalability testing under varied rule-base sizes, and long-term retraining analysis to tackle concept drift is needed.

VI. CONCLUSION

This work proposed a new methodology for modelling real-time intelligent systems by integrating FPN with data-driven rule learning via ANFIS. The primary methodological contribution, apart from the reported performance improvements, is a single model and execution scheme that integrates learned Sugeno-type fuzzy rules with an interpretable FPN reasoning engine, enabling concurrent, traceable inference across two layers (prediction and decision). From a functional standpoint, this paper illustrates how symbolic expert knowledge (FPR with CF/TH semantics) and data-driven learning can be combined into a single executable expert system that remains transparent and suitable for real-time operation. For this purpose, the proposed approach was tested in a real-time expert system for solar collector CD-making with five years of operational data collected from a Moroccan solar power plant under variable weather and soiling conditions. The results reveal that the improved prediction and decision performance of the ANFIS-enhanced setting is better than a probabilistic FPN baseline and a hand-tuned fuzzy-logic model due to the enhanced interpretability via FPN execution, as well as to a consistent inference mechanism by the decision quality using interpretable inference and the ability of responsive operation through concurrent decision making from the rule evaluation process under concurrent examination.

Data-Driven Neuro-Fuzzy learning becomes functional and interpretable in practice by mapping learned rules to a formal FPN execution model that provides traceability to reasoning and multi-layer decision. The tool will be further tested on other plants and climates, and expanded for new real-time applications in fault diagnosis and predictive maintenance. Real-time benchmarking (latency, throughput, scalability) as the rule base grows will also be planned, alongside investigation of scheduling strategies under limited resources. Ultimately, we seek formal verification and consistency checking of the learned rule base generated by the FPN tool to enhance its robustness.

REFERENCES

[1] S. M. Chen, J. S. Ke, and J. Chang, "Knowledge representation using fuzzy petri nets," *IEEE Trans. Knowl. Data Eng.*, vol. 2, pp. 311–319, 1990. [Online]. Available: http://dx.doi.org/10.1109/69.60794

[2] C. G. Looney, "Fuzzy petri nets for rule-based decisionmaking," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 18, pp. 178–183, 1988. [Online]. Available: http://dx.doi.org/10.1109/21.87067

[3] S. M. Chen, "Fuzzy backward reasoning using fuzzy petri nets," *IEEE Transactions on Systems, Man and Cybernetics, Part B (Cybernetics)*, vol. 30, pp. 846–856, 2000. [Online]. Available: http://dx.doi.org/10.1109/3477.891146

[4] A. Serji, E. B. Mermri, and M. Blej, "Modelling a real-time prediction system for solar collector reflectivity using fuzzy petri net," in *International Conference on Electronic Engineering and Renewable Energy Systems 2022, Saidia, Morocco*, 2023, pp. 815–821. [Online]. Available: http://dx.doi.org/10.1007/978-981-19-6223-3_84

[5] J.-S. R. Jang, "Anfis: Adaptive-network-based fuzzy inference system," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 23, no. 3, pp. 665–685, 1993. [Online]. Available: http://dx.doi.org/10.1109/21.256541

[6] T. Takagi and M. Sugeno, "Fuzzy identification of systems and its applications to modeling and control," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 15, no. 1, pp. 116–132, 1985. [Online]. Available: http://dx.doi.org/10.1109/TSMC.1985.6313399

[7] A. Konar, U. K. Chakraborty, and P. P. Wang, "Supervised learning on a fuzzy petri net," *Information Sciences*, vol. 172, pp. 397–416, 2005. [Online]. Available: http://dx.doi.org/10.1016/j.ins.2004.05.008

[8] A. Serji, E. B. Mermri, and M. Blej, "Fuzzy petri nets for real-time cleaning decisions in solar collectors," in *The 4th International Conference on Electronic Engineering and Renewable Energy Systems - Volume 2, 2024, Saidia, Morocco*, 2025, pp. 501–509. [Online]. Available: http://dx.doi.org/10.1007/978-981-97-9975-6_47

[9] H. Yuan, H. Yuan, and X. Li, "Fuzzy petri nets reasoning for application of electric control system fault diagnosis," in *IEEE Conference on Robotics, Automation and Mechatronics*, 2006, pp. 1–6. [Online]. Available: http://dx.doi.org/10.1109/RAMECH.2006.252679

[10] Y. Ye, Z. Jiang, X. Diao, and G. Du, "Extended event-condition-action rules and fuzzy petri nets based exception handling for workflow management," *Expert Systems with Applications*, vol. 38, pp. 10 847–10 861, 2011. [Online]. Available: http://dx.doi.org/10.1016/j.eswa.2011.02.097

[11] H. S. Hu, Z. W. Li, and A. Al-Ahmari, "Reversed fuzzy petri nets and their application for fault diagnosis," *Computers & Industrial Engineering*, vol. 60, pp. 505–510, 2011. [Online]. Available: http://dx.doi.org/10.1016/j.cie.2010.12.003

[12] Y. Zhong, "The design of a controller in fuzzy petri net," *Fuzzy Optimization and Decision Making*, vol. 7, no. 4, pp. 399–408, 2008. [Online]. Available: http://dx.doi.org/10.1007/s10700-008-9047-9

[13] A. J. Bugarin and S. Barro, "Fuzzy reasoning supported by petri nets," *IEEE Transactions on Fuzzy Systems*, vol. 2, pp. 135–150, 1994. [Online]. Available: http://dx.doi.org/10.1109/91.277962

[14] W. Pedrycz and F. Gomide, "A generalized fuzzy petri net model," *IEEE Transactions on Fuzzy Systems*, vol. 2, pp. 295–301, 1994. [Online]. Available: http://dx.doi.org/10.1109/91.324809

[15] M. Kouzehgar, M. A. Badamchizadeh, and S. Khanmohammadi, "Fuzzy petri nets for human behavior verification and validation," *International Journal of Advanced Computer Science and Applications*, vol. 2, no. 12, 2011. [Online]. Available: http://dx.doi.org/10.14569/IJACSA.2011.021216

[16] N. V. Nenkov and E. Z. Spasova, "Implementation of a neural network using simulator and petri nets*," *International Journal of Advanced Computer Science and Applications*, vol. 7, no. 1, 2016. [Online]. Available: http://dx.doi.org/10.14569/IJACSA.2016.070155

[17] A. Ahmadikatouli and H. Motameni, "Enrichment of object oriented petri net and object z aiming at business process optimization," *International Journal of Advanced Computer Science and Applications*, vol. 6, no. 7, 2015. [Online]. Available: http://dx.doi.org/10.14569/IJACSA.2015.060703

[18] A. E. S. Ahmed, "Modeling and assessing the power consumption behavior of sensor nodes using petri nets," *International Journal of Advanced Computer Science and Applications*, vol. 11, no. 8, 2020. [Online]. Available: http://dx.doi.org/10.14569/IJACSA.2020.0110823

[19] S. MTIBAA and M. TAGINA, "Managing changes in citizen-centric healthcare service platform using high level petri net," *International Journal of Advanced Computer Science and Applications*, vol. 3, no. 8, 2012. [Online]. Available: http://dx.doi.org/10.14569/IJACSA.2012.030813

[20] R. Patil, S. Tamane, and K. Patil, "Self organising fuzzy logic classifier for predicting type-2 diabetes mellitus using aco-ann," *International Journal of Advanced Computer Science and Applications*, vol. 11, no. 7, 2020. [Online]. Available: http://dx.doi.org/10.14569/IJACSA.2020.0110746

[21] A. R. Khan, H. U. Amin, and Z. U. Rehman, "Application of expert system with fuzzy logic in teachers' performance evaluation," *International Journal of Advanced Computer Science and Applications*, vol. 2, no. 2, 2011. [Online]. Available: http://dx.doi.org/10.14569/IJACSA.2011.020210

[22] A. Chabchoub, A. Hamouda, S. Al-Ahmadi, and A. Cherif, "Intelligent traffic light controller using fuzzy logic and image processing," *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 4, 2021. [Online]. Available: http://dx.doi.org/10.14569/IJACSA.2021.0120450

[23] S. ZENNED, H. CHAOUALI, and A. MAMI, "Fuzzy logic energy management strategy of a hybrid renewable energy system feeding a typical tunisian house," *International Journal of Advanced Computer Science and Applications*, vol. 8, no. 12, 2017. [Online]. Available: http://dx.doi.org/10.14569/IJACSA.2017.081226

[24] L. X. Wang, *A Course in Fuzzy Systems and Control*. Upper Saddle River, NJ, USA: Prentice Hall, 2003.

[25] H. F. Kwok, D. A. Linkens, M. Mahfouf, and G. H. Mills, "Rule-base derivation for intensive care ventilator control using anfis," *Artificial Intelligence in Medicine*, vol. 29, no. 3, pp. 185–201, 2003. [Online]. Available: http://dx.doi.org/10.1016/s0933-3657(02)00074-x

[26] A. Biswas, D. Majumder, and S. Sahu, "Assessing morningness of a group of people by using fuzzy expert system and adaptive neuro fuzzy inference model," in *Communications in Computer and Information Science*. Springer, 2011, vol. 140, pp. 47–56. [Online]. Available: http://dx.doi.org/10.1007/978-3-642-19263-0_6

[27] N. R. Rahim, S. Nordin, and R. M. Dom, "An adaptive neuro-fuzzy inference system (anfis) model for prediction of optimal dose in methadone maintenance therapy," in *IEEE 10th Control and System Graduate Research Colloquium (ICSGRC)*, 2019, pp. 195–200. [Online]. Available: http://dx.doi.org/10.1109/ICSGRC.2019.8837074

[28] A. Ghanbari, S. M. R. Kazemi, F. Mehmanpazir, and M. M. Nakhostin, "A cooperative ant colony optimization–genetic algorithm approach for construction of energy demand forecasting knowledge-based expert systems," *Knowledge-Based Systems*, vol. 39, pp. 194–206, 2013. [Online]. Available: http://dx.doi.org/10.1016/j.knosys.2012.10.017

[29] T. Khatib, A. Mohamed, and K. Sopian, "A review of photovoltaic systems size optimization techniques," *Renewable and Sustainable Energy Reviews*, vol. 22, pp. 454–465, 2013. [Online]. Available: http://dx.doi.org/10.1016/j.rser.2013.02.023

[30] A. Mellit and S. A. Kalogirou, "Artificial intelligence techniques for photovoltaic applications: A review," *Progress in Energy and Combustion Science*, vol. 34, no. 5, pp. 574–632, 2008. [Online]. Available: http://dx.doi.org/10.1016/j.pecs.2008.01.001

[31] W. Li, N. Zong, K. Liu, P. Li, and X. Ma, "A privacy-preserving group decision-making expert system for medical diagnosis based on dynamic knowledge base," *Wireless Networks*, vol. 30, no. 7, pp. 6237–6247, 2024. [Online]. Available: http://dx.doi.org/10.1007/s11276-020-02374-4

[32] A. Buscemi, V. Lo Brano, C. Chiaruzzi, G. Ciulla, and C. Kalogeri, "A validated energy model of a solar dish-stirling system considering the cleanliness of mirrors," *Applied Energy*, vol. 260, p. 114378, 2020. [Online]. Available: http://dx.doi.org/10.1016/j.apenergy.2019.114378

[33] G. Picotti, L. Moretti, M. E. Cholette, M. Binotti, R. Simonetti, E. Martelli, T. A. Steinberg, and G. Manzolini, "Optimization of cleaning strategies for heliostat fields in solar tower plants," *Solar Energy*, vol. 204, pp. 501–514, 2020. [Online]. Available: http://dx.doi.org/10.1016/j.solener.2020.04.032

[34] A. Heimsath and P. Nitz, "The effect of soiling on the reflectance of solar reflector materials - model for prediction of incidence angle dependent reflectance and attenuation due to dust deposition," *Solar Energy Materials and Solar Cells*, vol. 195, pp. 258–268, 2019. [Online]. Available: http://dx.doi.org/10.1016/j.solmat.2019.03.015

[35] A. Fernandez-Garcia, L. Alvarez-Rodrigo, L. Martinez-Arcos, R. Aguiar, and J. M. Marquez-Payes, "Study of different cleaning methods for solar reflectors used in csp plants," *Energy Procedia*, vol. 49, pp. 80–89, 2014. [Online]. Available: http://dx.doi.org/10.1016/j.egypro.2014.03.009

[36] F. Terhag, F. Wolfertstetter, S. Wilbert, T. Hirsch, and O. Schaudt, "Optimization of cleaning strategies based on ann algorithms assessing the benefit of soiling rate forecasts," in *International Conference on Concentrating Solar Power and Chemical Energy Systems 2019, Casablanca, Morocco*, 2019, pp. 22–1–22–10. [Online]. Available: http://dx.doi.org/10.1063/1.5117764

[37] M. Tanhaeean, S. F. Ghaderi, and M. Sheikhalishahi, "A decision-making framework for optimal maintenance management: An integrated simulation–mathematical programming–expert system approach," *Computers and Industrial Engineering*, vol. 185, p. 109671, 2023. [Online]. Available: http://dx.doi.org/10.1016/j.cie.2023.109671

[38] A. Sharma, R. K. Chakrabortty, V. Sharma, H. Marwaha, P. Singh, S. Mahajan, and A. K. Pandit, "A multi-criteria decision-making tool for the screening of asperger syndrome," *Multimedia Tools and Applications*, vol. 82, no. 22, pp. 34 095–34 111, 2023. [Online]. Available: http://dx.doi.org/10.1007/s11042-023-14996-9

[39] M. Charai, A. Mezrhab, and A. Merrouni, "Étude de la dégradation optique des concentrateurs solaires csp suite aux conditions météorologiques du maroc oriental," 2018, rapport de recherche. [Online]. Available: http://dx.doi.org/10.13140/RG.2.2.11949.33763

[40] S. Bouaddi, A. Ihlal, and A. Fernández-García, "Soiled csp solar reflectors modeling using dynamic linear models," *Solar Energy*, vol. 122, pp. 847–863, 2015. [Online]. Available: http://dx.doi.org/10.1016/j.solener.2015.09.044

[41] M. Coello and L. Boyle, "Simple model for predicting time series soiling of photovoltaic panels," *IEEE Journal of Photovoltaics*, vol. 9, no. 5, pp. 1382–1387, 2019. [Online]. Available: http://dx.doi.org/10.1109/JPHOTOV.2019.2919628

[42] A. Azouzoute, A. A. Merrouni, M. Garoum, and E. G. Bennouna, "Soiling loss of solar glass and mirror samples in the region with arid climate," *Energy Reports*, vol. 6, pp. 693–698, 2020. [Online]. Available: http://dx.doi.org/10.1016/j.egyr.2019.09.051

[43] M. Fathi, M. Abderrezek, and P. Grana, "Technical and economic assessment of cleaning protocol for photovoltaic power plants: Case of algerian sahara sites," *Solar Energy*, vol. 147, pp. 358–367, 2017. [Online]. Available: http://dx.doi.org/10.1016/j.solener.2017.03.053

[44] S. M. Chen, "A new approach to handling fuzzy decision-making problems," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 18, pp. 1012–1016, 1988. [Online]. Available: http://dx.doi.org/10.1109/21.23100

[45] C. V. Negoita, *Expert Systems and Fuzzy Systems*. Massachusetts: Benjamin/Cummings, 1985, vol. 16.

[46] C. G. Looney and A. A. Alfize, "Logical controls via boolean rule matrix transformations," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 17, pp. 1077–1082, 1987. [Online]. Available: http://dx.doi.org/10.1109/TSMC.1987.6499319

[47] L.-X. Wang, *A Course in Fuzzy Systems and Control*. Prentice Hall, 2003.

[48] C.-T. Lin and C. S. G. Lee, *Neural Fuzzy Systems: A Neuro-Fuzzy Synergism to Intelligent Systems*. Prentice Hall, 2004.

[49] S.-M. Chen and S.-H. Chang, "Multi-variable fuzzy forecasting based on fuzzy clustering and fuzzy rule interpolation techniques," *Information Sciences*, vol. 81, no. 3, pp. 177–201, 2001.

Trajectory Planning of Shipbuilding Welding Manipulator Based on Improved Whale Optimization Algorithm

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***Abstract*—Time-optimal trajectory planning for shipboard welding robotic arms is a challenging problem due to strong kinematic constraints and the nonlinear coupling between trajectory parameters and execution time. Although various intelligent optimization algorithms have been combined with robotic arm trajectory planning in existing studies, most approaches primarily focus on algorithmic performance improvement and lack a clear formulation of time optimization within polynomial trajectory planning.To address this gap, this study proposes an Improved Whale Optimization Algorithm (IWOA) based on the traditional quintic polynomial trajectory planning method. In the proposed method, the trajectory execution time is explicitly formulated as the optimization objective under kinematic constraints, and the IWOA is designed to stably and efficiently search the time parameter space of the quintic polynomial trajectory. Specifically, chaotic sequence initialization is employed to enhance population distribution, an adaptive weight mechanism is introduced to balance global exploration and local exploitation, and a hybrid co-optimization strategy combining differential evolution and genetic operators is integrated to improve robustness and convergence stability. Simulation experiments are conducted to evaluate the effectiveness of the proposed algorithms. The results demonstrated that, while satisfying robotic arms kinematic constraints, the proposed method achieves an 18.3% reduction in operating time compared with the unoptimized trajectory. These results indicate that the proposed approach provides a systematic and effective solution for time-efficient trajectory planning of shipboard welding robotic arms.**

Keywords*—Shipboard welding robotic arm; quintic polynomial; Improved Whale Optimization Algorithm; time-optimal trajectory planning

I. Introduction

In recent years, with the rapid development of China shipbuilding industry and the increasing complexity of ship hull structures, higher requirements have been imposed on welding quality, efficiency, and consistency during ship construction [1]. Ship welding tasks are typically characterized by large-scale structures, complex curved surfaces, harsh working environments, and long continuous weld seams, which pose significant challenges to traditional manual and semi-automatic welding methods [2]. These conventional approaches are increasingly unable to satisfy the demands for high efficiency, precision, and repeatability required in modern shipbuilding. The application of robotic arm welding technology has emerged as an effective solution to these challenges. Robotic welding systems can significantly improve welding stability, reduce labor intensity, and ensure consistent weld quality, particularly in complex and hazardous environments [3]. With advancements in sensing, control, and intelligent planning technologies, robotic arms have been widely adopted in various industrial manufacturing fields due to their flexibility, efficiency, and high positioning accuracy [4], [5]. Consequently, shipboard welding robotic arms have attracted extensive attention from researchers and industrial practitioners worldwide, leading to notable progress in both system design and motion planning methods [6]. In terms of system development and application, Zhang et al. [7] proposed a magnetic tracked mobile robot for welding vertical steel ship hulls, enabling stable adhesion and motion on large steel surfaces. Liu et al. [8] developed a trajectory and velocity planning method for complex curved-surface welding tasks involving spherical–pipe intersection structures, achieving smooth path transitions and adaptive speed control to improve weld formation quality. Liang et al. [9] designed an autonomous mobile welding robot capable of identifying discontinuous weld seams caused by drainage holes in ship cabins and performing autonomous welding operations. These studies demonstrate the feasibility and effectiveness of robotic welding systems in shipbuilding environments. However, during ship construction, welding tasks often involve plates, pipes, and complex spatial weld seams, which require not only accurate path planning but also high operational efficiency [10]. To further enhance productivity, time-optimal trajectory planning for welding robotic arms has become a critical research topic [11].

Current studies on robotic arm trajectory planning primarily focus on optimizing performance indices such as operating time, energy consumption, smoothness, and dynamic impact [12]. Among these objectives, minimizing execution time while satisfying kinematic and dynamic constraints is of particular importance for improving industrial production efficiency.Traditional trajectory planning methods based on polynomial interpolation typically rely on predefined segment times and path nodes [13]. Although these methods can guarantee trajectory continuity and smoothness, they often lack flexibility and are difficult to achieve true time-optimal performance under complex constraints. In recent years, intelligent optimization algorithms have been increasingly introduced into robotic arm trajectory time optimization, forming an important research direction in motion planning [14]. Commonly used intelligent optimization methods include ant colony optimization [15], sparrow search algorithm [16], particle swarm opti-

mization [17], and whale optimization algorithm [18]. These algorithms have demonstrated certain advantages in improving robotic arm operating efficiency; however, they still suffer from inherent limitations such as premature convergence, susceptibility to local optima, and insufficient global search capability, which ultimately restrict their optimization performance [19].

Inspired by the foraging behavior of humpback whales in bubble webs, the Whale Optimization Algorithm (WOA) has been widely applied to various engineering optimization problems due to its advantages such as simple structure, few control parameters, and fast convergence speed [20]. However, similar to other swarm intelligence algorithms, the standard Whale Optimization Algorithm has inherent defects, including rapid loss of population diversity and easy premature convergence to local optima [21]. These defects are particularly prominent when dealing with high-dimensional, nonlinear, and constrained optimization problems [22]. Although existing research has attempted to alleviate the above problems through isolated strategies such as parameter tuning and fusion with other metaheuristic operators, such improvements are mostly designed for general test functions. For scenarios with strict kinematic constraints and industrial efficiency requirements, such as time-optimal trajectory planning for welding robotic arms, its direct applicability is still very limited [23].

To address these challenges, this study proposes an Improved Whale Optimization Algorithm (IWOA) specifically tailored for the time-optimal trajectory planning problem of welding robotic arms. Unlike existing studies that apply generic hybrid optimization strategies, the proposed IWOA introduces a problem-oriented improvement framework that integrates chaotic initialization, adaptive parameter adjustment, and a coordinated hybrid mechanism combining differential evolution and genetic operators. These strategies are not simply combined, but are systematically designed to address distinct deficiencies of the standard WOA at different stages of the optimization process: chaotic initialization enhances early-stage population diversity, adaptive parameter adjustment dynamically balances global exploration and local exploitation, and the hybrid evolutionary operators improve convergence robustness in the later optimization phase. Comparative simulations conducted in MATLAB demonstrate that, under identical constraints, the proposed IWOA achieves superior time-optimal performance compared to the standard WOA, effectively reducing the execution time of robotic arm trajectories and validating its applicability to industrial welding scenarios.

II. Joint Trajectory Planning

A. Trajectory Interpolation Based on 5th-order Polynomials

The trajectory planning of robotic arms is generally divided into two categories: joint space method and Cartesian space method [24].The joint space method directly interpolates the angles of each joint, which is simple to calculate and easily satisfies joint constraints. The Cartesian space method first plans the pose path of the end effector and then solves the inverse kinematics to obtain the joint motion, resulting in high path accuracy. Ship welding tasks require high precision in motion paths; therefore, this study employs the Cartesian space trajectory planning method. This method can control the motion trajectory of the robotic arm's end effector, achieving the operational objective along a specified path—a method that is difficult to replace using joint space planning [25].Furthermore, this study introduces a fifth-order polynomial interpolation function. By performing fifth-order polynomial fitting on the position, velocity, and acceleration of the starting and ending points, the continuity and smoothness of the joint motion process are ensured, effectively avoiding abrupt changes in velocity and acceleration. The constraints of the fifth-order polynomial interpolation include the starting and ending angles, angular velocities, and angular accelerations, requiring the determination of six coefficients. The joint variables are assumed to satisfy Eq. (1):

$$\begin{cases} \theta_i(t) = a_0 + a_1 t + a_2 t^2 + a_3 t^3 + a_4 t^4 + a_5 t^5 \\ \dot{\theta}_i(t) = a_1 + 2a_2 t + 3a_3 t^2 + 4a_4 t^3 + 5a_5 t^4 \\ \ddot{\theta}_i(t) = 2a_2 + 6a_3 t + 12a_4 t^2 + 20a_5 t^3 \end{cases} \tag{1}$$

In Eq. (1), $i = 1, 2, 3, \ldots, n$ represents the n joints of the robotic arm; t is the running time of each joint; a_j are the interpolation coefficients of each joint; $\theta_i(t)$, $\dot{\theta}_i(t)$, and $\ddot{\theta}_i(t)$ denote the angular position, angular velocity, and angular acceleration of the robotic arm joint, respectively. The constraints for the fifth-degree polynomial are:

$$\begin{cases} \begin{cases} \theta(t_0) = \theta_0 \\ \theta(t_f) = \theta_f \end{cases} \\ \begin{cases} \dot{\theta}(t_0) = 0 \\ \dot{\theta}(t_f) = 0 \end{cases} \\ \begin{cases} \ddot{\theta}(t_0) = 0 \\ \ddot{\theta}(t_f) = 0 \end{cases} \end{cases} \tag{2}$$

In Eq. (2), t_0 and t_f represent the start time and end time of the robotic arm operation, respectively, and θ_0 and θ_f represent the start angle and end angle, respectively. From Eq. (1) and Eq. (2), the corresponding kinematic equations for each joint can be derived:

$$\begin{cases} \theta_0 = a_0 + a_1 t_0 + a_2 t_0^2 + a_3 t_0^3 + a_4 t_0^4 + a_5 t_0^5 \\ v_0 = a_1 + 2a_2 t_0 + 3a_3 t_0^2 + 4a_4 t_0^3 + 5a_5 t_0^4 \\ \alpha_0 = 2a_2 + 6a_3 t_0 + 12a_4 t_0^2 + 20a_5 t_0^3 \\ \theta_f = a_0 + a_1 t_f + a_2 t_f^2 + a_3 t_f^3 + a_4 t_f^4 + a_5 t_f^5 \\ v_f = a_1 + 2a_2 t_f + 3a_3 t_f^2 + 4a_4 t_f^3 + 5a_5 t_f^4 \\ \alpha_f = 2a_2 + 6a_3 t_f + 12a_4 t_f^2 + 20a_5 t_f^3 \end{cases} \tag{3}$$

Then, substitute the known θ_0, θ_f, v_0, v_f, α_0, and α_f into Eq. (3) to obtain the parameter matrix of the kinematic equation for each joint:

$$\begin{bmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{bmatrix} = \begin{bmatrix} 1 & t_0 & t_0^2 & t_0^3 & t_0^4 & t_0^5 \\ 0 & 1 & 2t_0 & 3t_0^2 & 4t_0^3 & 5t_0^4 \\ 0 & 0 & 2 & 6t_0 & 12t_0^2 & 20t_0^3 \\ 1 & t_f & t_f^2 & t_f^3 & t_f^4 & t_f^5 \\ 0 & 1 & 2t_f & 3t_f^2 & 4t_f^3 & 5t_f^4 \\ 0 & 0 & 2 & 6t_f & 12t_f^2 & 20t_f^3 \end{bmatrix}^{-1} \begin{bmatrix} \theta_0 \\ v_0 \\ \alpha_0 \\ \theta_f \\ v_f \\ \alpha_f \end{bmatrix} \tag{4}$$

By substituting the solved coefficient matrix from Eq. (4) into Eq. (1), the spatial trajectory function of the robotic arm joint is obtained.

B. Objective Function and Constraint Conditions

To meet the requirement of improving the operation efficiency of the welding robotic arm in the ship welding process, this study takes the motion cycle of the robotic arm reaching each target point as the optimization objective. Then, the objective function can be expressed as Eq. (5):

$$T = \sum_{i=1}^{n-1} T_i = \sum_{i=1}^{n-1} (t_{i+1} - t_i) \tag{5}$$

In Eq. (5), $i = 1, 2, \ldots, n$ represents n path points, and T represents the running time of the robotic arm end on each segment of the path.

Since the motion constraints in the joint space of the robotic arm are strictly satisfied during its movement, the problem of optimizing the running time of the robotic arm can be formulated as Eq. (6):

$$\min T = T_1 + T_2 + \cdots + T_{n-1} \tag{6}$$

Since the position, velocity, and acceleration of each joint of the robotic arm cannot exceed the rated limits of the motor and reducer during movement, it is necessary to impose physical limit constraints on the robotic arm. The constraint conditions are shown in Eq. (7):

$$\begin{cases} |\theta_i| \le q_{i\max} \\ |\dot{\theta}_i| \le v_{i\max} \\ |\ddot{\theta}_i| \le a_{i\max} \end{cases} \quad (i = 1, 2, \ldots, n) \tag{7}$$

θ_i, $\dot{\theta}_i$, and $\ddot{\theta}_i$ represent the angular position, angular velocity, and angular acceleration of the i-th joint, respectively; $q_{i\max}$, $v_{i\max}$, and $a_{i\max}$ represent the rated upper limits of the angular position, angular velocity, and angular acceleration of the corresponding joint, respectively; n is the total number of joints of the robotic arm.

III. Algorithm Principle

A. Original Whale Optimization Algorithm

The core of the Whale Optimization Algorithm is to imitate three behaviors of whales during predation.

Encircling prey:

$$\vec{D} = \left| \vec{C} \cdot \vec{X}^*(t) - \vec{X}(t) \right| \tag{8}$$

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A} \cdot \vec{D} \tag{9}$$

In Eq. (8) and Eq. (9), $\vec{X}^*(t)$ represents the current optimal position, $\vec{X}(t)$ is the current position of the whale, $\vec{D}$ is the distance between the current position and the optimal position, and $\vec{A}$ and $\vec{C}$ are system vectors that control the convergence and search range.

Bubble-net attack:

$$\vec{X}(t+1) = \vec{D}' \cdot e^{bl} \cdot \cos(2\pi l) + \vec{X}^*(t) \tag{10}$$

In Eq. (10), $\vec{X}(t+1)$ represents the position vector of the individual at generation $t+1$; $\vec{X}^*(t)$ represents the position vector of the optimal individual at generation t; $\vec{D}' = |\vec{X}^*(t) - \vec{X}(t)|$ represents the distance between the current individual and the optimal individual; b is a constant that controls the shape of the logarithmic spiral; l is a random number within the interval $[-1, 1]$.

Searching for prey:

$$\vec{D} = \left| \vec{C} \cdot \vec{X}_{rand} - \vec{X}(t) \right| \tag{11}$$

$$\vec{X}(t+1) = \vec{X}_{rand} - \vec{A} \cdot \vec{D} \tag{12}$$

As shown in Eq. (11) and Eq. (12), $\vec{X}_{rand}$ is the position of a randomly selected individual in the population. $\vec{A} = 2a \cdot r - a$, where a decreases linearly from 2 to 0 during the iteration process. $\vec{C} = 2 \cdot r$, where r is a random number in the interval $[0, 1]$. When $|\vec{A}| < 1$: the whale tends to the current optimal solution; when $|\vec{A}| \ge 1$: the whale randomly searches for other prey.

B. Improvement Mechanism

Due to the shortcomings of the WOA, such as being prone to premature convergence and falling into local optima, as well as strong randomness leading to unstable results, this study proposes the following improvement strategies to enhance the performance of the original Whale Optimization Algorithm in robotic arm trajectory planning:

1) Chaotic initialization: First, the Tent chaotic map is used to replace random initialization to avoid the problem of uneven initial distribution of the population.

$$x_{k+1} = \begin{cases} \dfrac{x_k}{0.5}, & 0 \le x_k < 0.5 \\ \dfrac{1 - x_k}{0.5}, & 0.5 \le x_k \le 1 \end{cases} \tag{13}$$

As shown in Eq. (13), the Tent chaotic map has ergodicity and pseudo-randomness, which can ensure that individuals are evenly distributed in the search space, thereby improving the diversity of the initial population. In addition, to enhance the local exploitation ability, a small chaotic disturbance is applied to the current global optimal solution during the iteration, and the disturbance amplitude is gradually reduced to prevent the algorithm from stagnating at a local optimum.

2) Adaptive parameter adjustment: To address the limitation of linear decrement of parameters in the Whale Optimization Algorithm, this study designs an adaptive control mechanism based on nonlinear functions and cosine functions:

$$a_t = 2\left(1 - \left(\frac{t}{T}\right)^2\right) \tag{14}$$

a_t is the control parameter at the t-th iteration, where t is the current number of iterations and T is the maximum number of iterations. Eq. (14) allows the algorithm to maintain stronger exploration ability in the early stage and gradually enhance exploitation in the later stage.

The spiral control factor b_t is defined as Eq. (15):

$$b_t = 1 + 1.5\left(1 - \frac{t}{T}\right) \tag{15}$$

which dynamically adjusts the spiral search behavior during the optimization process. In addition, the concept probability parameter p_t, which controls the selection between encircling search and spiral search, is defined as Eq. (16):

$$p_t = 0.5 + 0.5\cos\left(\pi\frac{t}{T}\right) \tag{16}$$

Eq. (16) controls the selection probability of encircling search and spiral search, achieving a dynamic balance between exploration and exploitation.

3) Integration of differential evolution and genetic operators: To enhance the ability to jump out of local optima, this study introduces the crossover operators of differential evolution and genetic algorithm into the Whale Optimization Algorithm after its iterative update.

Differential evolution and genetic operator fusion:

The rand/1/bin strategy is adopted to generate candidate individuals, improving the directionality of the search. The mathematical model is as follows:

$$V_i = X_{r1} + F \cdot (X_{r2} - X_{r3}) \tag{17}$$

$$U_{i,j} = \begin{cases} V_{i,j}, & \text{rand} \le CR \\ X_{i,j}, & \text{otherwise} \end{cases} \tag{18}$$

Eq. (17) and Eq. (18) enhance the directional search ability of the population. Among them, V_i represents the mutation vector of the i-th candidate individual, i.e., the newly generated candidate solution. X_{r1}, X_{r2}, X_{r3}: three different individuals randomly selected from the population, and different from the current individual X_i. F is the scaling factor, usually ranging from 0.4 to 0.90, and CR is the crossover probability, usually ranging from 0.6 to 0.95.

In addition to DE operators, arithmetic crossover and Gaussian mutation from genetic algorithms are introduced to improve local search capability. The arithmetic crossover is defined as Eq. (19):

$$X' = \alpha X_i + (1-\alpha)X_j, \alpha \in [0,1] \tag{19}$$

X' is a new candidate solution generated by arithmetic crossover, and α, as a crossover coefficient, is used to control the contribution proportion of the two parent individuals X_i and X_j to the new individual X'. X_i and X_j are the two original candidate solutions involved in the crossover. Eq. (19) enables the fusion of two parent individuals to generate a new candidate solution through linear interpolation, thereby increasing the diversity of the population and providing a foundation for subsequent improvement of local search ability.

C. Steps of the Improved Whale Optimization Algorithm

1) Initialize the number of whales and define relevant parameters.

2) Use the Tent chaotic map to generate the initial population, replacing the traditional random initialization to improve population diversity and global coverage capability.

3) During the iteration process, adaptively and nonlinearly adjust parameters a, b, and p to ensure exploration capability in the early stage and enhance convergence in the later stage.

4) Update the position: update the whale position according to Eq. (9) and Eq. (10) to approach the optimal solution. Perform spiral update according to Eq. (11), and then conduct global random search according to Eq. (12) and Eq. (13).

5) After the update, apply evolutionary operators to some individuals: use the rand/1/bin strategy for mutation and crossover to generate candidate solutions.

6) Perform arithmetic crossover and Gaussian perturbation on some individuals to enhance local exploitation capability.

7) Update the global optimal solution and fitness. If the maximum number of iterations T is reached, terminate the loop and output the optimal solution; otherwise, return to step 3 to continue the search.

The algorithm flowchart is shown in Fig. 1.

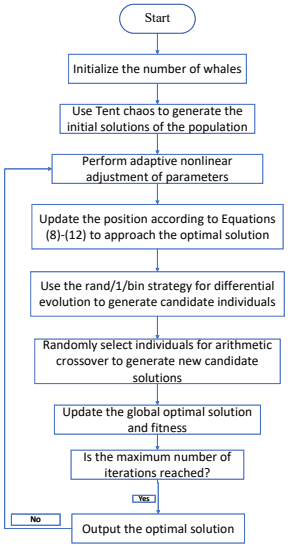
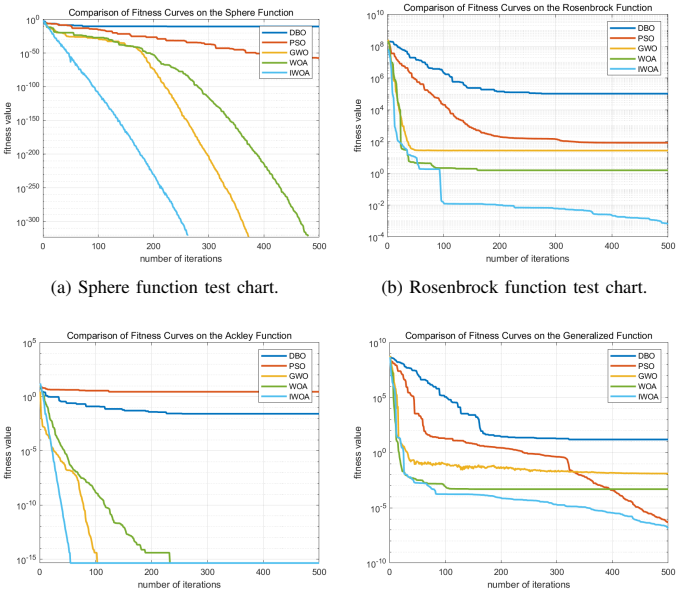


Fig. 1. Algorithm flowchart.

D. Validation of Algorithm Effectiveness

In this study, four classic CEC test functions are selected to verify the effectiveness of the Improved Whale Optimization Algorithm [26]: Sphere (F1), Rosenbrock (F5), Ackley (F10), and Generalized (F12) functions are used for test evaluation. These functions cover both unimodal and multimodal cases, and can evaluate the basic convergence performance, local



(a) Sphere function test chart.

(b) Rosenbrock function test chart.

(c) Ackley function test chart.

(d) Generalized function test chart.

Fig. 2. Comparison chart of different benchmark function algorithm tests.

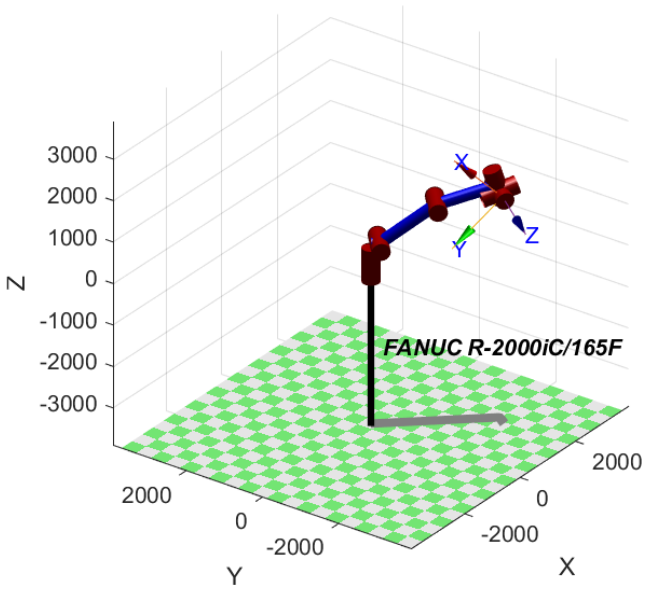


Fig. 3. Robotic arm model.

search ability and global search ability of the algorithm. The formulas of the selected test functions are shown in Table I.

In this algorithm validation, the IWOA is compared with the WOA, Dung Beetle Optimization algorithm (DBO), Particle Swarm Optimization algorithm (PSO), and Grey Wolf Optimization algorithm (GWO). The experimental parameters are set as follows: the population size is 50, the maximum number of iterations is 500, and the optimization dimension is 40. Each algorithm is run 30 times and the average results are taken to reduce the impact of randomness on the experimental results. The test results of each test function are shown in Table II.

It can be seen from Table II that IWOA exhibits excellent global optimization and convergence performance on all test functions. The best value is close to or reaches 0, the mean value is stable and the lowest, the standard deviation is the smallest, the result fluctuation is the least, and the convergence stability is the best. Fig. 2 shows the fitness iteration convergence diagram of each function.

The Sphere function is used to test the basic convergence performance of the algorithm. As can be seen from Fig. 2a, IWOA converges faster in the early stage and finally reaches the optimal value of 0, indicating that it has good global convergence ability. The Rosenbrock function is used to evaluate the local search performance. Fig. 2b shows that the algorithm decreases rapidly in the early stage, which benefits from the combination of Kent chaotic mapping and adaptive parameters. In contrast, the remaining algorithms converge slowly and are prone to falling into local optima. The Ackley function is used to verify the ability to escape from local optima. Fig. 2c shows that IWOA can quickly get rid of local traps and converge stably, while other algorithms are prone to stagnation. The Generalized function is used to measure the balance between global and local search. Fig. 2d shows that IWOA converges smoothly without premature convergence, showing stronger stability and global optimization performance.

IV. Simulation and Analysis

A. Robotic Arm Model

To verify the effectiveness of the algorithm, this study takes the R-2000iC/165F robotic arm of the industrial robot FANUC as the research object. First, the D-H modeling method is used to construct the robotic arm model, as shown in Fig. 3. The model includes a base and six robotic arm joints. The relevant parameters of the robotic arm model are shown in Table III, where i represents the link sequence number; a_{i-1} represents the link length, which is the length of the common normal between two rotational joint axes; the link twist α_{i-1} is the offset angle of the two joint axes; the link offset d_i is the vertical offset between two adjacent joints, that is, the offset distance along the z-axis; the joint angle θ_i is the rotation amount of the i-th joint relative to the initial position. The schematic diagram of the robotic arm joint coordinate system is shown in Fig. 4.

After establishing the coordinate system of the 6-degree-of-freedom robotic arm using D-H parameters, the obtained D-H transformation matrix needs to satisfy Eq. (20).

$$ {}^{i+1}_{i}A = \begin{bmatrix} \cos\theta_{i+1} & -\sin\theta_{i+1} & 0 & a_i \\ \sin\theta_{i+1}\cos\alpha_i & \cos\theta_{i+1}\cos\alpha_i & -\sin\alpha_i & -\sin\alpha_i d_{i+1} \\ \sin\theta_{i+1}\sin\alpha_i & \cos\theta_{i+1}\sin\alpha_i & \cos\alpha_i & \cos\alpha_i d_{i+1} \\ 0 & 0 & 0 & 0 \end{bmatrix} \tag{20} $$

${}^{i+1}_{i}A$ represents the homogeneous transformation matrix from d_i to d_{i+1}. By substituting the corresponding parameters in the D-H parameters into Eq. (20), the corresponding transformation matrix is obtained, and then $\{{}^{1}_{0}A, {}^{2}_{1}A, {}^{3}_{2}A, {}^{4}_{3}A, {}^{5}_{4}A, {}^{6}_{5}A\}$ is calculated, as shown in Eq. 21.

TABLE I. TEST FUNCTIONS

Function no.	Function name	Function formula	Search space	Optimal value
F1 (Unimodal)	Sphere	$f(x) = \sum_{i=1}^{n} x_i^2$	$[-100, 100]$	0
F5 (Unimodal)	Rosenbrock	$f_5(x) = \sum_{i=1}^{n-1} \left[100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2\right]$	$[-30, 30]$	0
F10(Multimodal)	Ackley	$f_{10}(x) = -20 \exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e$	$[-32, 32]$	0
F12(Multimodal)	Generalized	$f_{12}(x) = \frac{\pi}{n}\left[10\sin^2\left(\pi\frac{x_1+1}{4}\right) + \sum_{i=1}^{n-1}\left(\frac{x_i+1}{4}\right)^2\right] \left(1 + 10\sin^2\left(\pi\frac{x_n+1}{4}\right)\right) + \left(\frac{x_n+1}{4}\right)^2 + \sum_{i=1}^{n} U(x_i, 10, 100, 4)$	$[-50, 50]$	0

TABLE II. COMPARISON OF TEST FUNCTION RESULTS OF DIFFERENT ALGORITHMS

No.	Index	IWOA	WOA	GWO	PSO	DBO
F1	Best	0	0	0	3.472×10^{-57}	2.98×10^{-14}
	Worst	7.294×10^{-287}	7.294×10^{-287}	0	9.676×10^{-26}	9.931×10^{3}
	Mean	0	1.495×10^{-289}	9.676×10^{-26}	2.460×10^{-28}	3.187×10^{3}
	Std	0	0	0	4.465×10^{-27}	2.854×10^{3}
F5	Best	1.755×10^{-4}	2.53	2.721×10^{1}	9.003×10^{4}	2.196×10^{8}
	Worst	5.596×10^{-4}	2.66	2.721×10^{1}	9.003×10^{4}	7.573×10^{8}
	Mean	2.459×10^{-4}	2.536	2.721×10^{1}	9.003×10^{4}	4.754×10^{8}
	Std	8.641×10^{-5}	2.172×10^{-2}	7.178×10^{-15}	3.325×10^{-1}	1.244×10^{8}
F10	Best	4.441×10^{-16}	4.441×10^{-16}	4.441×10^{-16}	3.856	1.474×10
	Worst	4.441×10^{-16}	4.441×10^{-16}	4.441×10^{-16}	2.050×10	2.213×10
	Mean	4.441×10^{-16}	4.441×10^{-16}	4.441×10^{-16}	1.445×10	2.088×10
	Std	0	0	0	3.242	8.693×10^{-1}
F12	Best	2.564×10^{-7}	1.003×10^{-3}	1.969×10^{-2}	8.325×10^{-1}	3.615×10^{8}
	Worst	2.834×10^{-7}	1.009×10^{-3}	1.969×10^{-2}	8.347×10^{-1}	2.389×10^{9}
	Mean	2.714×10^{-7}	1.003×10^{-3}	1.969×10^{-2}	8.326×10^{-1}	1.146×10^{9}
	Std	4.241×10^{-9}	1.135×10^{-6}	3.494×10^{-18}	2.626×10^{-4}	4.120×10^{8}

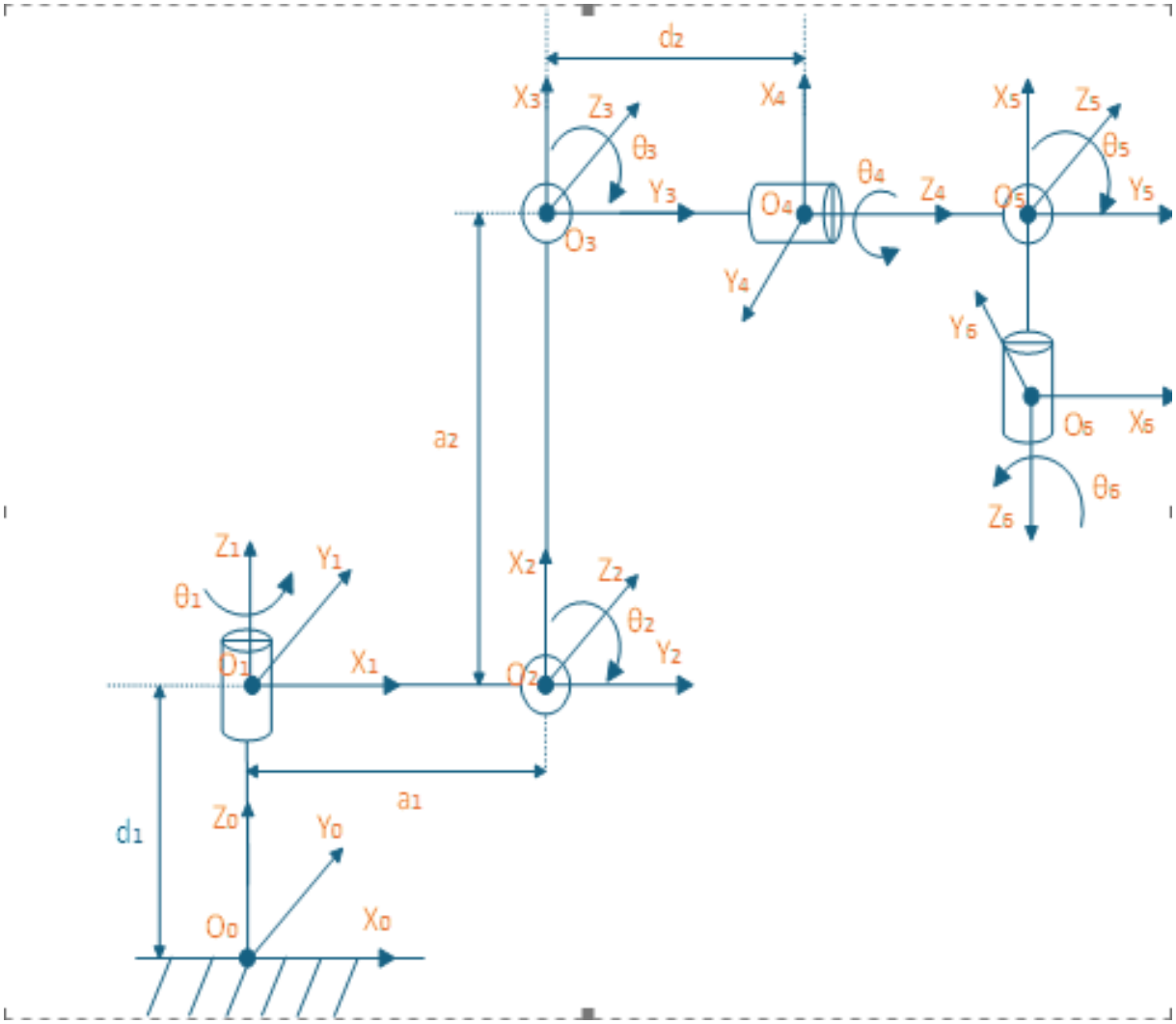


Fig. 4. Robotic arm joint coordinate system.

TABLE III. D-H PARAMETERS OF THE ROBOTIC ARM

Joint No. (i)	a_{i-1}	α_{i-1}	d_i	θ_i
1	175	$-\pi/2$	490	θ_1
2	1500	0	0	θ_2
3	1350	$-\pi/2$	0	θ_3
4	0	$\pi/2$	162	θ_4
5	0	$-\pi/2$	0	θ_5
6	0	0	220	θ_6

$$
\begin{aligned}
{}^{0}_{1}A &= \begin{bmatrix} C1 & -S1 & 0 & 175 \\ 0 & 0 & 1 & 490 \\ -S1 & -C1 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix};
{}^{2}_{1}A = \begin{bmatrix} C2 & -S2 & 0 & 1500 \\ S2 & C2 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix};
{}^{3}_{2}A = \begin{bmatrix} C3 & -S3 & 0 & 1350 \\ 0 & 0 & 1 & 0 \\ -S3 & -C3 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \\
{}^{4}_{3}A &= \begin{bmatrix} C4 & -S4 & 0 & 0 \\ 0 & 0 & -1 & -162 \\ S4 & C4 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix};
{}^{5}_{4}A = \begin{bmatrix} C5 & -S5 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ -S5 & -C5 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix};
{}^{6}_{5}A = \begin{bmatrix} C6 & -S6 & 0 & 0 \\ S6 & C6 & 0 & 0 \\ 0 & 0 & 1 & 220 \\ 0 & 0 & 0 & 1 \end{bmatrix}
\end{aligned}
\tag{21}
$$

In Eq. 22, $C1$ represents $\cos\theta_1$, and $S1$ represents $\sin\theta_1$. ${}^{6}_{0}A$ denotes the total transformation matrix from the robot base to the end-effector, that is, the position of the end of the link in coordinate system O_0 relative to the base, which is obtained in matrix form through Eq. 22.

$$ {}^{6}_{0}A = {}^{1}_{0}A^{2}_{1}A^{3}_{2}A^{4}_{3}A^{5}_{4}A^{6}_{5}A \tag{22} $$

By establishing the link structure model of the robotic arm using the D-H parameter method, the position and posture of the robotic arm's end-effector in the coordinate system can be obtained through the forward kinematics equations under the premise that each joint angle is known.

B. Robotic arm Trajectory Planning

To verify the effectiveness of the Improved Whale Optimization Algorithm in robotic arm trajectory planning, three waypoints are specified within the kinematic constraint space of the FANUC R-2000iC/165F robotic arm. Fifth-order polynomial interpolation is adopted for trajectory planning to ensure continuous velocity and acceleration of the robotic arm. On this basis, the Improved Whale Optimization Algorithm is used to optimize the trajectory time of the robotic arm, and a comparison is made with the original whale optimization algorithm. Table IV shows the Cartesian space information of the end-effector of the FANUC R-2000iC/165F robotic arm passing through the three specified waypoints. Then, the joint position information of the waypoints in the robotic arm is obtained through inverse kinematics analysis, and Table V presents the corresponding joint position information of these three waypoints.

During the process of passing through two path segments, the operation time of each joint in each path segment is set to 5 seconds. Meanwhile, to meet the constraint conditions of the robotic arm, the maximum angular velocity of the robotic arm joints is set to $\dot{\theta}_{j\max} = 3\,\text{rad/s}$, and the maximum angular acceleration is set to $\ddot{\theta}_{j\max} = 3.5\,\text{rad/s}^2$. According to the requirements of the ship spot welding process, the velocity of the robotic arm must be 0 when passing through each welding waypoint. By substituting the above three interpolation points into the fifth-order polynomial interpolation function and using MATLAB R2024a for trajectory planning of the robotic arm, the trajectory of the end-effector of the robotic arm in the workspace is obtained, as shown in Fig. 5. The position, velocity, and acceleration curves of the six joints after fifth-order polynomial trajectory planning are shown in Fig. 6.

It can be observed from Fig. 6 that the interpolation time combination of the fifth-order polynomial is (5, 5), so the total time is 10 s. Among them, the maximum angular velocity is 1.53 rad/s, and the maximum angular acceleration is 0.94 rad/s², which meet the constraint conditions of the robotic arm. However, to further improve the operating efficiency of the system, it is still necessary to optimize the trajectory to shorten the operating time on the basis of ensuring trajectory smoothness.

C. Optimal Time Planning of Robotic Arm

This study adopts the IWOA for time optimization of the robotic arm trajectory. In the experiment, the population size is set to 30, and the maximum number of iterations is 300. Due to the randomness of trajectory planning results, each algorithm is run 50 times, and the average value is taken as the performance evaluation index. To verify the algorithm performance, the motion time curves of joint angle, angular velocity, and angular acceleration between IWOA and the original WOA are compared and analyzed, as shown in Fig. 7.

It can be seen from Fig. 7 that the displacement, velocity, and acceleration curves of the robotic arm optimized by the WOA and the IWOA all show smooth and continuous changes without obvious mutations, indicating that the robotic arm can pass through each waypoint stably. Meanwhile, by sorting out the optimized data of each joint in Fig. 6 and Fig. 7, the optimization times of the fifth-order polynomial, WOA, and IWOA when passing through each waypoint are obtained, as shown in Table VI.

It can be seen from Table VI that the time combination of the fifth-order polynomial is (5, 5) with a total time of 10 s. The optimal time combination of WOA is (3.26, 2.48) and the total time is 5.74 s. The optimal time combination of IWOA is (2.76, 1.93) with a total time of 4.69 s. Both the WOA and IWOA algorithms can achieve the effect of optimizing the operation time, but the IWOA is more effective in optimization performance, which greatly improves the working efficiency of the robotic arm.

V. Experiments

A. Experimental Purpose

To further verify the feasibility and effectiveness of the robotic arm trajectory planning based on the Improved Whale Optimization Algorithm (IWOA) in actual industrial environments, this chapter designs a comparative experiment based on the RoboGuide simulation platform and the FANUC physical robotic arm system. By executing the same path task in both virtual and real environments, the performance of the trajectory generated by the algorithm in terms of path accuracy and time optimization effect is evaluated, thereby verifying the algorithm's implementability and robustness.

The simulation completed in the MATLAB environment is mainly used to verify the performance of IWOA-DEGA at the mathematical model level, including the time optimality and path smoothness of trajectory planning. At this stage, the focus is on evaluating the algorithm's global optimization capability and optimization effect. However, simulations only in MATLAB cannot fully reflect the execution feasibility of the algorithm in real robotic arm systems.

For this reason, this study further conducts engineering-level simulation in the FANUC RoboGuide platform. RoboGuide can realistically simulate the geometric structure, joint motion constraints, and dynamic characteristics of the robotic arm, and supports the modeling of external workpieces, fixtures, sensors, and other elements. By importing the optimal trajectory generated by IWOA into RoboGuide and setting a cuboid workpiece model consistent with the laboratory environment, the executability, safety, and spatial rationality of the planned trajectory in the actual space can be effectively verified.

TABLE IV. CARTESIAN SPACE INFORMATION CORRESPONDING TO THREE SPECIFIED WAYPOINTS

Waypoint	x	y	z
X_1	0.1	0.1	0.5
X_2	-1.5	0.75	2.344
X_3	0.5	0.5	2.0

TABLE V. JOINT INFORMATION CORRESPONDING TO EACH WAYPOINT (RAD)

Joint	X_1	X_2	X_3
1	-1.0228	2.6619	0.5174
2	-2.8352	-1.5037	-2.1353
3	-3.0950	0.9949	1.7531
4	1.2294	-0.4553	1.3274
5	2.4167	-0.2435	1.0696
6	0	0	0

TABLE VI. OPTIMIZATION RESULTS OF JOINT MOTION TIME

Method	$t_1(s)$	$t_2(s)$	Total Time $t(s)$
Fifth-order polynomial	5	5	10
WOA	3.26	2.48	5.74
IWOA	2.76	1.93	4.69

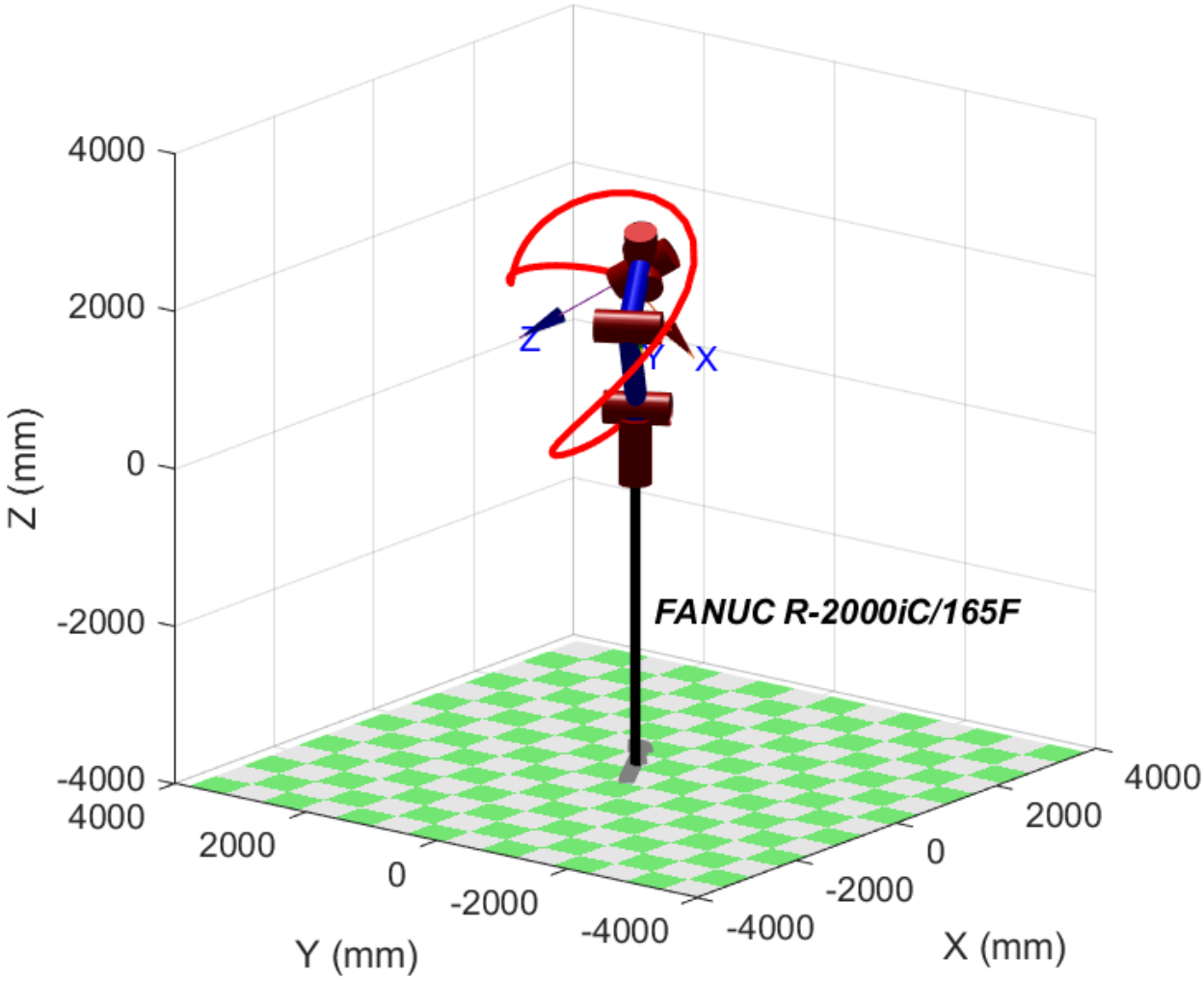


Fig. 5. Robot arm motion trajectory.

B. Experimental Platform and Equipment

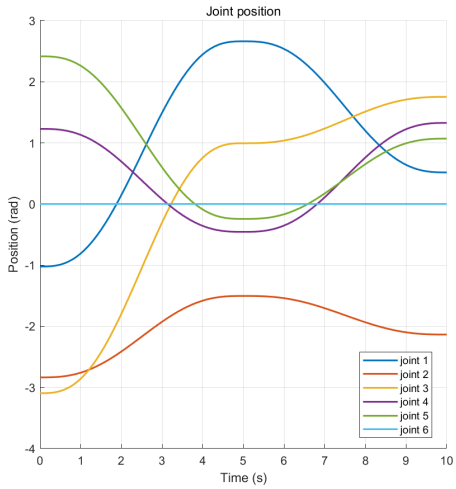
1) Simulation experiment platform: The simulation experiment is carried out based on the FANUC RoboGuide software. This platform can realize 3D modeling, path planning, collision detection, and offline programming of the robotic arm. The robotic arm model used in the experiment is FANUC R-2000iC/165F, and its virtual model is established in RoboGuide. A cuboid workpiece with dimensions of L×W×H = 300 mm × 200 mm × 150 mm is placed as the operation object. Four fixed waypoints (P1, P2, P3, P4) are selected on the surface of the workpiece, and the robotic arm needs to pass through these four waypoints in sequence to complete the trajectory movement.

2) Laboratory physical platform: The physical experiment constructs a test environment consistent with the simulation in the laboratory. The same FANUC R-2000iC/165F robotic arm is adopted, driven and controlled by the R-30iB control system. A cuboid workpiece with the same dimensions and position as in the simulation is placed on the test bench to ensure the consistency of experimental conditions. The robotic arm control program is generated through offline programming in RoboGuide and imported into the physical control system via the teach pendant for execution.

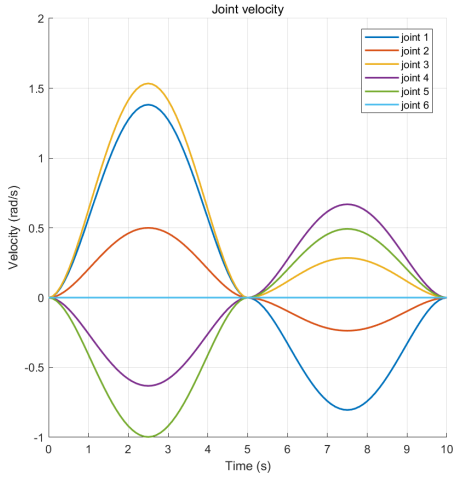
C. Experimental Results and Analysis

1) Simulation results: Fig. 8 shows the changes in the motion posture of the robotic arm when it passes through waypoints P1–P4 in sequence during the RoboGuide simulation. It can be seen from the figure that the end effector of the robotic arm moves smoothly and continuously without oscillation or sudden changes, indicating that the trajectory generated by IWOA has good dynamic smoothness and control stability. Consistent with the results obtained in the MATLAB simulation, the RoboGuide simulation further verifies the effectiveness of IWOA in terms of time optimization. According to the operation time statistics output by RoboGuide, the average operation time of the trajectory planned by IWOA is 18% less than that of the unoptimized trajectory, and the acceleration and deceleration transitions between each path segment are smoother, which effectively reduces the idle travel time of the robotic arm and unnecessary speed fluctuations.

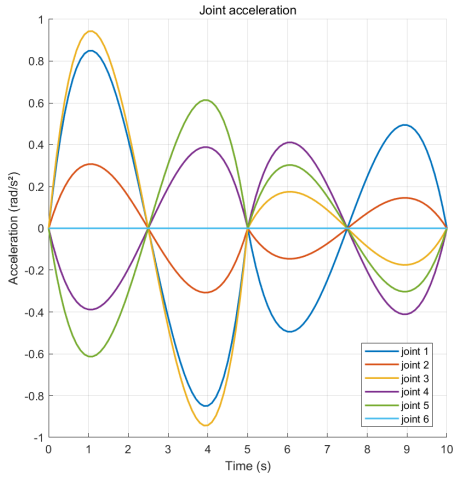
2) Physical experiment results: Fig. 9 shows the motion states of the FANUC R-2000iC/165F robotic arm in the laboratory as it passes through waypoints P1–P4 in sequence.



(a) Angular displacement variation curves of each joint.

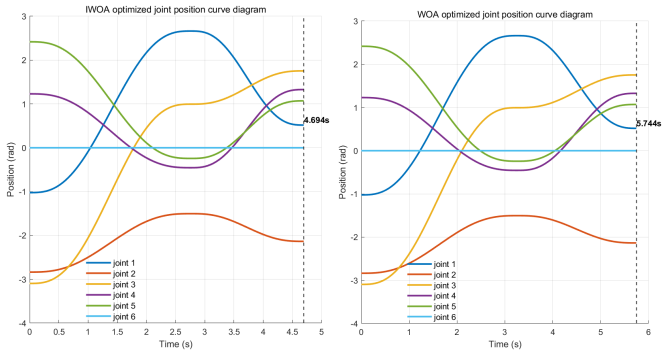


(b) Velocity variation curves of each joint.

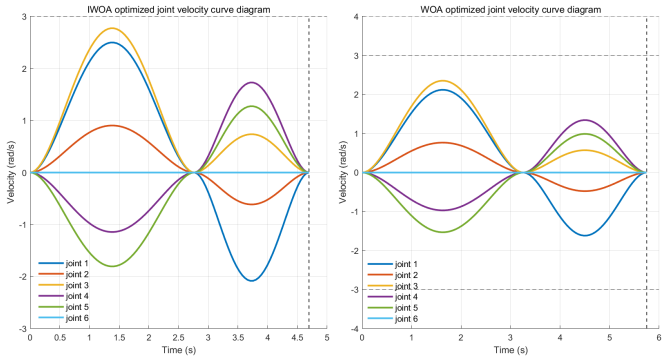


(c) Acceleration variation curves of each joint.

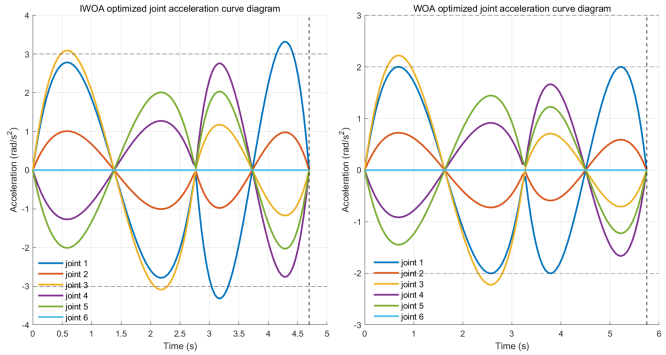
Fig. 6. Motion curve of six-degree-of-freedom robotic arm trajectory planning based on quintic polynomial interpolation.



(a) Comparison diagram of angular displacement curves of each joint.



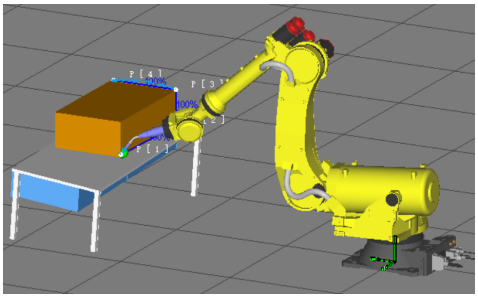
(b) Comparison diagram of angular velocity curves of each joint.



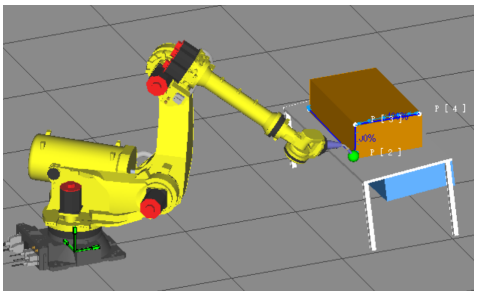
(c) Comparison diagram of angular acceleration curves of each joint.

Fig. 7. Comparison diagram of joint motion curves before and after the improved algorithm.

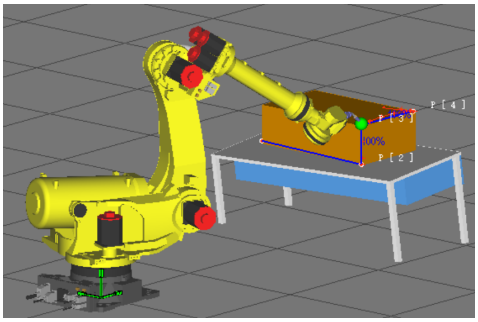
In the experiment, the robotic arm control program is generated by offline programming in RoboGuide, ensuring that the experimental path is completely consistent with the simulation path. It can be seen from the experimental results that the robotic arm moves smoothly and maintains consistent postures between each waypoint, with the end position error controlled within ±2 mm. More importantly, the operation time trend of the physical test is consistent with the simulation results. The trajectory optimized by IWOA reduces the average operation time by 16.4% compared with the original trajectory for the same task, verifying the time optimization effect of the algorithm in actual industrial control systems.



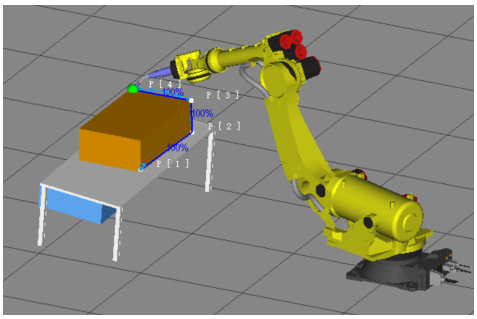
(a) The robotic arm reaches waypoint P1 in RoboGuide.



(b) The robotic arm reaches waypoint P2 in RoboGuide.



(c) The robotic arm reaches waypoint P3 in RoboGuide.

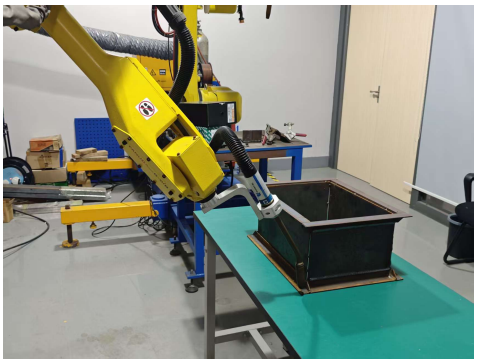


(d) The robotic arm reaches waypoint P4 in RoboGuide.

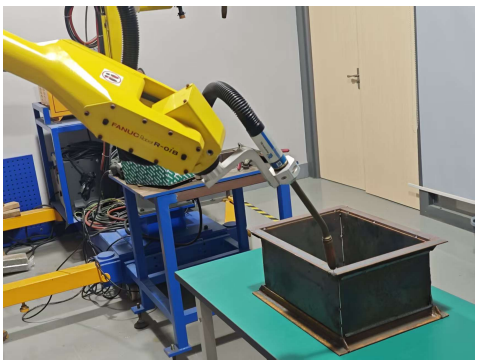
Fig. 8. Trajectory diagram of the robotic arm in RoboGuide simulation.



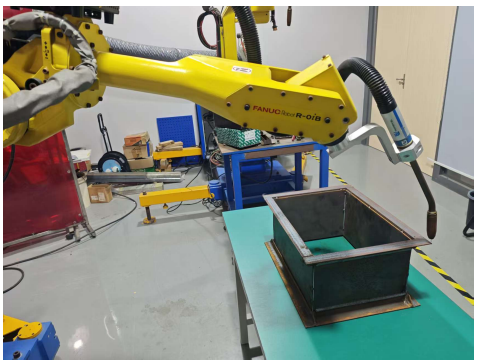
(a) The laboratory robotic arm reaches waypoint P1.



(b) The laboratory robotic arm reaches waypoint P2.



(c) The laboratory robotic arm reaches waypoint P3.



(d) The laboratory robotic arm reaches waypoint P4.

Fig. 9. Trajectory diagram of the laboratory robotic arm.

Through comparison, it is found that the physical experiment results are highly consistent with the RoboGuide simulation results in terms of path shape, attitude change, and operation time. This indicates that the IWOA can effectively generate time-optimal and executable robotic arm trajectories in real-world environments, demonstrating excellent engineering feasibility and application potential.

VI. Conclusion

This study proposes a trajectory planning for the FANUC R-2000iC/165F welding robotic arm based on an Improved Whale Optimization Algorithm (IWOA). The main theoretical contribution of this work lies in integrating quintic polynomial trajectory planning with the IWOA for time-optimal trajectory generation, thereby enhancing both the convergence speed and global optimization capability of traditional metaheuristic algorithms in robotic arm applications. Simulation and experimental results demonstrate that the IWOA significantly outperforms the original WOA in terms of trajectory optimization. Under identical kinematic constraints, the IWOA reduces the total operation time from 10 s to 4.69 s, compared with 5.74 s achieved by WOA. In RoboGuide simulation, the IWOA-optimized trajectory reduces average operation time by 18%, while physical experiments confirm a 16.4% reduction, with end-effector positioning errors controlled within ±2 mm. The results highlight the algorithm's effectiveness in generating smooth, continuous, and executable trajectories while maintaining operational safety. This also demonstrates that the metaheuristic algorithm employing chaotic mapping and adaptive parameter enhancement can effectively address the trade-off between global search and local optimization in high-dimensional trajectory optimization problems.

Despite these contributions, several limitations exist. The current study considers only a single robotic arm model and a limited number of waypoints, and does not account for dynamic external disturbances or varying payloads, which may affect real-world performance. Future research will extend the method to multi-arm coordinated welding tasks, incorporate dynamic obstacle avoidance, and explore real-time adaptive trajectory optimization under uncertain industrial environments.

References

[1] H. Zhang, Q. Zhuang, and G. Li, "Robot path planning method based on indoor spacetime grid model," vol. 16, 2024.

[2] S. Dian, J. Zhong, B. Guo, J. Liu, and R. Guo, "A smooth path planning method for mobile robot using a bes-incorporated modified qpso algorithm," *Expert Systems with Applications*, vol. 208, p. 118256, 2022.

[3] L. Liu, X. Wang, X. Yang, H. Liu, J. Li, and P. Wang, "Path planning techniques for mobile robots: Review and prospect," *Expert Systems with Applications*, vol. 227, p. 120254, 2023.

[4] S. Wu, Q. Ze, J. Dai, N. Udipi, G. H. Paulino, and R. Zhao, "Stretchable origami robotic arm with omnidirectional bending and twisting," *Proceedings of the National Academy of Sciences*, vol. 118, no. 36, p. e2110023118, 2021.

[5] J. Meng, S. Zhang, A. Bekyo, J. Olsoe, B. Baxter, and B. He, "Noninvasive electroencephalogram based control of a robotic arm for reach and grasp tasks," *Scientific reports*, vol. 6, no. 1, p. 38565, 2016.

[6] Y. Liu, Q. Tang, X. Tian, and S. Yang, "A novel offline programming approach of robot welding for multi-pipe intersection structures based on nsga-ii and measured 3d point-clouds," *Robotics and computer-integrated manufacturing*, vol. 83, p. 102549, 2023.

[7] X. Zhang, M. Zhang, S. Jiao, L. Sun, and M. Li, "Design and optimization of the wall climbing robot for magnetic particle detection of ship welds," *Journal of Marine Science and Engineering*, vol. 12, no. 4, p. 610, 2024.

[8] Y. Liu, Q. Tang, and X.-C. Tian, "Model-driven path planning for robotic plasma cutting of branch pipe with single y-groove based on pipe-rotating scheme," *Advances in Manufacturing*, vol. 12, no. 1, pp. 94–107, 2024.

[9] L. Guo and H. Zhang, "Autonomous mobile welding robot for discontinuous weld seam recognition and tracking," *The International Journal of Advanced Manufacturing Technology*, vol. 119, no. 7, pp. 5497–5509, 2022.

[10] J. Liu, Y. Cheng, X. Jing, X. Liu, and Y. Chen, "Prediction and optimization method for welding quality of components in ship construction," *Scientific Reports*, vol. 14, no. 1, p. 9353, 2024.

[11] Y. Du and Y. Chen, "Time optimal trajectory planning algorithm for robotic manipulator based on locally chaotic particle swarm optimization," *Chinese Journal of Electronics*, vol. 31, no. 5, pp. 906–914, 2022.

[12] H. Jiachen and F. Li-hui, "Robot path planning based on improved dung beetle optimizer algorithm," *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, vol. 46, no. 4, p. 235, 2024.

[13] F. Ding, R. Wang, T. Zhang, G. Zheng, Z. Wu, and S. Wang, "Real-time trajectory planning and tracking control of bionic underwater robot in dynamic environment," *Cyborg and Bionic Systems*, vol. 5, p. 0112, 2024.

[14] N. Wu, D. Jia, Z. Li, and Z. He, "Trajectory planning of robotic arm based on particle swarm optimization algorithm," *Applied Sciences*, vol. 14, no. 18, p. 8234, 2024.

[15] Q. Luo, H. Wang, Y. Zheng, and J. He, "Research on path planning of mobile robot based on improved ant colony algorithm," *Neural Computing and Applications*, vol. 32, no. 6, pp. 1555–1566, 2020.

[16] Z. Zhang, R. He, and K. Yang, "A bioinspired path planning approach for mobile robots based on improved sparrow search algorithm," *Advances in Manufacturing*, vol. 10, no. 1, pp. 114–130, 2022.

[17] L. Yiyang, J. Xi, B. Hongfei, W. Zhining, and S. Liangliang, "A general robot inverse kinematics solution method based on improved pso algorithm," *Ieee Access*, vol. 9, pp. 32 341–32 350, 2021.

[18] F. Gul, I. Mir, W. Rahiman, and T. U. Islam, "Novel implementation of multi-robot space exploration utilizing coordinated multi-robot exploration and frequency modified whale optimization algorithm," *IEEE access*, vol. 9, pp. 22 774–22 787, 2021.

[19] Y. Du and Y. Chen, "Time optimal trajectory planning algorithm for robotic manipulator based on locally chaotic particle swarm optimization," *Chinese Journal of Electronics*, vol. 31, no. 5, pp. 906–914, 2022.

[20] N. Rana, M. S. A. Latiff, S. M. Abdulhamid, and H. Chiroma, "Whale optimization algorithm: a systematic review of contemporary applications, modifications and developments," *Neural Computing and Applications*, vol. 32, no. 20, pp. 16 245–16 277, 2020.

[21] Z. A. A. Alyasseri, N. S. Ali, M. A. Al-Betar, S. N. Makhadmeh, N. Jamil, M. A. Awadallah, M. Braik, and S. Mirjalili, "Recent advances of whale optimization algorithm, its versions and applications," *Handbook of whale optimization algorithm*, pp. 9–31, 2024.

[22] M. S. Uzer and O. Inan, "Application of improved hybrid whale optimization algorithm to optimization problems," *Neural Computing and Applications*, vol. 35, no. 17, pp. 12 433–12 451, 2023.

[23] A. T. Elgohr, M. Elazab, A. Z. Emam, M. G. Mostafa, M. Al-Razgan, H. M. Kasem, and M. S. Elhadidy, "Particle swarm optimization vs. whale optimization algorithm for robotic arm path planning: A controlled study on the kuka kr4 r600," *Results in Engineering*, p. 108299, 2025.

[24] Y. Tan, J. Ouyang, Z. Zhang, Y. Lao, and P. Wen, "Path planning for spot welding robots based on improved ant colony algorithm," *Robotica*, vol. 41, no. 3, pp. 926–938, 2023.

[25] L. Zhang, Y. Wang, X. Zhao, P. Zhao, and L. He, "Time-optimal trajectory planning of serial manipulator based on adaptive cuckoo search algorithm," *Journal of Mechanical Science and Technology*, vol. 35, no. 7, pp. 3171–3181, 2021.

[26] Y. Du and Y. Chen, "Time optimal trajectory planning algorithm for robotic manipulator based on locally chaotic particle swarm optimization," *Chinese Journal of Electronics*, vol. 31, no. 5, pp. 906–914, 2022.

An RBAC-Based Access Control and Security Architecture for UAV Networks in Precision Agriculture Using Software-Defined Drone Networking

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***Abstract*—Unmanned Aerial Vehicles (UAVs), commonly referred to as drones, are widely employed in applications such as surveillance, delivery, mapping, and precision agriculture. Their flexibility, mobility, and cost effectiveness have accelerated their adoption in both civilian and industrial domains. However, the rapid evolution of UAV technologies introduces significant challenges related to limited resources, data processing constraints, and, most critically, security and privacy. Cyberattacks targeting UAV systems may result in data breaches, mission failures, operational disruptions, and risks to human safety. In our previous work, we proposed a lightweight identity authentication scheme based on Elliptic Curve Cryptography (ECC) and integrated it into a Software-Defined Drone Network (SDDN) architecture to ensure strong security with low computational overhead. Building on this foundation, the present study focuses on the agricultural domain, where UAVs are increasingly used for crop monitoring, precision farming, and environmental data collection. Due to the sensitivity of agricultural data and the involvement of multiple stakeholders, fine-grained access control is essential. The main contribution of this work is the design and evaluation of an SDDN-based security framework that integrates role-based access control (RBAC) with trust management to enable secure, scalable, and controlled UAV operations in agricultural environments. The framework restricts user actions according to predefined roles, improving system security and manageability. Simulation results demonstrate that the proposed approach effectively enforces access policies, enhances trust-aware decision making, and maintains low computational overhead suitable for resource-constrained UAV networks. Validation is conducted using Python and YAML-based configurations on Google Colab, confirming the practicality of the proposed solution.**

Keywords*—Unmanned Aerial Vehicles; Software-Defined Drone Network; role-based access control; security; attacks; trust management; authentication; access control

I. Introduction

In recent years, Unmanned Aerial Vehicles (UAVs), commonly known as drones, have seen rapid adoption across a wide range of civilian and industrial applications. Originally developed for military purposes, UAVs are now widely used in agriculture, environmental monitoring, logistics, infrastructure inspection, and public safety [1]. Their ability to operate remotely, cover large areas, and collect high-resolution data in real-time makes them valuable tools for both routine and critical missions. With the advancement of communication technologies and autonomous flight systems, UAVs are no longer limited to isolated tasks but increasingly operate in coordinated swarms, enabling more complex and large-scale operations [2]. However, this growth also introduces significant challenges related to data security, system integrity, and operational safety.

To address security challenges in dynamic and decentralized UAV environments, trust management plays a key role in evaluating the reliability of users, devices, and links. It enhances security by enabling data fusion, excluding malicious nodes, protecting privacy, and supporting context-aware services [3]. Trust management also improves decision-making through reputation and recommendation mechanisms, while optimizing resource allocation and scalability in multi-UAV systems.

Clustering complements trust management by organizing UAVs into hierarchical groups, improving scalability, energy efficiency, and control through designated cluster heads. Our previous work proposed a trust-based clustering approach for IoT systems, where nodes are evaluated based on trust levels, reputation, and recommendations to form reliable clusters. Malicious nodes are excluded, and a rehabilitation process allows trusted reintegration [4]. This method considers IoT constraints such as limited energy and processing.

However, trust alone is insufficient. Authentication remains critical to prevent attacks like spoofing, replay, and injection. Robust authentication protocols are necessary to verify identities and secure UAV coordination, especially in swarm-based or mission-critical scenarios.

In earlier work, we developed a lightweight identity authentication scheme tailored for UAV networks, utilizing Elliptic Curve Cryptography (ECC) within a SDDN architecture[5]. ECC, known for using smaller key sizes compared to Rivest–Shamir–Adleman (RSA) while maintaining equivalent security levels, was chosen due to its suitability for resource-constrained environments such as UAV systems [6], [15]. The proposed architecture enabled secure and scalable authentication by coordinating Drones (DR), a Ground Station (GS), and an Authentication Center (AC). The authentication phase involved message exchanges between these components, after which each drone generated a private key used for encrypt-

ing communications throughout the mission. To evaluate the robustness of the approach, we presented in [5], a case study demonstrating its resistance to various attacks and conducted a formal security analysis using the Automated Validation of Internet Security Protocols and Applications (AVISPA) tool, which confirmed the protocol's effectiveness.

In this work, we focus on the agricultural domain as the application context for our access control model, aiming to address the specific security needs of UAV swarm operations in precision farming. This work extends our previous efforts on UAV security by applying and enhancing those concepts in a real-world, domain-specific scenario. Unlike prior studies that approached UAV security from a general perspective, often focusing on isolated aspects such as authentication or trust evaluation, this study is centered on a concrete and highly relevant use case. In [7], the increasing integration of UAVs in agriculture for tasks like crop monitoring, soil analysis, and pesticide spraying highlights the need for structured and secure management of UAV functions and data. To address this, we propose in this work a comprehensive security architecture tailored to the agricultural UAV environment. This architecture integrated multiple layers: trust management for dynamic evaluation of UAV behavior and cluster head selection; lightweight authentication protocols based on ECC to verify identities with minimal computational overhead; and a RBAC model to ensure task-specific access rights. The RBAC model was demonstrated through a Python and YAML based implementation on Colab, simulating realistic role assignments, such as pilot, engineer, technician, etc. and evaluating their permissions to perform specific drone actions (e.g., takeoff, data capture, firmware updates). This end-to-end framework was supported by a detailed architectural diagram and tables summarizing each security layer, offering a unified view of how the different mechanisms interact to secure UAV operations. By grounding the simulation in a real-world scenario, this work not only demonstrated the applicability of access control in agriculture but also emphasized the importance of combining various security approaches to achieve scalable, reliable and context-aware UAV deployments.

The remainder of this study is structured as follows: Section II presents a review of related work on access control, trust management, and security frameworks in UAV networks. Section III outlines the main security challenges facing UAVs. Section IV summarizes our prior contributions related to lightweight authentication and trust-based node management which will be foundational components of the global architecture. Section V presents the research methodology, introducing the proposed role-based access control (RBAC) model tailored for Unmanned Aerial Vehicles (UAVs) in agricultural environments. This section also describes the integration of the proposed access control mechanism within a global Software-Defined Drone Network (SDDN) architecture, highlighting its core security components. Section VI discusses the experimental results and provides a detailed analysis of the performance and security implications of the proposed approach. Finally, the conclusion in Section VII summarizes the main findings of the study and outlines potential directions for future research.

II. Related Works

Several studies have explored the use of SDN architectures for Drones (SDDN) in UAV systems due to their scalability and flexibility in implementing diverse security mechanisms such as authentication, data integrity, and trust management. In this section, we summarize relevant contributions on securing a uav network based on SDDN as well as access control.

In their literature review, Alquwayzani and Albuali in [8] examined the integration of RBAC within Zero Trust Architectures (ZTA) for military UAV systems. They emphasized that RBAC improves security by restricting system privileges based on predefined roles, such as pilot, maintenance, or commander. This role-based restriction minimizes unauthorized access and potential data breaches, aligning with ZTA principles to enhance UAV system security.

In [9], Zhang et al. propose a decentralized access control mechanism for UAV swarms by integrating blockchain technology with Ciphertext-Policy Attribute-Based Encryption (CP-ABE). This approach aims to enhance data security by ensuring that only UAVs satisfying specific attribute-based policies can decrypt and access sensitive information stored on the blockchain. Unfortunately, this work while providing fine-grained access control, introduces significant computational complexity, particularly during encryption and decryption processes, in addition to policy update challenges and latency issues.

Lehmoud et al. (2025) [10] propose a comprehensive security architecture for UAV networks that leverages 5G, SDN/NFV, and AI techniques. Their design uses Curve448-based authentication and integrates SDN's global control to systematically distribute security policies across switches and UAVs. Anomaly detection is achieved through Shannon entropy and self-organizing maps in the NFV layer, ensuring rapid response to threats. While this work demonstrates the benefits of programmable security in SDDNs, it focuses heavily on detection and resilience—without explicitly addressing fine-grained access control policies for drone missions, which is a key distinction in our proposed framework.

Hu et al. (2024) [11] surveys emerging techniques in software-defined UAV networks and highlight several promising approaches: blockchain-assisted orchestration, SDN-NFV security slicing, and lightweight challenge–response authentication based on ECC. They note a trend towards decentralized identity management and programmable policies, though most implementations emphasize network-level protection rather than role- or attribute-based access control per mission. In contrast, our architecture layers in a full RBAC policy module, aligned with trust metrics—reputation, recommendations, and dynamic rehabilitation—enabling mission-tailored access governance embedded directly within the SDDN control plane.

After a comprehensive review of recent literature, it becomes evident that although some works have explored the integration of RBAC in UAV systems, and others have investigated the application of SDDN in agricultural contexts, there is a noticeable lack of research that combines these three elements within a unified framework. Furthermore, security components such as authentication and trust management are often treated separately rather than as part of an end-to-end architecture. In this study, we address this gap by proposing

an integrated approach that leverages RBAC, SDDN, and trust-based mechanisms to enhance the overall security and coordination of UAV swarms in agricultural missions. Our model offers a coherent and scalable solution that meets both the operational and security demands of precision farming environments.

III. UAV's Security Challenges

Security protocols for UAV's must be designed with low communication and computation costs, given the restricted onboard computing capabilities of these devices. To safeguard UAV networks against unauthorized access to sensitive information or potential harmful attacks, it is crucial to ensure a set of key security and privacy properties: authentication, confidentiality, integrity, authorization, non-repudiation, and availability. These are addressed in recent works on lightweight secure communication architectures and trust-based benchmarks in UAV systems [12], [13].

- Authentication: is fundamental for establishing secure communication within an UAV network. It enables the authentication and identification of UAVs participating in flight operations. Digital signature mechanisms are used to verify the trustworthiness of each UAV, allowing only authenticated UAVs to participate in the flight mission. Authentication also safeguards the UAV network from adversaries attempting to impersonate legitimate UAVs.
- Confidentiality: guarantees that data remains inaccessible or undisclosed to unauthorized individuals. Protecting sensitive data and data exchange between UAVs and the GS from unauthorized access is critical in UAV networks to prevent leaks of sensitive flight mission information, such as telemetry data and control commands. Encryption algorithms, both symmetric and asymmetric, can be employed to achieve confidentiality in UAV networks.
- Integrity: involves ensuring data consistency and trustworthiness during the communication process. Data integrity is crucial in UAV networks to prevent alterations like modifications, fabrications, substitutions, and data injections. The use of hash algorithms with advanced encryption mechanisms can be employed to ensure data integrity.
- Authorization: is a security method identifying a user's privileges or access levels to system resources. UAV networks should restrict access to data, allowing only authorized users to communicate with the network. Access control policies must be implemented to monitor and regulate access to resources.
- Non-Repudiation: prevents an entity from denying earlier agreements or activities. The UAV network must establish protocols to ensure non-repudiation through the adoption of a digital signature mechanism.
- Availability: refers to the immediate availability of services to authorized parties when needed for effective functioning. In mission-critical UAV networks, services must be available at all times without intentional or unintentional interruptions. Redundancy and backup mechanisms may be useful for highly critical information services to ensure availability. Additionally, the UAV system must be resilient against classical denial-of-service (DoS) attacks.

In this work, we focus on providing authentication, confidentiality, integrity, and authorization to our architecture to prevent and detect multiple types of attacks such as ID spoofing, man-in-the-middle, replay, Sybil, DoS, etc.

IV. Foundational Security Mechanisms and Prior Contributions

Let us recall that we proposed in previous papers [4], [5] different security measurements such as trust management for IoT networks in general and authentication based on SDDN architecture for UAVs. The trust management model excludes malicious nodes from an IoT network, while the authentication model ensures secure message exchanges between drones and the GS through the AC. Table I summarizes the main notations and their corresponding definitions used throughout the study.

TABLE I. Table of Notations used in the Proposed Architecture

Symbol	Description
GS	Ground Station
AC	Authority Center
$AuthC$	Authentication Controller
ACC	Access Control Controller
TMC	Trust Management Controller
CC	Centralized Controller
i	Index of drone in the network
DR_i	Drone i, where $DR_i \in \{DR_1, DR_2, \ldots, DR_n\}$
ID_{DRi}	Drone ID sent by drone DR_i
IDt_{DRi}	Drone ID already registered in the GS table
tab_{D_R}	Table of drone IDs created by GS
t	A prime number and the order of P
e	A network entity, where $e \in \{DR_i, GS, AC\}$
Pub_e	Public key of entity e
$Priv_e$	Private key of entity e
S	Digital signature
N	A nonce to prevent replay attacks
t	Timestamp
CH	Cluster Head
CM	Cluster Member
BS	Base Station
T	Trust Level
E	Energy Level
$Rep(a, b)$	Reputation value assigned by node a to node b
$RepTab_{DR}$	A table contains all reputation values of different DR_i

A. Trust Management Model

Trust management is a key component in securing IoT networks, helping to ensure reliable data fusion, protect user privacy, and exclude malicious nodes to maintain secure and dependable system operations. Our prior work [4] focused on IoT environments, where we implemented a clustering-based architecture involving CHs and CMs, managed by BSs. This hierarchical structure reduced the computational burden on individual nodes by delegating processing tasks to BSs, improving scalability, energy efficiency, and communication reliability across the network.

We designed a trust management system comprising four core algorithms: trust level calculation to evaluate node reliability, reputation assessment based on historical interactions, a recommendation mechanism for selecting new CHs, and a rehabilitation process to reintegrate previously blacklisted

nodes based on gradual trust recovery. These mechanisms were designed with resource-constrained IoT devices in mind, considering factors such as energy limits and processing capacity. This trust-based framework, initially proposed for general IoT applications, is now adapted to secure UAV networks in the agricultural domain. By integrating these mechanisms into clustered UAV architectures, we aim to enhance security, reliability, and efficiency in data collection and communication, particularly in large-scale deployments, where dynamic node behavior and harsh environmental conditions present ongoing challenges.

B. Authentication Model

We already proposed a study which introduces a secure authentication mechanism for SDDNs [5], ensuring trusted interactions among key entities: DRs, AC, and GS shown in Fig. 5. This model was divided into two phases: the authentication phase and the GS drones list confirmation phase. In the first phase, each drone initiated authentication by encrypting its identity and a random nonce using the AC's public key and sending this request to the AC. The AC decrypted the message and forwarded the drone's identity to the GS for verification. If the drone was recognized in the GS's registry, the GS confirmed the identity by returning an encrypted response with a new nonce to the AC. Following successful confirmation, the AC generated a public key for the authenticated drone and distributed it to the relevant network entities. The GS updated its internal drone table with the new key, while the drone computed its private key using a randomly chosen scalar to ensure confidentiality. Once all drones had been authenticated, the GS signed and broadcasted the finalized list of authorized drones, ensuring that each UAV was informed about its legitimate peers for communication. In the second phase, the GS initiated the mission by sending a start signal to all authenticated drones. Each drone then created role-specific messages, encrypted them using its private key, and transmitted them securely within the network. This approach ensured both the integrity and confidentiality of drone-to-drone communication throughout the operation.
These validated security mechanisms constitute the foundational components upon which the proposed access control model and global SDDN security architecture are constructed.

V. Research Methodology

A. Access Control Proposition

In UAV environments, access control is essential to ensure secure communication, data integrity, and mission reliability. Unauthorized access can lead to data breaches, manipulation of flight paths, or hostile takeovers, posing serious security and safety threats. Robust access control mechanisms help protect sensitive commands and telemetry data from interception or misuse. Moreover, they enable accountability and traceability in multi-user and multi-UAV systems. Thus, implementing strong and adaptive access control is critical for maintaining operational security and trust in UAV deployments [14].
In this study, we develop an access control model based on RBAC to detect and prevent unauthorized UAVs by assigning permissions according to predefined roles. This mechanism is combined with lightweight authentication and trust management, all integrated within a Software-Defined Drone Network (SDDN) architecture to provide a flexible and secure framework for UAV operations in agriculture.
In precision agriculture, the use of UAV swarms is becoming increasingly common for tasks such as crop monitoring, spraying, and soil analysis. To ensure secure and organized access to UAV functions and data, RBAC offers an effective solution. By assigning permissions according to user roles—such as field operator, drone technician, or system supervisor—RBAC reduces unauthorized access, limits operational risks, and streamlines task delegation. This model not only improves security but also enhances efficiency and accountability in managing UAV activities across large agricultural zones.

To illustrate the RBAC model in an agricultural UAV scenario, we implemented a simulation using Python and YAML configuration files on Google Colab. This setup allows us to define roles, permissions, and access rules in a clear and modular way.

1) Access policy definition: This policy, shown in Fig. 1, defines three operational roles relevant to UAV-based agricultural missions: *pilot*, *agri_engineer*, and *technician*. Each role is associated with a distinct set of permissions that determine what actions a user or agent can perform on a drone. The *pilot* role covers flight control operations, including arming, takeoff, landing, and autonomous return. The *agri_engineer* role includes tasks related to field data acquisition and analysis, such as collecting crop data, capturing aerial images, and analyzing soil conditions. Meanwhile, the *technician* role focuses on maintenance and operational readiness, enabling firmware updates, sensor calibration, and battery status checks. Roles are assigned to individual drones under the `assignments` section, thereby enforcing mission-specific and role-based access control within the swarm through a structured YAML policy embedded in the SDDN framework.

2) Access control function: The following function, as presented in Fig. 2, checks whether a user is allowed to perform a given action on a specific drone based on their assigned role.

This function implements a role-checking mechanism: it first verifies that the user has a role assigned for the given drone, then checks whether the requested action is permitted under that role.

3) Simulation results: We tested the function with a set of example scenarios, as shown in Fig. 3, to evaluate whether access is properly granted or denied.

These results, shown in Fig. 4, confirm that the access control mechanism correctly enforces permissions based on role assignments. Authorized actions, such as data collection by the agricultural engineer or drone landing by the pilot, are permitted. Unauthorized actions, such as a technician attempting to arm the drone, are denied as expected.

B. A Layered Model of the Global Architecture Proposition

The objective of the proposed global architecture is to establish a secure, scalable, and mission-aware UAV swarm framework that integrates authentication, trust management, and RBAC-based access control within an SDDN environment

```yaml
import yaml

# YAML swarm policy as a string
swarm_policy_yaml = """
roles:
  pilot:
    - arm
    - takeoff
    - land
    - return_home

  agri_engineer:
    - collect_crop_data
    - capture_images
    - analyze_soil

  technician:
    - update_firmware
    - calibrate_sensors
    - check_battery

assignments:
  drone_1:
    Dr. Sara: agri_engineer
    Captain Omar: pilot

  drone_2:
    Tech Ali: technician
    Captain Omar: pilot
"""
# Load it into a Python dictionary
policy = yaml.safe_load(swarm_policy_yaml)
```

Fig. 1. Access policy definition.

```python
def check_access(user, drone, action):
    assigned_users = policy["assignments"].get(drone, {})
    role = assigned_users.get(user)

    if not role:
        print(f"[X] {user} is not assigned to {drone}")
        return

    allowed_actions = policy["roles"].get(role, [])

    if action in allowed_actions:
        print(f"[√] {user} ({role}) is allowed to perform '{action}' on {drone}")
    else:
        print(f"[X] {user} ({role}) cannot perform '{action}' on {drone}")
```

Fig. 2. Access control function.

tailored for precision agriculture. Before detailing this architecture, we first outline our security objectives and introduce the network model.

In this proposition, while we adopted a UAV network for agriculture, we will merge the base station BS and the ground station GS because GS could perform BS task's made in our previous IoT network, while both serve as central communication points.

```python
check_access("Dr. Sara", "drone_1", "collect_crop_data")
check_access("Captain Omar", "drone_1", "land")
check_access("Tech Ali", "drone_1", "calibrate_sensors")
check_access("Visitor", "drone_2", "view_status")
```

Fig. 3. Results scenarios.

```
[√] Dr. Sara (agri_engineer) is allowed to perform 'collect_crop_data' on drone_1
[√] Captain Omar (pilot) is allowed to perform 'land' on drone_1
[X] Tech Ali is not assigned to drone_1
[X] Visitor is not assigned to drone_2
```

Fig. 4. Results output.

1) Security objectives: Our proposed solution is developed with the following security objectives:

- Establishing an SDDN architecture to enable efficient network management and dynamic reconfiguration, ensuring scalability for future enhancements. Additionally, the SDDN framework facilitates the rapid deployment of security mechanisms.
- Enabling mutual authentication between a legitimate DR and GS via AC by optimizing the number of exchanged messages during the authentication process.
- Preserving drone anonymity by preventing unauthorized entities from tracking its identity through encryption techniques.
- Ensuring secure communication between DR and between drones and the GS by employing private keys for message exchanges.
- Enhancing trust management by continuously evaluating node behavior, detecting malicious activity, and isolating compromised entities to maintain network integrity.
- Implementing access control mechanisms to restrict unauthorized access, enforce security policies, and dynamically manage permissions based on trust levels and authentication results.
- Strengthening the protocol's resilience against common security threats, including:
  -ID spoofing attacks
  -Man-in-the-Middle attacks
  -Replay attacks
  -Injection attacks
  -Malicious nodes infiltration
  -SYbil attacks
  -Data modification attacks
  -DoS attacks

This approach ensures a secure and scalable UAV network, while mitigating various cyber threats through authentication, trust management, and access control enforcement.

2) Basic concepts: In our proposal, we extend our previous [5] SDDN architecture model which is organized into three layers: the data plane, the control plane, and the application plane, as illustrated in Fig. 5.

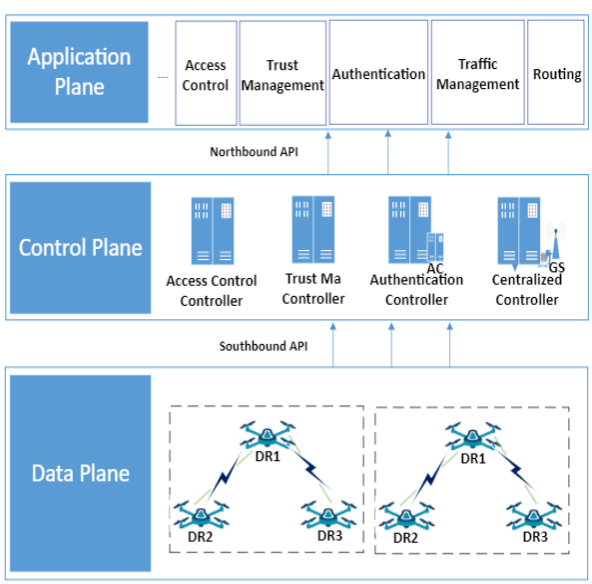


Fig. 5. Considered SDDN modeling.

- Data Plane: This layer comprises swarms of drones, which serve as the primary operational units within the UAV system. Each drone is constructed from lightweight materials and is outfitted with various components including sensors, actuators, payload devices, batteries, and GPS laser systems—to enhance maneuverability by minimizing weight. Typically, the navigation system and sensors are positioned at the front of the drone. Additionally, drones manufactured by different companies incorporate sophisticated features such as vibration damping, advanced communication modules, and compact onboard computing systems to effectively supervise, monitor, and control flight operations [16].These capabilities enable autonomous and semi-autonomous mission execution while supporting real-time data collection and coordination within the swarm. Furthermore, the modular hardware design allows drones to adapt to diverse agricultural tasks and operational conditions.
- Control Plane: This layer is composed of both centralized and decentralized controllers that work together to ensure secure and efficient UAV operations [17]. The centralized controller (CC), embodied by the GS, serves as the primary command and control center. It manages operational parameters, monitors drone sensors, oversees surveillance cameras, and enforces flight separation protocols. Additionally, the GS coordinates mission-critical activities, controls payload subsystems, and processes the data collected during drone operations.
  Complementing the GS, the control plane integrates several decentralized controllers to enhance security and system functionality. An Authentication Controller(AuthC), represented by the AC, verifies UAV system services by issuing certifications and generating cryptographic keys, thereby ensuring that all interactions are legitimate. To further secure the network, a Trust Management Controller (TMC) continuously evaluates the trustworthiness of nodes, aiding in dynamic decision-making and maintaining operational integrity. Moreover, an Access Control Controller enforces stringent policies to regulate node interactions and prevent unauthorized access to critical resources. Together, these controllers provide real-time problem resolution, robust data processing, and reliable networking services across the entire UAV environment.
- Application Plane: This layer represents the topmost level of our architecture, hosting both traditional network applications and drone-specific solutions. It delivers a broad range of services, including routing, traffic management, and security functions, alongside specialized applications such as mission planning, coordination, and data analytics tailored for UAV operations [16]. Additionally, this plane provides a comprehensive dashboard for real-time monitoring, performance visualization, and integration with external systems, ensuring dynamic control of network resources. To fortify security within this layer, we have integrated authentication, trust management, and access control mechanisms. These security measures guarantee that only authorized users and devices interact with the system, continuously assess the trustworthiness of communications, and enforce strict access policies to safeguard the integrity and efficiency of drone operations. Moreover, the application plane is designed to support future extensions such as UAV clustering, enabling scalable coordination and policy enforcement in large-scale agricultural deployments.

3) Security measures description: We detailed each proposed security measure in Table II and Table III, as well as in Fig. 6. We start by detailing the different steps of security measures shown in 5 layers as follows:

Layer 1: AUTHENTICATION: Authentication of DRs is performed through different steps as follows:

STEP 1-1:Authentication Initialization by DR_i :
To obtain its public key from AC, DR_i encrypts its identity ID_{DRi} using the public key of AC (Pub_{AC}), selects a random nonce N_{DRi} (to prevent replay attacks), and transmits the Init message to AC.

$$\text{Init} = (DR_i, AC, [\text{E}(ID_{DRi}, Pub_{AC}) — N_{DRi}]).$$

STEP 1-2: Request ID Verification by AC :
Upon receiving the message, AC decrypts it using its private key $Priv_{AC}$ to extract the drone's identity ID_{DRi}. It then forwards this ID to GS for verification to determine whether DR_i is under its control, using the Verif message.

$$\text{Verif} = (AC, GS, [\text{E}(ID_{DRi}, Pub_{GS}) — DR_i — N_{AC}]).$$

STEP 1-3: ID verification by GS:
The GS verifies the presence of the ID_{DRi} within its drone

Table Tab_{DR}. If the drone is recognized, we pass to the ID confirmation step, else, the authentication of DR_i is rejected.

STEP 1-4: ID confirmation by GS:
GS sends the Confirm message, which includes the encrypted ID using Pub_{AC} and a newly generated nonce N_{GS}.

Confirm = (GS,AC,[E(ID_{DRi},Pub_{AC})—N_{GS}]).

STEP 1-5: Pub_{DRi} Generation by AC:
Upon receiving confirmation from GS, AC generates the public key Pub_{DRi} for the authenticated drone and shares it with the registered entities in the network through the GenPub message.

GenPub = (AC,DR_i,[Pub_{DRi}—N_{AC}]).

STEP 1-6: Pub_{DRi} addition to Tab_{DR} :
GS updates its table, Tab_{DR}, which stores the drones DR_i and their corresponding IDs ID_{DRi}, by incorporating their public keys Pub_{DRi}.

STEP 1-7: $Priv_{DRi}$ Calculation by DR_i:
Once DR_i receives its assigned public key Pub_{DRi}, it selects a random number k and computes its private key as $Priv_{DRi} = k \cdot Pub_{DRi}$, ensuring that no external entity can derive it.

STEP 1-8: Signature calculation of Tab_{DR} by GS:
After the authentication of all DR_i, Tab_{DR} will be signed and broadcasted by GS to all authenticated drones, ensuring that each drone is informed about the legitimate drones authorized for communication during the mission.

STEP 1-9: Begin mission by GS:
After that, GS transmits the following message to begin the mission.

$$\text{BeginMiss} = (\text{GS}, \text{DR}_i, [S \mid\mid N_{\text{GS}}, t])$$

Layer 2: INTEGRITY AND CONFIDENTIALITY:
The following steps ensure integrity and confidentiality:

STEP 2-1: Message creation by DR_i:
When the mission begins, DR_i will start communicating by creating messages according to their role.

STEP 2-2: Message encryption with $Priv_{DRi}$ by DR_i:
Before sending any message, each drone uses its private key $Priv_{DRi}$ to encrypt it so that all messages are secured against integrity and confidentiality attacks.

STEP 2-3: Send message by DR_i:
After encryption, messages are secured and could be sent safely between different drones.

Layer 3: CLUSTERING:
Clustering enhances scalability, energy efficiency, and communication reliability in UAVs.

STEP 3-1:DR_i Clustering by GS In this step, GS will divide drones DR_i according to their positions and identify CHs and CMs.

Layer 4: TRUST MANAGEMENT:
The following steps ensure trust management during drones missions:

STEP 4-1: Trust Initialization:
GS provides for all drones a common starting trust level T_{DRi}=1

STEP 4-2: T_{DRi} calculation
T_{DRi}=T_{DRi}+x : T_{DRi} will decrease when nodes fail to respond to messages (-0.2), neglect to send important updates (-0.1), or transmit false information (-0.3).

STEP 4-3: Drone Exclusion:
DR_i will be excluded when its T_{DRi} attaints -1.

STEP 4-4: Blacklist Creation:
GS creates a blacklist for the malicious drones excluded from the network.

STEP 4-5: Reputation Calculation:
Every drone DR_i calculates the reputation value of other nodes according to their responses to requests.

STEP 4-6: Reputation Table Creation:
DR_i creates a Rep_{TabDR} containing all reputation values of different DR_i.

STEP 4-7: CH Selection:
GS use these reputation values to select the CH. CH will have the best reputation value Max rep(CH,DR_i).

STEP 4-8: DR_i Notification about new CH:
GS notifies other DR_i about the new CH.

STEP 4-9: Resolve Tie:
When 2 DR_i have the same reputation value, GS will select the max ID_{DRi} to choose the CH.

STEP 4-10: Send Recommendation:
CH uses the reputation values of its CMs to formulate and send a recommendation for GS to be replaced when its energy level falls below a threshold.

STEP 4-11: Well_behave Check:
When an excluded DR_i well behave it will have a chance to get back to the network.

STEP 4-12: Positive Trust Update:
T_{DRi} will increase by 0.1 for its good behavior by sending real notifications to GS about its state and detected events in

the network T_{DRi}= T_{DRi}+0.1.

STEP 4-13: Rehabilitation:
When T_{DRi} reaches 0, the malicious drone regains its trustworthiness and is removed from the blacklist.

Layer 5: ACCESS CONTROL:
Users authorization is ensured through the following steps:

STEP 5-1: Service Access Demand:
When a user U_j wants to perform an action using DR_i, an access demand will be sent to the Centralized Controller (CC).

STEP 5-2: Policy Request from CC to ACC:
CC should verify the access control policy of U_j already stored in the Access Control Controller (ACC).

STEP 5-3: Policy Response from ACC to CC:
ACC searches for U_j's access control policy and sends it back to CC.

STEP 5-4: User Role Request:
As a verification step, CC asks U_j about its role to match it to the role in the policy.

STEP 5-5: Access Control Function:
In ACC, the access control function implements a role-checking mechanism: First, it verifies that the user U_j has a role assigned for the given drone DR_i, then checks whether the requested action is allowed under that role.

STEP 5-6: Access Decision Notification:
After applying the function, U_j will be informed if access is confirmed or denied.

The following Table II and Table III summarizes the different security measurements.

4) Layered model description: As previously introduced, Fig. 6 illustrates the proposed layered model outlining the key components of our security environment. This figure shows the different steps of each mechanism to ensure a high-security level for an UAV network. The upper layer is about drones authentication, it details the process from ID_{DRi} verification by GS through AC to $Priv_{DRi}$ and Tab_{DR} signature calculation. Also, after the mission begins, messages are encrypted before being sent between the different components of the environment to ensure the integrity and confidentiality in Layer 2 services. Layer 3 is about clustering drones by GS before trust management process in Layer 4. In this layer, different steps are described such as trust level calculation, blacklist of malicious nodes creation, reputation calculation, recommendations and rehabilitation. The last layer (Layer 5) details access control steps from the user's service access demand to the access confirmation or denial according to RBAC policies. As a single table for the 5 layers becomes too long we have to split this table in two: Layer 1 and Layer 2 are represented in Table II and Layer 3, Layer 4 and Layer 5 are represented in Table III.

The second part of the splitted table, which is Table III, represents the Layers 3, 4 and 5.

VI. Results and Discussion

The proposed security architecture addresses the growing need for structured and lightweight protection mechanisms in agricultural UAV networks, where multiple stakeholders interact within a dynamic and resource-constrained environment. The experimental results obtained from the RBAC simulation demonstrate that role-based access control can be effectively implemented within an SDDN context to regulate user actions and enforce permission boundaries. By explicitly defining roles, permissions, and access rules through configuration files, the system ensures consistency, transparency, and reduced risk of unauthorized operations.

Recent works have explored security and access control in UAV networks using decentralized and zero-trust approaches. Dong et al. [18] propose a blockchain-based authentication scheme for multi-cluster UAV systems, improving robustness but introducing non-negligible computational and communication overhead. Similarly, Xie et al. [19] present a blockchain-assisted zero-trust model emphasizing continuous identity verification. In contrast, the proposed architecture relies on a lightweight ECC-based authentication combined with RBAC and trust management within an SDDN framework, enabling fine-grained access control with lower complexity and improved suitability for large-scale agricultural UAV deployments.

The RBAC evaluation confirms the feasibility of enforcing fine-grained access control without introducing excessive complexity, which is particularly important in agricultural scenarios involving farmers, operators, and service providers with distinct operational privileges. Furthermore, the modular design of the architecture detailed through operational phases, interaction schemes, and configuration tables facilitates extensibility and supports the integration of additional security and management mechanisms. In addition, the experimental observations highlight the practical alignment between the proposed access control logic and the operational requirements of agricultural UAV missions. The clear separation of control responsibilities and data access privileges contributes to improved system reliability and reduces the likelihood of configuration errors during mission execution. These characteristics are particularly valuable in real-world deployments, where operational simplicity and predictable behavior are essential for maintaining secure and efficient UAV-assisted agricultural services.

Nevertheless, this study has certain limitations. The experimental evaluation focuses specifically on the RBAC component, while other security mechanisms are validated through formal analysis rather than full-scale simulation. Additionally, performance metrics such as communication latency, energy overhead, and scalability under dense UAV swarm conditions are not yet quantitatively assessed, which may impact the generalizability of the results.

Future work will address these limitations by extending the validation of the complete architecture through inference-based modeling and formal verification, enabling formal reasoning over trust evolution and access decisions in dynamic environments. In addition, the integration of a lightweight

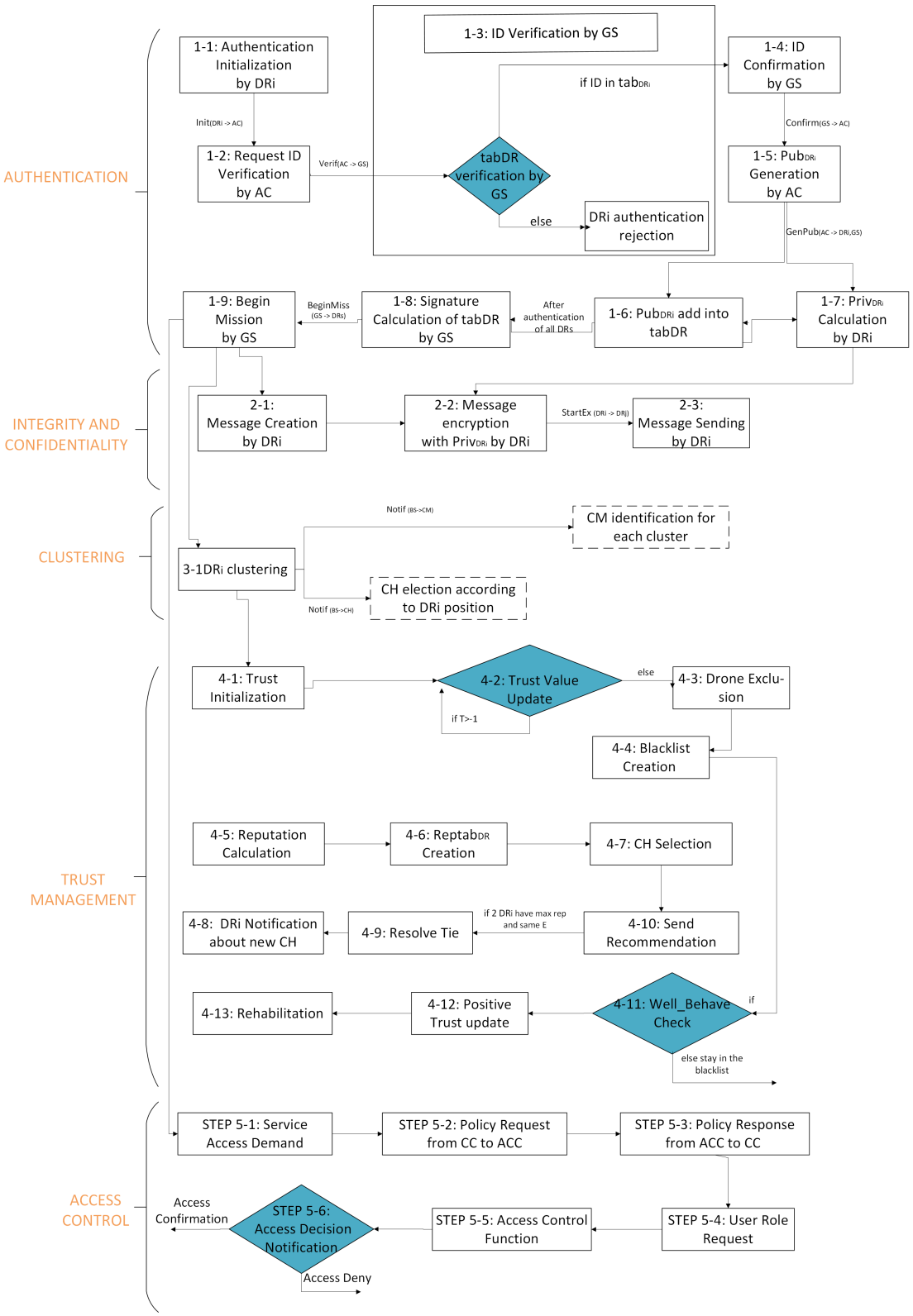


Fig. 6. Layered model description.

TABLE II. TABLE OF MESSAGES EXCHANGED (PART 1)

Steps	Service	Active Entities	Data Units	Data Units Parameter	Subservices	Sender	Receiver
1-1	Authentication Initialization by DR_i	DR_i, AC	Init	(DR_i,AC, [E(ID_{DRi},Pub_{AC})	-ID_{DRi} encryption with Pub_{AC}. -Addition of a random nonce N_{DRi}.	DR_i	AC
1-2	Request ID Verification by AC	AC, GS	Verif	(AC,GS, [E(ID_{DRi},Pub_{GS}) —DR_i—N_{AC}])	-ID_{DRi} encryption with Pub_{GS}. -Include the drone DR_i and addition of a random nonce N_{AC}	AC	GS
1-3	ID Verification by GS	GS	N.C	N.C	- ID_{DRi} verification by GS if it exists in Tab_DR or not. -If the ID is included in the table a confirmation will be sent from GS to AC . Else, DR_i rejection of authentication.	N.C	N.C
1-4	ID Confirmation by GS	GS, AC	Confirm	(GS, AC, [E(ID_{DR_i}, Pub_{AC}) || N_{GS}])	-Confirmation of the existence of ID_{DRi} in its drone table Tab_{DR}. -ID_{DRi} encryption with Pub_{AC}. -Addition of a random nonce N_{GS}.	GS	AC
1-5	Pub_{DRi} Generation by AC	AC, DR_i, GS	GenPub	(AC, DR_i, [Pub_{DRi}‖N_{AC}])	-Pub_{DRi} generation by AC so DR_i could calculate its private key $Priv_{DRi}$. -AC includes Pub_{DRi} and a nonce N_{AC}.	AC	DR_i, GS
1-6	Pub_{DRi} Addition in Tab_{DR}	GS	N.C	N.C	- Pub_{DRi} addition to GS table which already contains ID_{DRi} of drones which will start the mission.	N.C	N.C
1-7	$Priv_{DRi}$ Calculation by DR_i	DR_i	N.C	N.C	-Pub_{DRi} reception by DR_i -$Priv_{DRi}$ calculation using Pub_{DRi} and a random number k	N.C	N.C
1-8	Signature calculation of Tab_{DR} by GS	GS	N.C	N.C	-Digital signature S of Tab_{DR} calculation using GS private key $Priv_{GS}$. - Digital signature of Tab_D_R is shared with authenticated drones to identify legitimate nodes before mission start.	N.C	N.C
1-9	Beginning of the Mission by GS	GS, D_{Rs}	BeginMiss	(GS, DR_i, [S‖N_{GS}‖t])	-Start of the mission indication after a successful authentication phase. - GS sent S which contain the updates tab_D signed by $Priv_{GS}$, a nonce N_{GS} and a timestamp t.	GS	D_{Rs}
2-1	Create Message	DR_i	Msg	(DR_i, role, payload)	- Message generation by DR_i based on its assigned role in the mission.	DR_i	N.C
2-2	Message Encryption	DR_i	EncMsg	(DR_i, [E(payload, $Priv_{DR_i}$)])	- Message encryption using private key $Priv_{DR_i}$ to ensure confidentiality and integrity.	DR_i	N.C
2-3	Send Message	DR_i	EncMsg	(DR_i, DR_j, [E(payload, $Priv_{DR_i}$)])	- Transmission of the encrypted message to a peer drone DR_j.	DR_i	DR_j

TABLE III. TABLE OF MESSAGES EXCHANGED (PART 2)

Steps	Service	Active Entities	Data Units	Data Units Parameter	Subservices	Sender	Receiver
3-1	DR_i Clustering by GS	GS	Cluster	(GS, DR_i)	- GS clusters DR_i based on their positions and identifies CHs and CMs.	GS	DR_i
4-1	Trust Initialization	GS	InitTrust	(GS, $T_{DR_i} = 1$)	- GS assigns an initial trust value $T_{DR_i} = 1$ to all drones.	GS	DR_i
4-2	Trust Value Update	GS	UpdateTrust	($T_{DR_i} = t_{DR_i} + x$)	- Trust decreases due to non-responsiveness (-0.2), neglect (-0.1), or false data (-0.3).	GS	N.C
4-3	Drone Exclusion	GS	Excl	($T_{DR_i} = -1$)	- DR_i is excluded when trust level reaches -1.	GS	N.C
4-4	Blacklist Creation	GS	Blacklist	(GS, List)	- GS creates a blacklist for malicious or excluded drones.	GS	DR_i
4-5	Reputation Calculation	DR_i	RepCalc	(DR_i, other nodes)	- Each drone calculates reputations of others based on their behavior.	DR_i	N.C
4-6	Reputation Table Creation	DR_i	$RepTab_{DR}$	(DR_i, table)	- DR_i builds $RepTab_{DR}$ containing reputations of other drones.	DR_i	N.C
4-7	CH Selection	GS	SelectCH	max(Rep(CH, DR_i))	- GS selects CH with highest reputation.	GS	DR_i
4-8	DR_i Notification about new CH	GS	NotifyCH	(GS, CH info)	- GS notifies all DR_i of the selected CH.	GS	DR_i
4-9	Resolve Tie	GS	TieBreak	max(ID_{DR_i})	- If reputations are equal, GS selects CH by highest ID.	GS	DR_i
4-10	Send Recommendation	CH	Reco	(CH, GS)	- CH recommends replacement if its energy drops below threshold.	CH	GS
4-11	Well Behave Check	GS	CheckBehavior	(DR_i)	- If excluded DR_i behaves well, it's reconsidered.	DR_i	GS
4-12	Positive Trust Update	GS	TrustBoost	($T_{DR_i} = t_{DR_i} + 0.1$)	- Trust increases for good behavior and real alerts sent.	GS	N.C
4-13	Rehabilitation	GS	Rehab	($T_{DR_i} \geq 0$)	- If $T_{DR_i} \geq 0$, the drone is removed from the blacklist.	GS	DR_i
5-1	Service Access Demand	U_j, CC	AccessReq	(U_j, DR_i)	- U_j sends a request to access a service on DR_i to the Centralized Controller (CC).	U_j	CC
5-2	Policy Request from CC to ACC	CC, ACC	PolicyReq	(CC, U_j)	- CC asks ACC for the stored access control policy of user U_j.	CC	ACC
5-3	Policy Response from ACC to CC	ACC, CC	PolicyResp	(Policy(U_j))	- ACC retrieves U_j's policy and sends it back to CC.	ACC	CC
5-4	User Role Request	CC, U_j	RoleReq	(CC, U_j)	- CC asks U_j for its role to match with the access control policy.	CC	U_j
5-5	Access Control Function	ACC	Role-Check	(U_j, Role, Action)	- ACC verifies that U_j has a valid role and that the action is allowed for DR_i.	ACC	CC
5-6	Access Decision Notification	CC, U_j	AccessResp	(Confirm / Deny)	- CC sends a confirmation or denial of access to U_j based on policy check.	CC	U_j

clustering mechanism will be explored to enhance scalability, reduce control overhead, and improve resilience in large-scale agricultural UAV swarm scenarios.

VII. Conclusion

The integration of UAVs into agricultural environments represents a major advancement in precision farming, enabling efficient data acquisition, resource optimization, and real-time monitoring. However, these benefits also introduce significant security challenges due to the distributed, dynamic, and multi-stakeholder nature of agricultural UAV systems.

In this work, we proposed a comprehensive and lightweight security architecture tailored for Software-Defined Drone Networks (SDDNs) operating in agricultural contexts. The proposed framework provides a global and structured security vision that combines multiple complementary mechanisms, including ECC-based identity authentication, secure communication ensuring integrity and confidentiality, trust management based on dynamic behavioral evaluation, and role-based access control (RBAC). The architecture is detailed through clearly defined operational phases, interaction workflows, and configuration tables, offering a coherent end-to-end security model rather than an isolated mechanism. This holistic design enables controlled access, accountability, and adaptability in environments involving diverse actors such as farmers, operators, and service providers. From an implementation perspective, the experimental evaluation in this study focuses on the RBAC component, which was simulated using Python and YAML configuration files in a cloud-based environment. The results confirm that the proposed RBAC model enables clear, consistent, and enforceable access policies aligned with predefined roles, demonstrating its practicality within an agricultural UAV setting. The remaining security components, including ECC-based authentication and trust management, have been formally validated in our previous work using AVISPA, ensuring their robustness against common security threats.

Overall, this study establishes a solid security baseline for agricultural UAV networks by combining architectural design, formal validation, and targeted simulation. Future work will focus on formal inference-based validation of the complete architecture, the integration of lightweight clustering mechanisms for scalable swarm management, and performance evaluation under large-scale and highly dynamic UAV deployments.

References

[1] Z. Wang, Y. Li, S. Wu, Y. Zhou, L. Yang, Y. Xu, and Q. Pan, "A survey on cybersecurity attacks and defenses for unmanned aerial systems," *Journal of Systems Architecture*, vol. 138, p. 102870, 2023.

[2] A. A. Baktayan, A. T. Zahary, A. Sikora, et al., "Computational offloading into UAV swarm networks: a systematic literature review," *EURASIP Journal on Wireless Communications and Networking*, vol. 69, 2024.

[3] S. Ogunbunmi, Y. Chen, E. Blasch, and G. Chen, "A survey on reputation systems for UAV networks," *Drones*, vol. 8, no. 6, p. 253, 2024.

[4] N. Kammoun, A. B. C. Douss, and R. Abassi, "Trust-based algorithms for securing IoT clusters in an edge computing environment," in *Proc. IEEE 10th Int. Conf. Communications and Networking (ComNet)*, Tunis, Tunisia, Nov. 2023, pp. 1–6.

[5] N. Kammoun, A. B. C. Douss, and R. Abassi, "A novel lightweight authentication mechanism for UAVs based on SDDN architecture," in *Proc. 20th Int. Conf. Wireless and Mobile Computing, Networking and Communications (WiMob)*, Paris, France, Oct. 2024, pp. 1–6.

[6] M. A. Alazab, R. H. Abdalla, S. H. Ismail, et al., "FPGA-based dual-layer authentication scheme utilizing AES and ECC for unmanned aerial vehicles," *EURASIP Journal on Wireless Communications and Networking*, vol. 2024, Article 91, 2024.

[7] A. Smith, B. Li, and C. Wang, "Leveraging precision agriculture techniques using UAVs and emerging disruptive technologies," *Energy Nexus*, vol. 14, p. 100300, 2024.

[8] A. Alquwayzani and R. Albuali, "Integrating role-based access control within Zero Trust architectures for securing military UAV systems," *Journal of Cybersecurity and Defense*, vol. 12, no. 3, pp. 145–158, 2023.

[9] Y. Zhang, H. Liu, M. Wang, X. Chen, and J. Li, "Decentralized access control for UAV swarms using blockchain and attribute-based encryption," in *Proc. IEEE Int. Conf. Blockchain and Distributed Systems (BDS)*, 2023, pp. 102–110.

[10] A. A. M. Lehmoud, N. T. Obeis, and A. F. Mutar, "Design security architecture for unmanned aerial vehicles by 5G cloud network based implementation of SDN with NFV and AI," *Electric Electronics and Informatics (EEI)*, vol. 12, no. 1, Article 4239, 2023.

[11] X. Hu, Y. Li, Q. Zhang, et al., "Empowering UAV communications with AI-assisted software-defined networks: A review on performance, security, and efficiency," *Journal of Network and Systems Management*, vol. 31, pp. 69–90, 2025.

[12] M. H. Al-Salem and R. Raza, "Development of a Lightweight Secure Communication System for UAVs Enhanced by an Unconventional Chaotic Communication Architecture," *Journal of Intelligent & Robotic Systems*, vol. 111, art. 85, 2025.

[13] F. T. Madhuvanthi and A. Revathi, "A survey on UAV network for secure communication and attack detection: A focus on Q-learning, blockchain, IRS and mmWave technologies," *KSII Transactions on Internet and Information Systems*, vol. 18, no. 3, pp. 779–800, 2024.

[14] W. Shafik, M. Matinkhah, and F. Shokoor, "Cybersecurity in unmanned aerial vehicles: A review," *Int. J. Smart Sensing and Intelligent Systems (IJSSIS)*, vol. 16, no. 1, pp. 1–12, 2023, doi: 10.2478/ijssis-2023-0012.

[15] M. Usman, R. Amin, H. Aldabbas, and B. Alouffi, "Lightweight challenge–response authentication in SDN-based UAVs using elliptic curve cryptography," *Electronics*, vol. 11, no. 7, p. 1026, 2022.

[16] M. H. Alsharif, A. K. Sutradhar, and S. Kim, "Software-defined networking for unmanned aerial vehicle systems: Architecture, challenges, and future directions," *IEEE Access*, vol. 12, pp. 115430–115452, 2024.

[17] J. Kang and T. Shon, "SDN-enabled control and communication frameworks for cooperative UAV networks: A comprehensive review," *Computer Networks*, vol. 245, p. 110927, 2025.

[18] Y. Dong, H. Li, and X. Chen, "Blockchain-based secure authentication and access control for multi-cluster UAV networks," *Ad Hoc Networks*, vol. 146, p. 103157, 2023.

[19] J. Xie, Z. Zhang, and L. Wang, "A zero-trust security framework for UAV networks with lightweight identity verification," *IEEE Internet of Things Journal*, vol. 11, no. 4, pp. 6123–6136, 2024.

A Soft and Hard Mixture-of-Experts Approach for Improved ADR Extraction from Patient-Generated Narratives

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***Abstract*—Traditional single-architecture neural models, including monolithic transformer-based and sequence-to-sequence architectures, often struggle to extract Adverse Drug Reactions (ADRs) from patient-generated health narratives due to informal language, high linguistic variability, and complex relationships among drugs, diseases, and adverse events. Although Mixture-of-Experts (MoE) architectures have demonstrated strong performance across various Natural Language Processing (NLP) tasks, their effectiveness for ADR extraction from unstructured patient narratives remains largely unexplored. This study investigates the application of MoE architectures, specifically Soft MoE and Hard MoE, for ADR extraction from patient-generated content. The task is formulated as a sequence-to-sequence generation problem and evaluated on the PsyTAR dataset using both strict and relaxed evaluation metrics. Experimental results demonstrate that Soft MoE consistently outperforms Hard MoE, achieving a relaxed F1-score of 80.40% compared to 79.40%. These findings highlight the critical role of expert-routing strategies in capturing linguistic variability in patient narratives and establish MoE architectures as a competitive and reliable approach for automated ADR extraction in biomedical text mining and pharmacovigilance applications.**

***Keywords*—Adverse Drug Reaction; Mixture-of-Experts; Soft and Hard MoE; sequence-to-sequence; patient narratives; biomedical text mining**

I. Introduction

An Adverse Drug Reaction is an unintended and harmful effect that occurs after the use of a drug at its normal therapeutic dose [1]. Adverse Drug Reactions are a significant contributor to morbidity and mortality rates worldwide [2]. Their timely detection and monitoring have immense importance in order to improve the safety of drugs and to support various pharmacovigilance activities. Typically, ADR data is collected through passive spontaneous reporting systems, which usually suffer from under-reporting and delayed reporting [3]. Nevertheless, with the rapid growth in user-generated content on social media and health-related forums, valuable information regarding patient experiences has become increasingly available in real time [4]. Millions of users actively share their medication experiences within online communities, frequently reporting potential side effects almost in real-time [5]. Consequently, it opened a promising avenue for the early ADR detection, potentially overcoming the drawbacks of traditional systems. However, leveraging social media data for ADR detection poses significant challenges because of the informal, unstructured, and noisy nature of text generated by users [6]. Patients often describe their experiences in various ways, using colloquial expressions, abbreviations, or implicit mentions of symptoms, making automatic extraction of ADRs a challenging task [7].

In light of these challenges, more and more researchers have become interested in using Natural Language Processing methods to automatically identify ADRs not explicitly written in structured formats, such as medical forums and social media [8]. Early studies have mainly focused on rule-based systems, machine learning, and deep learning methods. The early rule-based systems were interpretable yet often could not generalize to linguistic variability or unseen expressions [9]. While machine learning methods introduced data-driven learning capabilities, they still depended on extensive manual feature engineering [10]. The emergence of deep learning, especially the transformer-based models [11], has marked a major advancement by enabling models to automatically capture semantic and contextual relationships in text. Despite their substantial success, most of these models generally require a vast amount of annotated biomedical corpora, which limits their applicability in real-world pharmacovigilance scenarios where such data are often limited.

More recently, Large Language Models have shown remarkable potential for biomedical information extraction, due to the rich contextual representation they can learn from massive amounts of text data [12]. LLMs can generalize across a wide range of linguistic patterns, making them particularly apt at dealing with the noisy and unstructured language used on social media and patient narratives. However, monolithic architectures, whether standard transformers or LLMs, rely on a single generalized network to handle all inputs, which can be suboptimal for capturing the highly specific and varied expressions of Adverse Drug Reactions. This limitation motivates the exploration of the Mixture-of-Experts paradigm, which leverages multiple specialized sub-networks to process different types of input patterns dynamically. While MoE models achieved state-of-the-art results in general language understanding and other specialized domains [13], their effectiveness and optimal configuration for the specific domain of ADR extraction have not been largely explored. Thus, the present work systematically investigates the performance of the MoE architectures for ADR extraction from patient narratives. In particular, a comparison is conducted between Soft MoE, where all experts contribute to each input, and Hard MoE, where only a subset of experts is activated, in an

attempt to establish which of the approaches better captures the semantic variability of ADRs. Through this comparison analysis, the present study investigates whether the specialization capabilities of MoE can lead to improvement in extraction performance on this challenging domain, including insights into their applicability in biomedical text mining.

The main contributions of this work are as follows:

- This study investigates the MOE approach for the specialized task of ADR extraction from patient-generated narratives.
- Comparative analysis of the two primary MoE variants (Soft MoE and Hard MoE) to determine their efficacy in capturing the high semantic variability present in user-generated medical text.
- An experimental evaluation is conducted on the PsyTAR dataset using strict and relaxed metrics to assess the effectiveness of MoE in this task.

The rest of the study is organized as follows: Section II reviews related work. Then, Section III describes the materials and methods, covering the dataset, model architecture, and evaluation metrics. The results will be reported and discussed in Section IV. Finally, Section V concludes the study and outlines future work directions.

II. Background and Related Work

Research on Adverse Drug Reaction extraction has evolved rapidly with the advancement of NLP techniques. Early studies focused on applying rule-based and lexicon-driven systems, which relied on handcrafted patterns and domain-specific vocabularies such as MedDRA to identify ADR mentions [14],[15]. Although these approaches offered transparency, they struggled with the linguistic variability and ambiguity present in real-world patient narratives. Subsequent work introduced machine learning-based models to learn statistical patterns from annotated corpora [16]. These methods improved generalization but still depended heavily on manual feature design and lacked the ability to capture deep contextual semantics.

The advent of deep learning marked an important turning point in ADR extraction, with architectures such as Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) enabling automatic feature learning from raw text [17], a significant improvement over manual feature engineering [18]. Many of these models often struggled with long-range dependencies and contextual subtleties inherent in biomedical language. The breakthrough came with transformer-based architectures, which exploit a self-attention mechanism to capture complex contextual relationships across entire sequences. Models like BERT and its domain-specific variants, such as BioBERT and PubMedBERT, demonstrated unprecedented performance on automatic learning of rich contextual and semantic representations from vast amounts of textual data [11]. This reduced the need to manually perform feature engineering and allowed a more effective handling of the linguistic variations observed in both the formal literature and the informal narratives of patients [19].

Building upon this foundation of specialized transformers, the field has progressed toward Large Language Models, which extend this architecture to much larger and more powerful systems through pre-training on huge and diverse text corpora. This extreme scaling allows LLMs to have superior generalization and powerful few-shot capabilities, which make them very promising in handling the complexity of information extraction tasks even when the use of annotated data is limited [20]. A major innovation within these recent LLMs that has been aimed at handling such a large scale efficiently is the Mixture-of-Experts architecture. In contrast to dense models that activate the full network for every input, MoE relies on a sparse structure where the routing network dynamically routes the tokens to the appropriate specialized experts. The potential of this paradigm for complex biomedical tasks was demonstrated by [21], who developed MOEBQA, an MoE-adapted model for Biomedical Question Answering. Their model used a router to assign different types of professional questions to specialized experts, which significantly improved performance by alleviating parameter competition across diverse question types, achieving state-of-the-art results. In [22], the authors proposed MOELoRA, which combines MoE with parameter-efficient fine-tuning to efficiently learn separate parameters for various tasks while maintaining a small number of trainable parameters, demonstrating superior performance on a multi-task Chinese medical dataset. This approach was later extended to Named Entity Recognition (NER) in work by [23], who proposed BOND-MoE, a model that integrates a MoE layer into a BERT-based framework. In their contribution, experiments verify that assignment of predictions to multiple experts is effective in collectively improving performance as well as in effectively overcoming noisy, distantly supervised labels in various instances of NER tasks across multiple datasets, achieving performance superior to BERT

Though Mixture-of-Experts architecture have demonstrated success in different NLP and biomedical text mining tasks, their application to the Adverse Drug Reaction extraction task remains largely unexplored. Despite substantial progress achieved by deep learning, transformer-based, and large language model approaches, existing ADR extraction methods still largely depend on monolithic architectures that process all inputs using a single shared representation space. This design may impact their ability to effectively capture the high linguistic variability and heterogeneous expression patterns characteristic of patient-generated narratives. Moreover, although MoE-based models have demonstrated effectiveness in related biomedical NLP tasks such as question answering and named entity recognition, prior work has not systematically examined their use for ADR extraction, nor has it investigated how different expert-routing strategies influence performance in this domain. This gap motivates the present study, which evaluates both Soft and Hard MoE variants, assessing their respective strengths and limitations for ADR extraction from patient narratives.

III. Methodology

This study aims to assess the performance of the Mixture-of-Experts mechanism on the task of extracting Adverse Drug Reactions from patient narratives. The primary goal is to test the efficiency of the architecture by performing a comparative performance analysis between the two main variants of this architecture, Soft MoE and Hard MoE, within the same domain. The main hypothesis is that the MoE paradigm, due to

its specialized sub-networks, can more effectively capture the high semantic variability and diverse ADR categories found in the text compared to a monolithic model.

A. Problem Formulation

In this work, the task of Adverse Drug Reaction extraction from a patient's narrative is formulated as a sequence-to-sequence (Seq2Seq) problem. Given an input text $X = (x_1, x_2, \ldots, x_T)$ that describes a patient's experience with a medication in their own words, the task is to generate an output sequence $Y = (y_1, y_2, \ldots, y_N)$ listing all mentioned adverse reactions separated by commas. Each output token y_i represents a word or a phrase describing an ADR that is mentioned in the input text. This formulation is effective for patient-generated content, which tends to be informal, unstructured, and may contain multiple ADRs using varied expressions. ADR generation as a textual list, rather than performing token-level classification, allows the model to better capture contextual and semantic relationships and to produce concise and accurate ADR outputs directly from the narrative text.

B. Dataset

The PsyTAR (Psychiatric Treatment Adverse Reactions) dataset [24] is a psychiatric adverse reaction dataset that captures how patients describe the perceived effects and adverse reactions associated with psychiatric medications in real-world settings. The dataset consisted of patient-generated reviews, collected from the online health platform Ask a Patient, on four commonly prescribed antidepressants: Zoloft, Lexapro, Cymbalta, and Effexor XR, which belong to two classes: Selective Serotonin Reuptake Inhibitors (SSRIs) and Serotonin–Norepinephrine Reuptake Inhibitors (SNRIs). The dataset was developed in a multi-step process through sentence segmentation and comprehensive manual annotation. 6,009 sentences were extracted from 891 drug reviews and labeled regarding semantic categories such as Adverse Drug Reactions (ADRs) (2,168 sentences), Withdrawal Symptoms (WDs) (438 sentences), Signs and Symptoms of Illness (SSIs) (789 sentences), Drug Indications (DIs) (517 sentences), Drug Effectiveness (EF) (1,087 sentences), and Drug Ineffectiveness (INF) (337 sentences). Within the ADR-labeled subset, 4,813 distinct ADR mentions were identified [28]. For this study, only sentences annotated with ADRs were retained, while non-ADR sentences were excluded. After filtering, the final corpus used for ADR extraction comprised 1,981 sentences, providing a focused and high-quality subset for investigating patient-reported Adverse Drug Reactions in psychiatric treatments.

C. Model Architecture

In this work, the Mixture-of-Experts mechanism is investigated and applied within an encoder-decoder framework for a challenging application: Adverse Drug Reaction extraction from patient narratives. The problem is formulated as a Seq2Seq generation task, and therefore, the model maps a textual patient description to a list of ADR mentions. While the standard Seq2Seq architectures can capture complex linguistic dependencies, they often fail under heterogeneous biomedical language, which may contain ADR expressions of different styles, domains, and granularities. To overcome this limitation, a Mixture-of-Experts mechanism is introduced to enable the model to distribute the learning process across multiple expert networks, each one potentially specializing in different linguistic or semantic aspects of ADR expressions. Fig. 1 illustrates the integration of the Mixture-of-Experts mechanism inside the Transformer encoder-decoder architecture used for ADR extraction. In the standard Transformer block, the Feed-Forward Network (FFN), a two-layer position-wise neural network applied independently to each token, is responsible for transforming intermediate hidden representations after the self-attention operation. In the proposed architecture, this FFN component is replaced by an MoE layer, which routes each token representation to one or more expert networks. Two routing strategies are explored: Soft MoE, where all experts contribute proportionally to their gating probabilities, and Hard MoE, where only the Top-k experts (k=2) are activated for each token. This modification preserves the overall encoder–decoder structure of the model while introducing specialization among experts, enabling more flexible and adaptive representation learning for ADR extraction.

1) Mixture-of-Experts: The Mixture-of-Experts [25] mechanism enhances the model's representational capacity by introducing a set of K expert networks, each designed to learn a specific subspace of the input representation. A gating network determines how much each expert contributes to processing a given input. Formally, let $H = (h_1, h_2, \ldots, h_T)$ denote the encoder's hidden representations of the input text. The gating network G produces a vector of scores $g = (g_1, g_2, \ldots, g_K)$ corresponding to the K experts:

$$g = G(H) \tag{1}$$

where, each g_k denotes the relevance of expert E_k for the current input. The output from the encoder is routed through the MoE layer to generate a refined representation H', which the decoder will take as an input:

$$H' = \sum_{k=1}^{K} \alpha_k \, E_k(H) \tag{2}$$

where, α_k are weights given by the gating mechanism, which are determined differently in the Soft and Hard variants. Then, the decoder subsequently predicts the output sequence of ADR mentions based on H'. This type of structure allows the model to learn different linguistic patterns while still sharing an encoder–decoder architecture.

a) Soft MoE: In the Soft MoE configuration, all experts contribute to the processing of every input, but to a different extent. The gating network uses a softmax function to produce a probability distribution over all experts:

$$\alpha = \text{Softmax}(G(H)) \tag{3}$$

Each expert E_k processes the entire encoder representation H, generating an output $O_k = E_k(H)$. The final representation fed into the decoder is a weighted sum of all the expert outputs:

$$H' = \sum_{k=1}^{K} \alpha_k O_k \tag{4}$$

This allows the model to make use of a mixture of several expert knowledge sources for each input, leading to smooth sharing of information between experts. However, activating

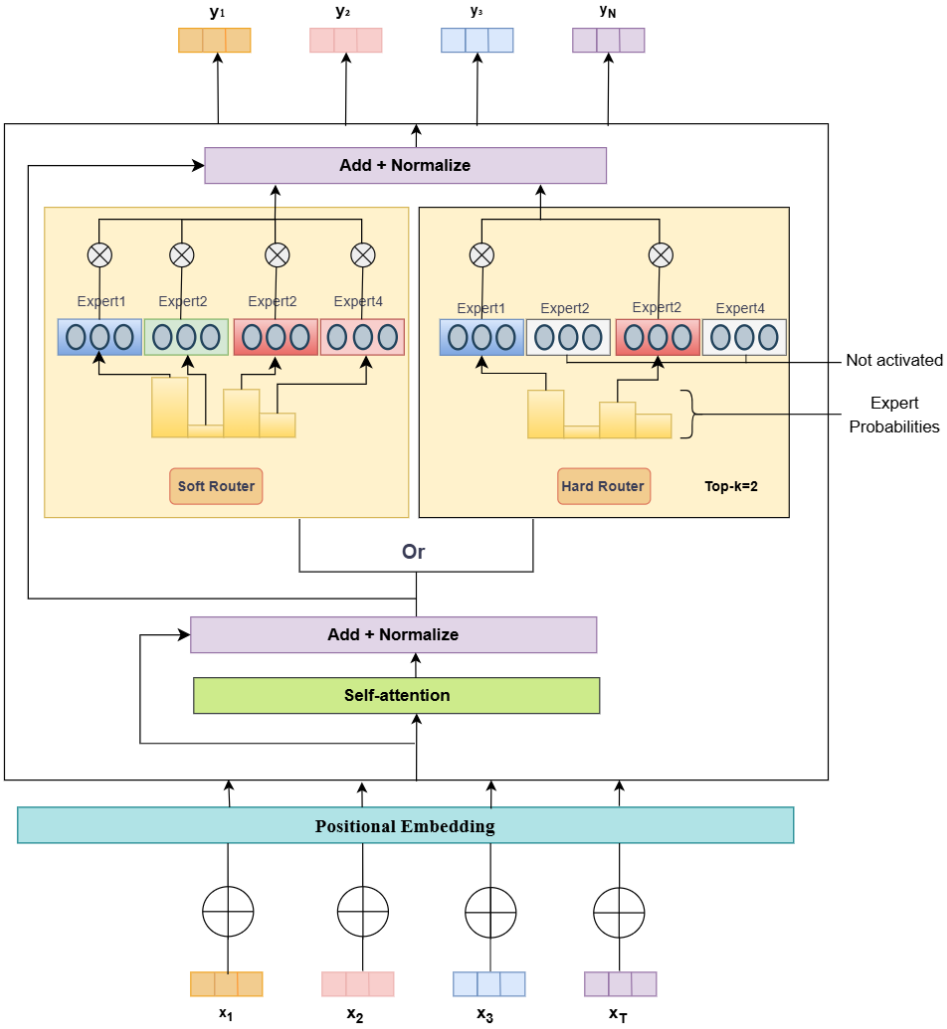


Fig. 1. Overall architecture of the proposed Mixture-of-Experts for ADR extraction.

all experts for every input increases computational cost and may result in redundancy.

b) Hard MoE: The hard version of MoE uses a sparse routing strategy, where only a subset of experts, typically the top-k according to the gating scores, are activated for any given input. The gating network computes scores $g = G(H)$, and only the experts with the highest k scores are selected. The weights α_k for the selected experts are usually set to 1 (a simple sum) or re-normalized via softmax over the top-k scores, while others are set to zero:

$$H' = \sum_{k \in \text{Top-}k(g)} \alpha_k E_k(H) \tag{5}$$

This selective routing greatly reduces computation and allows each expert to specialize in a narrower subset of the input space, thereby promoting more distinct expert behavior. However, without proper intervention, this approach introduces a significant challenge: the gating network may collapse, consistently favoring a small subset of experts while allowing others to stagnate, a phenomenon known as expert collapse. This issue is mitigated, and stable training as well as balanced expert utilization are ensured through an auxiliary load-balancing loss term [26]. This loss penalizes uneven usage of the experts and thus encourages the gating network to distribute the inputs more uniformly across the set of experts. By this regularization, all experts get enough training signals and contribute meaningfully to the overall performance of the model. This prevents a small set of experts from dominating.

Both MoE variants are integrated at the interface between the encoder and decoder, enabling the experts to refine intermediate representations before decoding. This comparative study focuses on how the Soft and Hard routing strategies influence model specialization and performance for the ADR extraction task. A concise comparison of the two variants is presented in Table I.

D. Evaluation Metrics

Since extracting ADRs inherently incorporates ambiguity in defining the entity boundaries of patient narratives, performance evaluation is essential. The standard metrics, such as precision, recall, and F1-score, allow for a basic understanding of how well models can identify correct mentions of ADRs.

TABLE I. KEY CHARACTERISTICS COMPARISON BETWEEN SOFT AND HARD MOE MECHANISMS

Features	Soft MoE	Hard MoE
Routing Mechanism	Dense / All Expert Routing	Sparse / Top-k Routing
Expert Selection	Only the top-k experts are selected and activated for a given input	All experts are activated for each input
Gating Function	Use Softmax function to generate a probability distribution for all experts	Top-k discrete routing with gradient approximation
Load Balancing	- KL divergence balance loss - Optional : Naturally balanced due to continious soft gating but can still be benificial	- Explicit balance loss (MSE) - Mandatory : To prevent expert to become overloaded
Training Stability	More stable due to soft combination	Can suffer from expert collapse
Computational Cost	Higher cost because all experts must be computed in full	Lower cost because only k experts are activated and computed
Robustness	Higher: Robust to routing variations since multiple experts contribute jointly, reducing the impact of the individual routing errors	Lower: Highly sensitive to router errors. If an incorrect expert is selected, the performance can significantly degrade

However, the strict evaluation methods, since they require an exact boundary match between the predicted and gold-standard entities, are inflexible and often fail to consider the partially correct predictions that still offer useful ADR information. To handle this limitation, a relaxed evaluation strategy is adopted [27] in which predictions that partially overlap with the gold-standard entities are considered as valid matches. These partial matches are recognized by calculating the cosine similarity between the embeddings of predicted and reference entities by setting a threshold of 0.8, which is sufficient to consider semantic similarity. This dual evaluation framework evaluates not only the model's precision in boundary extraction but also its ability to recognize semantically relevant ADRs when the predicted and true boundaries do not perfectly match.

The predicted entities are grouped into five categories as illustrated in Fig. 2:

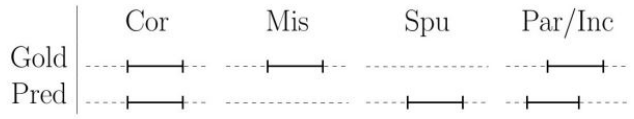


Fig. 2. Visual representation of Correct (Cor), Missed (Mis), Spurious (Spu), and Partial/Incorrect (Par/Inc) entity alignments [27].

- Correct (Cor): Predicted ADRs that match the gold standard exactly in both span and content.
- Partial (Par): Predicted ADRs that partially overlap with a gold-standard entity or are semantically similar, identified using cosine similarity above the threshold.
- Incorrect (Inc): Predicted ADRs overlapping a gold standard entity but not exceeding the similarity threshold.
- Spurious (Spu): Predicted ADRs that do not correspond to any gold-standard entity.
- Missed (Mis): Gold-standard ADRs that were not predicted by the model.

Using these categories, the main evaluation metrics are defined as follows:

Precision:

$$\text{Precision} = \frac{Cor + (Par \times 0.5)}{Cor + Par + Inc + Miss} \tag{6}$$

Recall:

$$\text{Recall} = \frac{Cor + (Par \times 0.5)}{Cor + Par + Inc + Spu} \tag{7}$$

F1-Score:

$$\text{F1} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \tag{8}$$

For strict evaluation, partial matches are excluded (Par=0), and only exact matches are considered as correct. This provides an exact measure of the model's capability in identifying ADRs correctly. In contrast, the relaxed evaluation includes partial matches, allowing for a more flexible assessment that accounts for semantically relevant extractions even when the predicted span does not align exactly with the gold standard. The proposed framework for this combined evaluation will make sure that both exact and partially correct ADR predictions are suitably assessed to provide a comprehensive view of model performance in extracting Adverse Drug Reactions from patient-generated texts.

IV. EXPERIMENTAL RESULT ANALYSIS AND DISCUSSION

A. Experimental Settings

A set of experiments involving both Soft MoE and Hard MoE architectures has been conducted to estimate the performance of Mixture-of-Experts network architectures. A variety of encoder-decoder models of the T5 family have been investigated in the experiment involving Soft MoE. These variants include T5 base, Flan-T5 base (instruction-tuned), T5 small (efficient small model), BioT5-base (biomedically tuned), and Long-T5-tglobal-base (long-context model). T5-base is used as the tokenizer in this architecture type. For the Hard MoE, experiments were carried out using BART-based architectures, including BART-base, BART-large, mBART-large-50 (multilingual version), and BioBART-base (biomedical variant), with BART-base used as the tokenizer in this experiment as well. A

top-k = 2 routing strategy has been employed to select the two most relevant experts given the input, ensuring both efficiency and expert specialization.

Through various tests of model combinations and hyperparameter values, the final set of values was chosen based on overall performance and the stability of training observed during experimentation. All of these scenarios had been optimized using AdamW optimizer with a learning rate of 3e-5 and trained for 12 epochs with small batch sizes due to computational constraints. A description of the full hyperparameters, including the number of experts, hidden dimensions, optimizer, and batch sizes in both architectures, is provided in Table II.

TABLE II. EXPERIMENTAL HYPERPARAMETER SETTINGS FOR SOFT AND HARD MOE

Model Hyperparameters	Soft MoE	Hard MoE
num_expert	5	4
hidden_dim	512	512
num_beans	4	4
optimizer	AdamW	AdamW
learning rate	3e-5	3e-5
train batch_size	4	6
test batch_size	4	4
epochs	12	7

B. Result Analysis

Table III presents the performance comparison between the Soft and Hard MoE models under both strict and relaxed evaluation settings. The findings show a consistent and notable performance difference that can be directly related to their underlying architectural principles. As the table demonstrates, the Soft MoE model performs better overall, attaining a strict F1-score of 72.90% compared to the 71.60% achieved by the Hard MoE. This performance gap of 1.3 F1-score under the most strict parameters is not negligible and is sustained under relaxed parameters as well, where Soft MoE outperforms by 1% F1-score (80.40% vs. 79.40%). To further contextualize these results, the analysis is extended by including benchmark results from the MultiADE research study [29], which evaluated span-based, generative, and large language model approaches on the PsyTAR dataset. As shown in Table III, the proposed Soft MoE achieves a strict F1-score of 72.90%, outperforming both the best-performing span-based (68.50%) and generative models (68.20%) models, GPT-4 and Llama-3 models in a 5-shot setting, which achieved 58.80% and 57.70%, respectively. This comparison underscores that the proposed Soft MoE model not only surpasses its Hard MoE counterpart but also achieves competitive performance among existing approaches for ADR extraction from the PsyTAR dataset.

The performance gain by Soft MoE might be due to its adaptive and collaborative gating mechanism, which allows multiple experts to jointly contribute towards processing each input. The flexible routing enables smooth information sharing between the experts, enabling the model to capture fine-grained contextual cues and semantic subtleties that frequently occur in user-generated medical texts. Adaptability to such heterogeneity is particularly helpful for ADR extraction from social media, where the expressions of adverse effects are often informal, fragmented, or context-dependent. By leveraging the combined expertise of multiple sub-networks, the Soft MoE demonstrates a more nuanced understanding of these heterogeneous textual patterns. In contrast, Hard MoE activates only a limited set of experts for each token or sequence. Hence, there are more discrete decision boundaries. This can be beneficial because it is computationally efficient, but might suppress contributions by relevant experts for more complex levels of linguistic and ambiguous representations. This may be the most reasonable explanation for the observed gap: the Hard MoE fails to fully leverage its capacity when dealing with noisy and contextually rich data.

Overall, it is evident that the results presented above have established strong empirical support for the routing strategy playing a crucial role in influencing the performance of MoE-based architectures in ADR extraction tasks. The capability of the Soft MoE to leverage distributed knowledge makes it well-suited for the context of real-world digital pharmacovigilance applications.

C. Discussion

The experimental results demontrate effectiveness of the MoE paradigm in the extraction of ADRs from patient-generated narratives. Both Soft and Hard MoE variants leverage specialized sub-networks, enabling the models to handle the semantic variability and informal language commonly used by patients, an aspect where conventional monolithic models often struggle. However, the Soft MoE model shows superior performance due to its ability to aggregate knowledge from various experts simultaneously. This collaborative routing technique enables the model to better understand nuanced expressions, implicit mentions, and context-dependent ADRs, which are frequent in patient narratives. In contrast, Hard MoE, while computationally efficient, may miss some complex interactions between experts, leading to slightly lower performance. This architectural difference also affects response time and deployability. The sparse expert routing of Hard MoE enables faster inference, making it more suitable for latency-sensitive or high-throughput pharmacovigilance systems. By comparison, the denser expert activation in Soft MoE incurs higher computational overhead per prediction in exchange for enhanced extraction accuracy.

The MoE architecture has several practical advantages. Its modularity can be scaled with minimal increase in training cost, and the routing mechanism promotes balanced expert utilization, avoiding overfitting to specific patterns. Compared to standard transformer models, MoE achieves competitive performance without significantly increasing model size or resource requirements, making it a cost-effective and flexible approach for real-world applications.

Further, this architecture naturally supports the integration of many expert knowledge sources, which can be extended to domain-specific biomedical experts or external knowledge bases in future studies. This adaptability makes MoE a robust solution for pharmacovigilance tasks, capable of handling linguistic diversity, improving semantic precision, and ultimately improving automated monitoring of drug safety.

Despite these advantages, the Mixture-of-Experts architecture presents inherent limitations related to routing behavior

TABLE III. PERFORMANCE COMPARISON OF SOFT AND HARD MOE MODELS WITH BENCHMARK RESULTS ON THE PSYTAR DATASET

Model		Strict			Relaxed		
		P	**R**	**F1**	**P**	**R**	**F1**
Benchmark Models (MultiADE Study [29])	Llama-3 (5-shot)	–	–	57.70%	–	–	–
	GPT-4 (5-shot)	–	–	58.80%	–	–	–
	Fine-tuned (BART Generative Model)	–	–	68.20%	–	–	–
	Fine-tuned (Span-based)	–	–	68.50%	–	–	–
Our Models	**Hard MoE**	72.40%	70.70%	71.60%	80.40%	78.50%	79.40%
	Soft MoE	73.20%	72.60%	**72.90%**	80.80%	80.10%	**80.40%**

and computational complexity. Model performance remains sensitive to the quality of the gating mechanism, particularly in the Hard MoE setting, where suboptimal expert selection may lead to information loss for linguistically ambiguous ADR expressions. In addition, the Soft MoE configuration requires activating all experts for each input, which increases computational cost and may limit scalability in resource-constrained pharmacovigilance applications. Furthermore, expert specialization emerges implicitly during training and is not explicitly enforced, which may result in overlapping expert representations rather than clearly distinct expertise.

In summary, the study confirms that MoE architectures not only deliver strong results in ADR extraction but also provide a modular, efficient, and adaptable framework that can be further optimized for biomedical text mining

V. CONCLUSION

In this study, the use of a Mixture-of-Experts architecture was investigated for the task of Adverse Drug Reaction extraction from patient-generated narratives, where the task is challenging due to the informal, diverse, and context-dependent nature of such texts. The performance of Soft MoE and Hard MoE architectures was compared to highlight the impact of routing strategies on model performance. Experimental results demonstrate that the Soft MoE outperforms the Hard MoE in terms of precision, recall, and F1-measure in both strict and relaxed evaluations. This improvement can be attributed to the Soft MoE's ability to integrate contributions from multiple experts simultaneously, enabling a richer contextual understanding and better handling of informal and subtle language typical for social media and patient reviews.

As a direction for future work, it would be promising to enhance the MoE framework through the integration of external biomedical knowledge bases, such as medical ontologies, pharmacological databases, or drug–disease interaction graphs, to better reinforce the model's domain awareness and semantic precision. Additionally, incorporating mechanisms to capture complex drug–drug interactions and contextual dependencies could further refine ADR extraction and contribute to a more comprehensive view of patient-reported pharmacovigilance data. Ultimately, these advancements could bring MoE-based systems closer to real-world applications in automated drug safety monitoring.

REFERENCES

[1] Y. Zhang, S. Cui, and H. Gao, "Adverse drug reaction detection on social media with deep linguistic features", *Journal of Biomedical Informatics*, 2020, doi: 10.1016/j.jbi.2020.103437.

[2] O. Oyebode and R. Orji, "Identifying adverse drug reactions from patient reviews on social media using natural language processing", *Health Informatics Journal*, 2023, doi: 10.1177/14604582221136712.

[3] P. García-Abeijon, C. Costa, M. Taracido, M. Teresa Herdeiro, C. Torre, A. Figueiras, "Factors Associated with Underreporting of Adverse Drug Reactions by Health Care Professionals: A Systematic Review Update", *Journal of Drug Safety*, 2023, doi: 10.1007/s40264-023-01302-7.

[4] S. Golder, K. O'Connor, Y. Wang, A. Klein, and G. Gonzalez Hernandez, "The value of social media analysis for adverse events detection and pharmacovigilance: A scoping review", *Journal of Medical Internet Research*, 2024, doi: 10.2196/59167.

[5] A. Dirkson, S. Verberne, W. Kraaij, G. van Oortmerssen, and H. Gelderblom, "Automated gathering of real-world data from online patient forums can complement pharmacovigilance for rare cancers", *Scientific Reports*, 2022, doi: 10.1038/s41598-022-13894-8.

[6] R. Deepalakshmi, P. Manikandan, V. Manikandan, "Detecting Adverse Drug Reactions from Twitter Data Using Natural Language Processing and Deep Learning", *Journal of Information Systems Engineering and Management*, 2025, doi: 10.52783/jisem.v10i30s.4896.

[7] C. Wu, F. Wu, J. Liu, S. Wu, Y. Huang, and X. Xie, "Detecting Tweets Mentioning Drug Name and Adverse Drug Reaction with Hierarchical Tweet Representation and Multi-Head Self-Attention", in *Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining*, 2019, pp. 34–37, doi: 10.18653/v1/W18-5909.

[8] J.Y. Huang, W.P. Lee 1, K.D. Lee, "Predicting Adverse Drug Reactions from Social Media Posts: Data Balance, Feature Selection and Deep Learning", *Healthcare*, 2022, doi: 10.3390/healthcare10040618.

[9] M. Tiftikci, A. Özgür, Y. He, and J. Hur, "Machine learning-based identification and rule-based normalization of adverse drug reactions in drug labels", *BMC Bioinformatics*, 2019, doi: 10.1186/s12859-019-3195-5.

[10] O. Elbiach, H. Grissette, and E. H. Nfaoui, "Adverse Drug Reactions Detection from Social Media: an Empirical Evaluation of Machine Learning Techniques", in *Conference: 2023 14th International Conference on Intelligent Systems: Theories and Applications (SITA)*, 2023, doi: 10.1109/SITA60746.2023.10373604.

[11] O. Elbiach, H. Grissette, and E. H. Nfaoui, "Leveraging Transformer Models for Enhanced Pharmacovigilance: A Comparative Analysis of ADR Extraction from Biomedical and Social Media Texts", *Artificial Intelligence (AI)*, 2025, doi: 10.3390/ai6020031.

[12] O. Elbiach, H. Grissette, and E. H. Nfaoui, "Benchmarking large language models for adverse drug reaction extraction in social media and clinical texts", *Results in Engineering*, 2025, doi: 10.1016/j.rineng.2025.107362.

[13] W. Cai, J. Jiang, F. Wang, J. Tang, S. Kim, and J. Huang, "A Survey on Mixture of Experts in Large Language Models", *IEEE Transactions on Knowledge and Data Engineering*, vol. 14, pp. 3896-3915, 2025, doi: 10.1109/TKDE.2025.3554028.

[14] S. Lee, H. Woo, C. Chun Lee, G. Kim, J.Y Kim, and S. Lee, "Drug_SNSMiner: standard pharmacovigilance pipeline for detection of adverse drug reaction using SNS data", *Scientific Reports*, vol. 20, 2023, doi: 10.1038/s41598-023-28912-6.

[15] S. Modi, K. A. Kasmiran, N. M. Sharef, and M. Y. Sharum, "Extracting adverse drug events from clinical Notes: A systematic review of approaches used", *Journal of Biomedical Informatics*, vol. 151, 2024, doi: 10.1016/j.jbi.2024.104603.

[16] P. Joshi, M. Vedhanayagam, and R. Ramesh, "An Ensembled SVM-Based Approach for Predicting Adverse Drug Reactions", *Current Bioinformatics*, vol. 16, pp. 422-432, 2019, doi: 10.2174/1574893615999200707141420.

[17] d. Fan,S. Zhou1,Y. Li, R. Zhang, "Deep learning approaches for extracting adverse events and indications of dietary supplements from clinical text", *Journal of the American Medical Informatics Association*, vol. 16, pp. 422-432, 2021, doi: 10.1093/jamia/ocaa218.

[18] B. Khemani, S. Malave, S. Shinde, M. Shukla, R. Shikalgar, and H. Talwar, "AI-driven pharmacovigilance: Enhancing adverse drug reaction detection with deep learning and NLP", *MethodsX*, 2025, doi: 10.1016/j.mex.2025.103460.

[19] F. Dong, W. Guo, J. Liu, T. A. Patterson, and H. Hong, "BERT-based language model for accurate drug adverse event extraction from social media: implementation, evaluation, and contributions to pharmacovigilance practices", *Frontiers in Public Health*, 2024, doi: 10.3389/fpubh.2024.1392180.

[20] M. M. Zitu, D. Owen, A. Manne, P. Wei, and L. Li, "Large Language Models for Adverse Drug Events: A Clinical Perspective", *Journal of Clinical Medicine*, 2025, doi: 10.3390/jcm14155490.

[21] D. Dai, W. Jiang, J. Zhang, W. Peng, Y. Lyu, Z. Sui et al., "Mixture of Experts for Biomedical Question Answering", *arXiv*, 2022, doi: 10.48550/arXiv.2204.07469.

[22] Q. Liu, X. Wu, X. Zhao, Y. Zhu, D. Xu, F. Tian et al., "MOELoRA: An MOE-based Parameter Efficient Fine-Tuning Method for Multi-task Medical Applications", *arXiv*, 2024, doi: 10.48550/arXiv.2310.18339.

[23] X. Chen, K. Li, T. Song, and J. Guo, "'Mix of Experts Language Model for Named Entity Recognition", *arXiv*, 2024, doi: 10.48550/arXiv.2404.19192.

[24] M. Zolnoori, K. W. Fung, T. B. Patrick, P. Fontelo, H. Kharrazi, A. Faiola et al., "The PsyTAR dataset: From patients generated narratives to a corpus of adverse drug events and effectiveness of psychiatric medications", *Data in Brief*, vol. 24, 2019, doi: 10.1016/j.dib.2019.103838.

[25] T. Shen, M. Ott, M. Auli, and M. Ranzato, "Mixture Models for Diverse Machine Translation: Tricks of the Trade", *arXiv*, 2019, doi: 10.48550/arXiv.1902.07816.

[26] N. Omi, S. Sen, and A. Farhadi, "Load Balancing Mixture of Experts with Similarity Preserving Routers", *arXiv*, 2025, doi: 10.48550/arXiv.2506.14038.

[27] S. Scaboro, B. Portelli, E. Chersoni, E. Santus, and G. Serra, "Extensive Evaluation of Transformer-based Architectures for Adverse Drug Events Extraction", *Knowledge-Based Systems*, vol. 275, 2023, doi: 10.48550/arXiv.2306.05276.

[28] M. Zolnoori, K. W. Fung, T. B. Patrick, P. Fontelo, H. Kharrazi, A. Faiola et al., "A systematic approach for developing a corpus of patient-reported adverse drug events: A case study for SSRI and SNRI medications", *Journal of Biomedical Informatics*, vol. 90, 2019, doi: 10.1007/s001090000086.

[29] X. Dai, S. Karimi, A. Sarker, B. Hachey, and C. Paris, "MultiADE: A Multi-domain benchmark for Adverse Drug Event extraction", *Journal of Biomedical Informatics*, 2024, doi: 10.1016/j.jbi.2024.104744.

Achieving Long-Term Autonomy: A Self-Correcting Deep Reinforcement Learning Agent for Edge IoT Using Digital Twin-Based Drift Compensation

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***Abstract*—Ensuring long-term autonomy in Edge AI systems remains one of the most persistent challenges in environmental monitoring and biorisk management. Over time, the degradation of low-cost sensors—particularly sensor drift—leads to cumulative measurement errors, distorted state perception, and catastrophic decision failures in Deep Reinforcement Learning (DRL) agents. This paper proposes a novel Self-Correcting Deep Reinforcement Learning (SCDRL) framework that enables robust, long-term autonomy through in-loop drift compensation. The proposed Self-Correcting Agent (SCA) integrates a dual-input architecture combining (i) the local, drifted sensor reading and (ii) a stable reference prediction from a macro-scale Digital Twin (DT). By learning to correlate both signals, the agent implicitly estimates and neutralizes sensor bias in real time, achieving self-calibration without human intervention. To validate this approach, a nine-year simulation of autonomous water management was conducted using real-world hourly climate data from Arequipa, Peru. Results show that a conventional "blind" DRL agent suffers complete performance collapse as drift accumulates, whereas the proposed SCA maintains stable operation indefinitely. Quantitatively, the SCA achieved a 722% higher cumulative reward (415,662 vs. 57,556) and a 53% reduction in plant stress (RMSE 0.2238 vs. 0.4762). These findings establish a validated blueprint for fault-tolerant Edge AI, demonstrating that the fusion of local sensing with digital twin predictions enables self-calibrating agents capable of sustained, reliable autonomy in real-world, resource-constrained environments.**

Keywords*—Deep Reinforcement Learning (DRL); Edge AI; Internet of Things (IoT); digital twin; sensor drift; fault tolerance; autonomous systems; self-correcting systems

I. Introduction

The proliferation of Edge Computing and the Internet of Things (IoT) has enabled a new generation of autonomous systems capable of real-time decision-making without reliance on high-latency cloud connections [1], [22]. Deep Reinforcement Learning (DRL) has emerged as the state-of-the-art policy framework for controlling these systems in complex, dynamic environments [2], [3]. This is particularly true for critical applications such as autonomous biorisk management, where deployments are, by design, long-term, physically inaccessible, and resource-constrained [4].

This paradigm, however, faces a critical and often unaddressed vulnerability: the physical degradation of low-cost sensors. While DRL agents are trained to respond to sensor observations $y(t)$, these observations are an imperfect representation of the true ground-truth state $x(t)$. Over time, all physical sensors are subject to both high-frequency noise $\eta(t)$ and, more insidiously, a low-frequency, time-varying bias $\delta(t)$. This phenomenon, widely known in data stream mining as concept drift [5], [6] and in sensing literature as sensor drift [7], creates a non-stationary environment where the statistical properties of the data change over time. The perceived state can thus be formally modeled as:

$$y(t) = x(t) + \eta(t) + \delta(t) \tag{1}$$

As this drift $\delta(t)$ accumulates, the agent's perceived reality (its state s_t) diverges from the ground truth, leading to a cascade of suboptimal policy decisions and eventual, catastrophic system failure. While existing methods attempt to mitigate this, they are insufficient for fully autonomous, in-loop correction.

This paper proposes a novel Self-Correcting Deep Reinforcement Learning (SCDRL) framework. Our architecture overcomes drift by leveraging a macro-scale Digital Twin (DT) [8], [9] as a reliable, drift-free reference. We transition the agent from a "blind" 1D state representation $s_t = [y(t)]$ to an "aware" 2D state $s_t = [y(t), \hat{x}_{DT}(t)]$. We demonstrate that the DRL policy, driven by a reward based on the true state, learns to implicitly use the DT to auto-calibrate its policy and neutralize the sensor drift in real-time.

To validate this, our 9-year benchmark simulation shows the 'Blind' agent's performance catastrophically collapses, while our Self-Correcting Agent (SCA) achieves a 722% higher cumulative reward and reduces plant stress (RMSE) by 53%.

The specific contributions of this paper are summarized as follows:

- We propose a novel Self-Correcting Deep Reinforcement Learning (SCDRL) architecture that fuses local sensor data with Digital Twin predictions to detect and compensate for sensor drift in real-time.
- We demonstrate that this dual-input approach allows the agent to implicitly learn a calibration policy without requiring supervised labels or offline retraining.
- We validate the framework through a 9-year benchmark simulation using real-world ERA5-Land climate data, proving that the SCA maintains long-term autonomy while standard agents fail.

The remainder of this paper is structured as follows: Section II reviews related work in drift compensation. Section III details the POMDP formulation and our proposed SCA framework. Section IV describes the experimental setup. Section V presents and analyzes the 9-year benchmark results. Section VI discusses the implications of our findings, and Section VII concludes the work.

II. Related Work

The challenge of sensor drift, defined by the non-stationary bias $\delta(t)$ in Eq. (1), is a fundamental problem in dynamic data analysis. In the sensing literature, this is explicitly termed sensor drift [7]. More broadly, in the data stream mining and machine learning fields, it is a well-studied phenomenon known as concept drift [5], [6], where the statistical properties of data streams evolve over time. Current approaches to mitigation can be broadly categorized into three families, each with critical limitations that our work addresses.

A. Statistical and Model-Based Compensation

The first family of approaches, often grouped under multivariate calibration or chemometrics, attempts to explicitly model and subtract the drift. This challenge has been extensively documented, with numerous reviews detailing the statistical and machine learning methods applied to this problem [10].

These methods generally fall into two categories. First, static calibration models that treat drift as a signal to be characterized and removed. A classic, highly-cited example is the use of classifier or regressor ensembles—often using Support Vector Machines (SVM) or Partial Least Squares (PLS)—to build a predictive model that maps the drifted sensor data back to a "clean" state [11]. Second, adaptive filtering techniques, such as the Kalman Filter [12]. However, the Kalman Filter is highly effective at removing zero-mean, high-frequency noise $\eta(t)$, but it fundamentally assumes a stationary (non-drifting) process and thus fails to correct for the non-stationary, cumulative bias of $\delta(t)$.

While powerful, both categories share a fatal flaw for true autonomy: they require extensive, offline pre-characterization of the sensor in a laboratory to build their initial drift model [11], [10]. They are not truly adaptive and are rendered obsolete when new, unforeseen drift patterns emerge in the field.

Limitation: These methods are static or require supervised retraining. They cannot perform in-loop, real-time compensation for unexpected drift patterns and require periodic, costly offline recalibration with a known ground-truth signal.

B. Transfer Learning and Domain Adaptation

A complementary strategy to address sensor drift interprets it as a domain shift problem, where a model initially trained on a stable source domain (e.g., Day 0) must adapt to a continuously evolving target domain (e.g., Day 1000). In this context, transfer learning and domain adaptation methods are employed to align the feature distributions between domains. Recent studies have demonstrated that adversarial learning [13], feature alignment [14], and domain-invariant representation learning [15] can effectively reduce discrepancies caused by drift.

Limitation: Despite their success, these methods often depend on (a) access to labeled samples from the target (drifted) domain for fine-tuning, (b) high computational resources for re-training, or (c) both. Such requirements are impractical for Edge AI devices operating under strict energy and hardware constraints.

C. Robust Reinforcement Learning (R-DRL)

A third line of research seeks to mitigate the impact of sensor drift by training agents that are inherently robust to perturbations in their observations. Robust DRL (R-DRL) methods typically formulate the learning process as a minimax optimization problem, where the agent learns a policy that maximizes expected reward under the worst-case disturbance scenarios [16], [17], [23].

Limitation: However, robustness alone is insufficient. While these methods encourage insensitivity to noise, the goal in drift scenarios is not to ignore faulty signals but to recognize and adapt to them. An agent that becomes overly robust may inadvertently disregard meaningful variations, becoming effectively "blind" to real environmental changes.

TABLE I. Comparison of Drift Compensation Approaches vs. Proposed SCA

Approach	Handling Method	Execution	Supervision	Autonomy
Statistical / SVM [11]	Re-calibration	Offline	Supervised	Low
Kalman Filter [12]	Noise Filtering	Real-Time	Unsupervised	Medium
Domain Adapt. [13]	Feature Align.	Offline (Retrain)	Supervised	Low
Robust DRL [17]	Desensitization	Real-Time	Unsupervised	Medium
Proposed SCA	**DT Fusion**	**Real-Time**	**Implicit (None)**	**High**

D. The Research Gap and Our Contribution

As reviewed and summarized in Table I, no existing framework provides a mechanism for a low-power, autonomous DRL agent to perform *in-loop, real-time drift compensation*. The research gap is the absence of a reliable, drift-free "anchor" or "source of truth" that the edge agent can use to calibrate itself.

Our work fills this gap. We propose that a macro-scale Digital Twin (DT) [8], [9], while too complex to run on the edge, can serve as this "anchor". Our Self-Correcting Agent (SCA) is the first, to our knowledge, to use a dual-input state $[y(t), \hat{x}_{DT}(t)]$ to learn an implicit calibration policy, thereby solving the long-term autonomy challenge posed by sensor drift.

III. Proposed Framework and Methodology

The central challenge addressed in this work is the failure of autonomous DRL agents when faced with non-stationary, drifting sensor inputs. This section formally models this challenge as a Partially Observable Markov Decision Process (POMDP) and introduces our proposed Self-Correcting Agent (SCA) architecture, which leverages a Digital Twin (DT) for in-loop drift compensation.

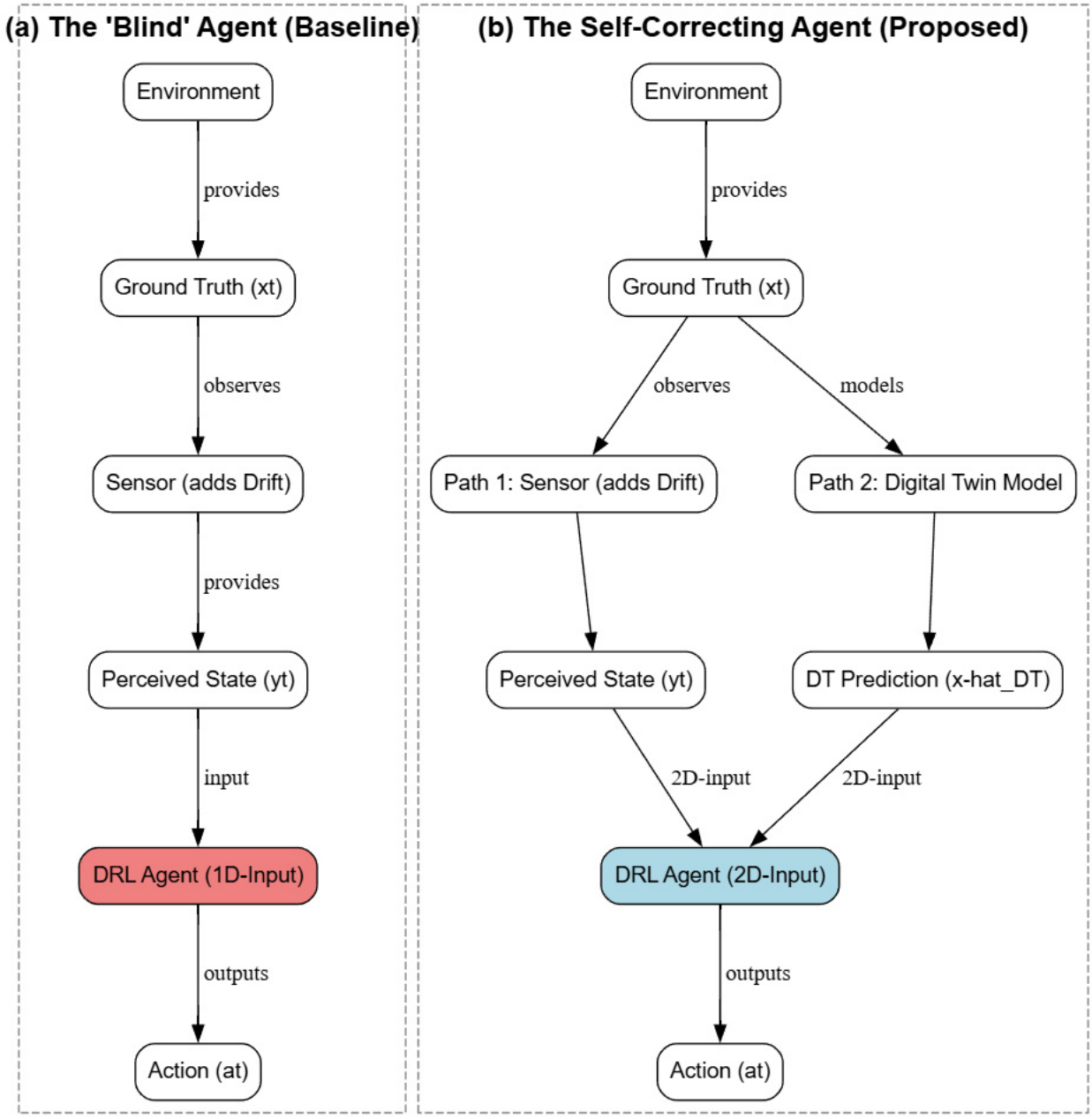


Fig. 1. System architecture comparison. (a) The baseline 'Blind' agent receiving single, drifting sensor observations. (b) The proposed Self-Correcting Agent (SCA) fusing local sensor readings with digital twin predictions for in-loop drift compensation.

A. Problem Formulation as a POMDP

We model the autonomous control task as a Partially Observable Markov Decision Process (POMDP), defined by the tuple $(\mathcal{S}, \mathcal{A}, \mathcal{T}, \mathcal{R}, \Omega, \mathcal{O})$.

- $\mathcal{S}$: The set of true, unobservable environment states, $s_t \in \mathcal{S}$, which is the true ground-truth soil moisture $x(t)$.
- $\mathcal{A}$: The set of discrete actions $\mathcal{A} = \{a_0, a_1, a_2\}$, representing {DO_NOTHING, WATER_PULSE_S, WATER_PULSE_L}.
- $\mathcal{T}$: The state transition function $P(s_{t+1}|s_t, a_t)$, governed by the physics of the simulation environment.
- $\mathcal{R}$: The reward function $R(s_t, a_t)$. Critically, the reward is a function of the *true state* s_t. We define R as a Gaussian function encouraging an ideal setpoint, x_{ideal}, penalized by an action cost $C(a_t)$:

$$R(s_t, a_t) = \alpha \cdot \exp\left(-\frac{(x(t) - x_{ideal})^2}{2\sigma^2}\right) - \beta \cdot C(a_t) \quad (2)$$

- Ω: The set of observations. The agent sees an observation $o_t \in \Omega$.

- $\mathcal{O}$: The observation probability function $\mathcal{O}(o_t|s_t)$. This is the core of the problem. The observation o_t is a corrupted version of the true state $x(t)$ [from Eq. (3)]:

$$o_t = \mathcal{O}(s_t) = x(t) + \eta(t) + \delta(t) \tag{3}$$

The objective is to find an optimal policy $\pi(a_t|o_t)$ that maximizes the expected discounted cumulative reward $E[\sum_{t=0}^{T} \gamma^t R(s_t, a_t)]$.

B. Proposed Self-Correcting Architecture (SCA)

To solve this POMDP, we propose the SCA, which explicitly accounts for the drift $\delta(t)$, as illustrated in Fig. 1(b).

1) The 'Blind' Agent (Baseline): As depicted in Fig. 1(a), the baseline DRL agent relies solely on the corrupted sensor signal. It is trained on a 1D observation space $\Omega^{(1D)}$:

$$s_t^{(1D)} = o_t = [y(t)] \tag{4}$$

The policy $\pi_{blind}(a_t|s_t^{(1D)})$ fails as the environment becomes non-stationary ($t \to \infty$ and $\delta(t) \to \infty$).

2) The Self-Correcting Agent (SCA): Our proposed SCA agent is designed to be "aware" of the drift by augmenting the observation space to $\Omega^{(2D)}$:

$$s_t^{(2D)} = [y(t), \hat{x}_{DT}(t)] \tag{5}$$

where, $y(t)$ is the unreliable local sensor and $\hat{x}_{DT}(t)$ is the reliable prediction from the Digital Twin. The agent is provided with two signals and tasked to maximize the reward. The DRL optimization process will discover that $R(t)$ has a high mutual information with $\hat{x}_{DT}(t)$ and a diminishing correlation with $y(t)$, allowing it to learn a "self-correcting" policy.

C. Simulation Environment Design

A custom simulation environment was implemented in Python using the `Gymnasium` framework [18].

1) Environment Physics (The Digital Twin): The core simulation, which serves as the 'perfect' prediction source $\hat{x}_{DT}(t)$, is a physics-based model of soil moisture. It is driven by a 9-year historical dataset (2015-2023) of hourly climate data (temperature, precipitation) for Arequipa, Peru, sourced from the ERA5-Land dataset via Google Earth Engine.

We intentionally assume a 'perfect' DT in this study to establish a clear proof-of-concept. This assumption is methodologically necessary to isolate the agent's core ability: learning to differentiate between a known-reliable signal (the DT) and a known-corrupted signal (the sensor). Investigating the SCA's resilience against an imperfect or noisy DT model is a critical next step, but is left for future work.

2) Sensor Drift Simulation Model: A 'SensorWrapper' class implements Eq. (3). It corrupts the ground truth $x(t)$ before passing it to the agent. At each step t, the drift $\delta(t)$ is accumulated:

$$\delta(t) = \delta(t-1) + \delta_{step} \tag{6}$$

where, δ_{step} is a small constant representing the daily drift rate, divided by 24, simulating a relentless, cumulative bias.

A linear, cumulative drift model was deliberately chosen over a more complex stochastic model. This approach simulates a "worst-case scenario" for the policy, where the bias is systematic, relentless, and never self-corrects. This provides a clear and stringent test of the agent's ability to compensate for long-term, non-stationary failure modes, as opposed to simple, high-frequency random noise.

IV. Experimental Setup

To validate the hypothesis, we designed a rigorous computational experiment to compare the 'Blind' agent against our proposed SCA.

A. Agent Implementation

Both agents were implemented in Python using the `Stable-Baselines3` framework [19], [20]. The core learning algorithm employed was the Deep Q-Network (DQN) [2], a value-based method. The policy architecture consisted of a multilayer perceptron (MLP) with two hidden layers of 64 units each ($[64, 64]$) and ReLU activation functions, following standard RL baselines [21].

- Agent 1: 'Blind' Agent (Baseline). Trained and executed using the 1D observation space $s_t^{(1D)} = [y(t)]$.
- Agent 2: Self-Correcting Agent (SCA). Trained and executed using the 2D observation space $s_t^{(2D)} = [y(t), \hat{x}_{DT}(t)]$.

B. Training Protocol

Agents were trained on a "clean" dataset (one year, 2024) with minimal noise ($\sigma_\eta = 0.01$) and near-zero drift ($\delta_{day} = 0.001$) to simulate "Day 0" performance. Both agents were trained for 50,000 timesteps using identical hyperparameters (Table II).

TABLE II. DRL Hyperparameters used for Training

Parameter	Value
DRL Algorithm	DQN (Deep Q-Network)
Policy Network	MLP
Network Architecture	$[64, 64]$ (Hidden Layers)
Learning Rate	1.0×10^{-4}
Replay Buffer Size	50,000
Batch Size	64
Discount Factor (γ)	0.99
Target Network Update Freq.	1,000 steps
Training Timesteps	50,000

C. Long-Term Benchmark Protocol

The benchmark evaluated the *resilience* of the pre-trained, "frozen" agents.

- Dataset: Executed on a 9-year (2015-2023) unseen test dataset (78,887 timesteps).
- Test Environment: Configured with significant degradation: sensor noise $\sigma_\eta = 0.02$ and a sensor drift rate $\delta_{day} = 0.001$.

D. Evaluation Metrics

We defined three primary metrics to quantify performance:

1) Cumulative Reward: The primary objective function $\sum_{t=0}^{T} R(t)$, balancing health and cost.
2) Plant Stress (RMSE): A direct measure of health, defined as the Root Mean Square Error between the *ground-truth moisture* $x(t)$ and the ideal setpoint $x_{ideal} = 0.6$:

$$\text{Stress (RMSE)} = \sqrt{\frac{1}{T}\sum_{t=0}^{T}(x(t) - x_{ideal})^2} \quad (7)$$

A lower RMSE indicates lower biological stress.
3) Water Consumption: A measure of resource efficiency, calculated as $\sum_{t=0}^{T} C_W(a_t)$, where $C_W(a_t)$ is 0.1 for a short pulse and 0.2 for a long pulse.

V. Results and Analysis

The 9-year benchmark simulation provides a definitive validation of our hypothesis, demonstrating the 'Blind' agent's failure and the SCA's robust resilience.

A. Quantitative Performance Analysis

The aggregate performance over the entire 78,887-hour simulation is summarized in Table III.

TABLE III. Quantitative Benchmark Results (9-Year Simulation)

Metric	'Blind' Agent (1D)	SCA (2D)
Total Cumulative Reward	57,555.94	**415,662.20**
Plant Stress (RMSE)	0.4762	**0.2238**
Water Consumption (Units)	156.00	716.40

The quantitative data reveals a stark divergence:

- Cumulative Reward: The SCA achieved a total reward of 415,662, a 722% increase over the 'Blind' agent (57,556), demonstrating profound operational value.
- Plant Stress (RMSE): The SCA maintained an average RMSE of 0.2238, a 53% reduction in plant stress compared to the 'Blind' agent (0.4762), confirming its superior ability to maintain system homeostasis.
- Water Consumption: The 'Blind' agent consumed only 156 units, while the SCA consumed 716.4. This is not inefficiency; it shows the 'Blind' agent stopped working. As sensor drift accumulated, its perceived state became erroneous, causing a suboptimal policy of inaction. The SCA's higher consumption is the correct behavior of a system operating as intended.

B. Qualitative Analysis: Reward Degradation

As illustrated in Fig. 2, the plot clearly shows three phases. In Phase 1 (Days 0-500), both agents perform optimally as sensor drift is still small enough to be masked by noise. However, in Phase 2 (Days 500-1000), the 'Blind' agent, represented by the red dashed line, enters a rapid, catastrophic collapse as the accumulated drift invalidates its policy. Finally, in Phase 3 (Days 1000+), the 'Blind' agent's reward flatlines near zero, indicating total control failure. In stark contrast, the SCA, shown as the blue solid line, maintains its high-reward, optimal policy indefinitely.

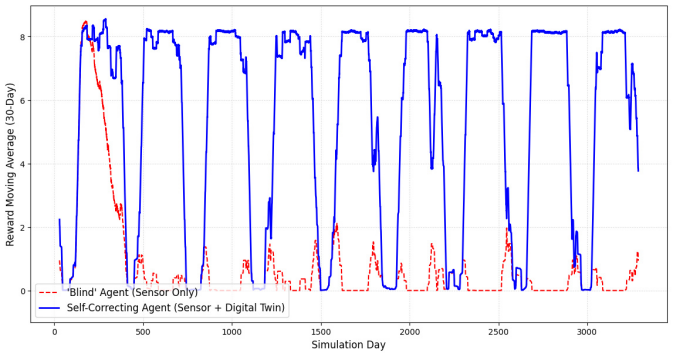


Fig. 2. Comparative analysis of cumulative reward using a 30-day moving average.

C. Analysis of Control Behavior and Plant Stress

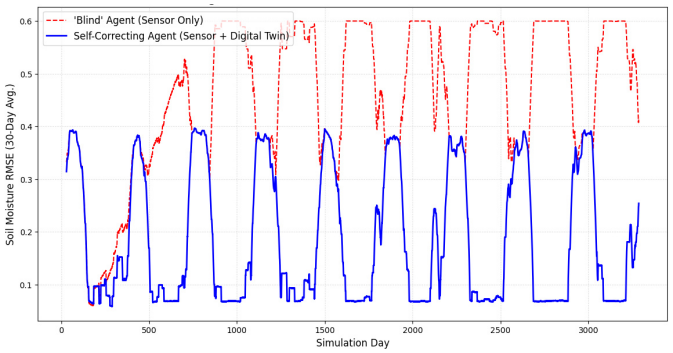


Fig. 3. Comparative analysis of plant stress (RMSE) over the 9-year test period.

Fig. 3 illustrates the direct impact of these policies on the plant physical health. The plot of the 'Blind' agent's RMSE (red dashed line) mirrors its reward collapse. As the agent loses control, the RMSE rises to a sustained high level of approximately 0.6, indicating a complete failure to maintain system homeostasis.

Conversely, the SCA's RMSE (blue solid line) remains in a low, stable band. This demonstrates that the agent successfully learned to use its 2D-state observation to identify the correlation between the reward signal and the stable DT prediction, effectively treating the local sensor as an unreliable signal to be ignored. This behavior confirms the self-correcting hypothesis and ensures long-term autonomy.

VI. Discussion

The results presented in Section V provide a conclusive answer to our research question. The quantitative and qualitative data demonstrate that a standard 'Blind' DRL agent

is incapable of long-term autonomous operation in a non-stationary (drifting) environment, while our proposed SCA architecture achieves near-perfect resilience.

A. Interpretation of Emergent Behavior

The core finding is the *emergent behavior* of the SCA. Presented with a 2D state $s_t^{(2D)} = [y(t), \hat{x}_{DT}(t)]$ and a reward $R(t)$ based on the true state $x(t)$, the agent successfully solved the POMDP. It correctly identified that the DT prediction $\hat{x}_{DT}(t)$ had a high mutual information with the reward, while $y(t)$ had a degrading correlation. The agent's policy effectively learned to use $\hat{x}_{DT}(t)$ as its "source of truth", demonstrating that the DRL policy, without explicit programming, can learn *in-loop fault detection and correction*.

B. Analysis of Agent Failure (The 'Blind' Agent)

The failure of the 'Blind' agent highlights a fundamental flaw in many current Edge AI implementations. Its policy, optimal on "Day 0", became catastrophically suboptimal as the sensor input drifted. This is evident in the `Water Consumption` metric (Table III). The 'Blind' agent's low consumption (156 units) is not efficiency; it is policy failure. The agent's erroneous observations $y(t)$ caused it to converge on "DO_NOTHING" as the least-costly action, abandoning its task. The SCA's higher consumption (716 units) is the correct behavior of a functioning system. However, regarding resource efficiency in physical deployments, unconstrained actuation risks over-correction (e.g., oscillating valves due to sensor noise). While the current DRL reward function penalizes deviations from the Digital Twin's optimal reference to mitigate this, future real-world implementations would benefit from a dedicated 'safety layer.' This layer would enforce hard constraints, such as a maximum daily irrigation cap or a hysteresis threshold, ensuring that the agent's self-correction capabilities do not lead to resource waste even in highly volatile sensing environments.

C. Limitations and Future Work

This study provides a definitive proof-of-concept, but its findings are established under specific simulation assumptions that create clear avenues for future research:

1) Perfect Digital Twin: As stated in our methodology, this study *intentionally* assumed a 'perfect' Digital Twin. This was a necessary design choice to establish a clear proof-of-concept and to isolate the agent's core ability to self-correct against a corrupted signal. A critical avenue for future work is to quantify the SCA's resilience when the DT itself is an imperfect or noisy predictive model.
2) Simulation vs. Reality: This benchmark was conducted entirely in simulation. The next logical step is to deploy this SCA framework on a physical hardware testbed (such as an ESP32) to validate its performance against real-world, physical sensor drift.
3) Drift Model: Our simulation deliberately used a linear, cumulative bias to test the policy against a systematic, "worst-case" failure scenario, rather than simple random noise. Having established this baseline, future research should now explore more complex drift models (stochastic, intermittent) to further test the SCA's robustness.

Regarding resource efficiency, although the SCA exhibits higher water consumption than the failing Blind agent, this consumption represents necessary interventions to prevent crop loss. To address the potential risk of over-correction (e.g., oscillating actuations due to sensor noise), the current DRL reward function penalizes deviations from the Digital Twin's optimal reference. For future real-world deployments, strict resource constraints can be enforced by implementing a 'safety layer' that imposes a maximum daily irrigation cap or a hysteresis threshold. This would ensure that the agent's self-correction capabilities do not lead to resource waste even in highly volatile sensing environments

VII. Conclusion

The long-term autonomy of Edge AI and IoT systems is fundamentally compromised by the physical-world reality of sensor drift. Standard DRL agents are incapable of compensating for this non-stationary, cumulative error, leading to catastrophic policy failure.

In this paper, we proposed and validated a Self-Correcting DRL Agent (SCA) architecture. This framework overcomes sensor drift by augmenting the agent's state with a stable, drift-free reference from a Digital Twin (DT). The agent learns an optimal policy that can differentiate between the unreliable, drifting local sensor and the reliable DT prediction, effectively performing real-time, in-loop auto-calibration.

Our 9-year benchmark simulation demonstrated the definitive superiority of this approach. The SCA achieved a 722% higher cumulative reward and a 53% reduction in system stress (RMSE) compared to an identical 'Blind' agent, which suffered a complete performance collapse.

This work provides a validated blueprint for the next generation of truly autonomous, fault-tolerant, and resilient Edge AI systems. By fusing the high-frequency local observations of edge devices with the high-fidelity macro-predictions of Digital Twins, we can create self-calibrating systems capable of robust, long-term operation in the complex and changing real world.

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References

[1] W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, "Edge computing: Vision and challenges," *IEEE Internet of Things Journal*, vol. 3, no. 5, pp. 637-646, 2016.

[2] V. Mnih, K. Kavukcuoglu, D. Silver, et al., "Human-level control through deep reinforcement learning," *Nature*, vol. 518, no. 7540, pp. 529-533, 2015.

[3] N. C. Luong, D. T. Hoang, S. Gong, D. Niyato, P. Wang, Y. C. Liang, and D. I. Kim, "Applications of deep reinforcement learning in communications and networking: A survey," *IEEE Communications Surveys & Tutorials*, vol. 21, no. 4, pp. 3133-3174, 2019.

[4] H. Sallouh, et al., "IoT for long-term environmental monitoring: challenges and opportunities," *IEEE Internet of Things Journal*, vol. 8, no. 12, pp. 9307-9326, 2021.

[5] J. Gama, I. Žliobaitė, A. Bifet, M. Pechenizkiy, and A. Bouchachia, "A survey on concept drift adaptation," *ACM Computing Surveys (CSUR)*, vol. 46, no. 4, Article 44, 37 pages, 2014.

[6] J. Lu, A. Liu, F. Dong, F. Gu, J. Gama, and G. Zhang, "Learning under concept drift: A review," *IEEE Transactions on Knowledge and Data Engineering*, vol. 31, no. 12, pp. 2346-2363, 2018.

[7] A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, "Internet of Things: A Survey on Enabling Technologies, Protocols, and Applications," *IEEE Communications Surveys & Tutorials*, vol. 17, no. 4, pp. 2347-2376, 2015.

[8] M. Grieves, "Digital twin: manufacturing excellence through virtual factory replication," *White Paper, Florida Institute of Technology*, 2014.

[9] F. Tao, H. Zhang, A. Liu, and A. Y. C. Nee, "Digital twin in industry: State-of-the-art," *IEEE Transactions on Industrial Informatics*, vol. 15, no. 4, pp. 2405-2415, 2018.

[10] M. Fernández-Delgado, A. J. S. Sánchez, J. M. G. R. Sánchez, and S. R. L. V. Sánchez, "A review on the application of statistical and machine learning methods for sensor drift compensation in artificial olfaction," *Artificial Intelligence Review*, vol. 52, no. 1, pp. 289-316, 2019.

[11] A. Vergara, S. Vembu, T. Ayhan, M. A. Ryan, M. L. Homer, and R. Huerta, "Chemical gas sensor drift compensation using classifier and regressor ensembles," *Sensors and Actuators B: Chemical*, vol. 166-167, pp. 320-329, 2012.

[12] G. Welch and G. Bishop, "An introduction to the Kalman filter," Tech. Rep. TR 95-041, University of North Carolina at Chapel Hill, 1995.

[13] Y. Ganin, E. Ustinova, H. Ajakan, P. Germain, H. Larochelle, F. Laviolette, M. Marchand, and V. Lempitsky, "Domain-adversarial training of neural networks," *Journal of Machine Learning Research*, vol. 17, no. 59, pp. 1-35, 2016.

[14] M. Wang and W. Deng, "Deep visual domain adaptation: A survey," *Neurocomputing*, vol. 312, pp. 135-153, 2018.

[15] E. Tzeng, J. Hoffman, K. Saenko, and T. Darrell, "Adversarial discriminative domain adaptation," *In Proceedings of the IEEE conference on computer vision and pattern recognition (CVPR)*, pp. 7167-7176, 2017.

[16] J. Morimoto and K. Doya, "Robust reinforcement learning," *Neural Computation*, vol. 17, no. 2, pp. 335-359, 2005.

[17] L. Pinto, J. Davidson, R. Sukthankar, and A. Gupta, "Robust adversarial reinforcement learning," *In Proceedings of the International Conference on Machine Learning (ICML)*, pp. 2817-2826, 2017.

[18] M. Towers, A. Kwiatkowski, J. Terry, J. U. Balis, G. De Cola, T. Deleu, et al., "Gymnasium: A standard interface for reinforcement learning environments," *arXiv preprint arXiv:2407.17032*, 2024.

[19] A. Raffin, A. Hill, A. Gleave, A. Kanervisto, M. Ernestus, and N. Dormann, "Stable-Baselines3: Reliable Reinforcement Learning Implementations," *Journal of Machine Learning Research (JMLR)*, vol. 22, no. 268, pp. 1-8, 2021.

[20] M. Hessel, J. Modayil, H. Van Hasselt, T. Schaul, G. Ostrovski, W. Dabney, D. Horgan, B. Piot, M. Azar, and D. Silver, "Rainbow: Combining improvements in deep reinforcement learning," *In Proceedings of the AAAI Conference on Artificial Intelligence (AAAI)*, vol. 32, no. 1, 2018.

[21] P. Henderson, R. Islam, P. Bachman, J. Pineau, D. Precup, and D. Meger, "Deep reinforcement learning that matters," *In Proceedings of the AAAI Conference on Artificial Intelligence (AAAI)*, vol. 32, no. 1, 2018.

[22] D. Xu, T. Li, Y. Li, X. Su, S. Tarkoma, T. Jiang, J. Crowcroft, and P. Hui, "Edge intelligence: Architectures, challenges, and applications," *arXiv preprint arXiv:2003.12172*, 2020.

[23] A. Tamar, S. Mannor, and H. Xu, "Scaling up robust MDPs using function approximation," *In Proceedings of the International Conference on Machine Learning (ICML)*, pp. 181-189, 2014.

Sustainable and Ethical AI-Driven Recognition in Robotics: Integrating ESG Analytics and Human–Robot Interaction

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***Abstract*—Environmental, Social, and Governance (ESG) information has become an essential component in evaluating corporate responsibility and long-term resilience. However, its incremental value in predicting firm profitability remains insufficiently understood. This study investigates whether integrating *ESG analytics* with traditional financial ratios enhances the machine-learning classification of firms into high- and low-profitability categories. Using a multi-industry dataset that combines firm-level ESG pillar scores with accounting-based financial indicators, three supervised learning models—Decision Trees, Random Forests, and Support Vector Machines (SVM)—are developed and evaluated. Model validation is conducted through cross-validation, and predictive performance is assessed using Accuracy, F1-score, and the Area Under the ROC Curve (AUROC). To isolate the specific contribution of ESG factors, ablation experiments and feature-importance analyses are performed. The findings reveal that the Random Forest model provides the most consistent and robust predictive performance (Accuracy = 0.89, F1-score = 0.88, AUROC = 0.93), with Environmental and Governance dimensions emerging as the most influential ESG predictors. The novelty of this research lies in establishing a clear mechanism linking ESG analytics to financial performance and in proposing an ESG-aware evaluation framework, rather than introducing a new predictive model or dataset.**

***Keywords*—Artificial intelligence; robotic recognition; human–robot interaction; explainable AI; ESG analytics; sustainable robotics**

I. Introduction

Artificial intelligence (AI) is reshaping the field of robotics, enabling machines to see, learn, and adapt in real-time. A key element in this transformation is robotic recognition—the ability to process and interpret sensory inputs such as images, sound, and motion. This capability forms the backbone of autonomous systems used in sectors ranging from manufacturing and logistics to healthcare and education [1], [2].

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Today's recognition systems go beyond simply identifying objects or navigating space. They now include capabilities like reading emotions, interpreting social cues, and making decisions in unpredictable environments. These advances have been driven largely by deep learning and reinforcement learning, which allow robots to extract meaning from complex data sources [3], [4]. Convolutional neural networks and transformer models have made major strides in areas like face recognition and gesture detection. Meanwhile, multimodal learning—which combines vision, sound, and touch—helps robots better understand human intent.

But these achievements come at a cost. Modern AI systems require significant computational power, which increases energy consumption and raises concerns about environmental impact [5], [6]. In parallel, the growing role of robots in society raises ethical and cultural questions: Can robots show empathy? Are their decisions transparent and fair? Are they culturally appropriate in different settings? [7], [8].

This study argues that sustainable robotics must go beyond technical performance. It must integrate ethical design principles, promote explainable AI, and be evaluated through the lens of environmental, social, and governance (ESG) standards. We propose a framework that positions robotic recognition not just as a technical problem, but as a multidimensional challenge involving ethics, resource use, and economic value.

1) Contributions: This study offers a comprehensive synthesis of key AI-based recognition methods and traces their evolution toward more sustainable and ethically aligned frameworks. It further examines system architectures that incorporate human-centered and ethical components, summarizes representative applications, and analyzes their environmental and financial implications. In addition, the research provides empirical evidence linking ESG indicators with recognition performance. Distinct from prior studies that primarily emphasize the development of novel recognition models or im-

provements in predictive accuracy, the originality of this work lies elsewhere. Specifically, it introduces a structured ESG-to-performance linkage mechanism that maps environmental, social, and governance dimensions to measurable system-level indicators within recognition-driven robotics. Moreover, it proposes an ESG-aware evaluation methodology that complements traditional performance metrics by integrating sustainability, ethical, and governance considerations. Together, these contributions extend the existing literature on sustainable AI, ethical robotics, ESG analytics, and human–robot interaction by establishing a clear and measurable connection between ESG principles and recognition system performance.

2) Study Organization: Section II reviews related work on AI-enabled recognition in robotics and responsible AI. Section III presents the core recognition methods used in robotic perception. Section IV describes the proposed system architecture and the ethical integration points for sustainable deployment. Section V discusses system architectures for responsible robotics, emphasizing transparency, robustness, and human-centered design. Section VI outlines key application domains and practical use cases. Section VII examines sustainability and environmental considerations of recognition systems. Section VIII discusses financial and governance implications from an ESG perspective. Section IX reports the experimental results and the ESG correlation analysis. Finally, Section X concludes the study and highlights future directions.

II. Related Work

AI-powered robotics has evolved from rule-based automation to learning-enabled systems that can perceive, interpret, and act in dynamic environments. Beyond improving recognition accuracy, recent work increasingly highlights requirements for transparency, safety, human trust, and responsible deployment [2], [4], [9].

A. AI in Human–Robot Interaction

Human–Robot Interaction (HRI) is a central domain where AI enhances robots' ability to interpret and adapt to human behavior in industrial and service contexts [1], [2], [9]. Recent studies also emphasize collaboration safety and situational awareness in shared spaces, including AI-enabled risk assessment and standardization considerations [10], [11]. In social and sensitive contexts such as healthcare and education, research highlights the importance of user trust, appropriate behavior, and explainability [7], [12]. At the same time, ethical and legal debates examine accountability boundaries and the implications of increasing autonomy [8], [13].

B. Deep Learning, Reinforcement Learning, and Multimodal Perception

Deep learning has significantly advanced robotic recognition, enabling object detection, scene understanding, and human-centered perception [3], [14]. Reinforcement learning further supports adaptive decision-making in complex environments, including navigation and collaborative manipulation [15], [16]. Multimodal perception—combining vision, audio, and other signals—improves robustness and context awareness, especially in HRI settings where intent and emotion cues matter [12], [17], [18]. However, many studies still evaluate systems under controlled conditions, leaving challenges under domain shift, sensor noise, and real-time constraints insufficiently addressed.

C. Social Robotics, Transparency, and Ethical AI

Social robotics research increasingly focuses on emotional intelligence, user acceptance, and transparent interaction. Transparency and explainability are emphasized as necessary conditions for trust, particularly when recognition outputs affect human-facing decisions [4], [18]. Ethical AI discussions address fairness, privacy, and accountability as robots become more embedded in daily life and public services [8], [13]. Despite progress, the literature often treats ethics as a conceptual layer rather than an end-to-end design requirement linked to architecture, deployment constraints, and measurable outcomes.

D. Sustainability and Responsible AI

The environmental impact of AI technologies has drawn growing concern. Training deep neural networks can be energy-intensive, especially at scale. To address this, researchers have proposed eco-friendly strategies such as model compression, quantization, and adaptive sensing [5], [6]. At the same time, ethical AI frameworks are being developed to ensure fairness, protect user privacy, and support accountable decision-making [8], [18].

E. ESG Analytics and Robotic Governance

Environmental, social, and governance (ESG) analytics offer structured ways to assess the societal impact of technologies. Integrating ESG principles into robotic design can encourage transparency, responsible automation, and alignment with long-term sustainability goals [19]. Yet, few studies systematically connect ESG metrics to technical performance, operational efficiency, and financial implications in robotics. This study addresses that gap by discussing how ESG performance can be considered alongside recognition quality, system efficiency, and ethical design choices.

F. Challenges and Limitations in Existing Approaches

Prior work reveals recurring limitations that motivate the need for integrated evaluation:

- Generalization and domain shift: models trained on curated datasets may degrade in new environments, cultures, or lighting conditions.
- Safety and verification: safety-oriented methods exist, yet strong guarantees remain limited for learning-based perception in open-world HRI [10], [11].
- Explainability and trust: black-box recognition can reduce user acceptance and complicate accountability in sensitive domains [7], [18].
- Energy and resource constraints: large models increase compute demand and carbon footprint, motivating efficiency-first design [5], [6].
- Fragmented evaluation: many studies optimize accuracy without jointly tracking ethical, environmental, and governance indicators needed for responsible deployment [20].

G. Positioning and Contribution of this Study

While previous studies explore recognition methods, interaction design, and responsible AI themes, an integrated view that links technical recognition approaches with ethical, sustainability, and ESG/financial considerations remains limited. Table I summarizes representative prior work, their limitations, and how this study addresses the identified gaps.

III. Core Recognition Methods in Robotics

A. Computer Vision and Deep Learning

Computer vision is fundamental to robotic recognition. Convolutional neural networks (CNNs) are widely used for detecting and classifying objects, segmenting images, and recognizing human gestures. More recently, transformer-based models have improved generalization across different environments and tasks [3], [14]. In collaborative settings, robots use visual input to track human movement and predict intent, enabling safer and more intuitive interaction.

B. Reinforcement Learning in Dynamic Environments

Reinforcement learning (RL) gives robots the ability to learn by trial and error, adapting to complex and changing environments. Both model-free and model-based RL techniques are used to optimize navigation, decision-making, and task planning [15]. When combined with deep perception models, RL enables robots to make sense of their surroundings and take appropriate actions—completing the loop from sensing to planning to acting.

C. Multimodal and Cross-Modal Learning

Multimodal learning allows robots to integrate information from different types of sensors—visual, auditory, tactile, and linguistic. This gives them a richer understanding of the world and helps reduce errors in noisy or ambiguous environments. Cross-modal learning techniques further align these inputs, making recognition more reliable in real-world social settings.

D. Foundation Models and Transfer

Foundation models, which are pre-trained on vast datasets, offer powerful tools for transfer learning across multiple tasks and domains. However, they require careful optimization—such as compression or distillation—to be usable in resource-constrained robotic platforms [6]. Managing this trade-off between performance and sustainability is key to scaling intelligent robotics in practice. Fig. 1 presents a taxonomy of AI-based recognition methods in robotics, including vision-based models, reinforcement learning, multimodal fusion, and foundation models, highlighting the diversity of approaches considered in the literature.

IV. System Architecture and Ethical Integration

Robotic systems are typically layered across sensing, perception, cognition, and actuation. Edge–cloud hybrids reduce latency and bandwidth, while supporting privacy and sustainability goals [1]. Ethics-aware hooks include XAI modules, risk monitors, and cultural-adaptation layers to keep interaction transparent and inclusive [4], [7].

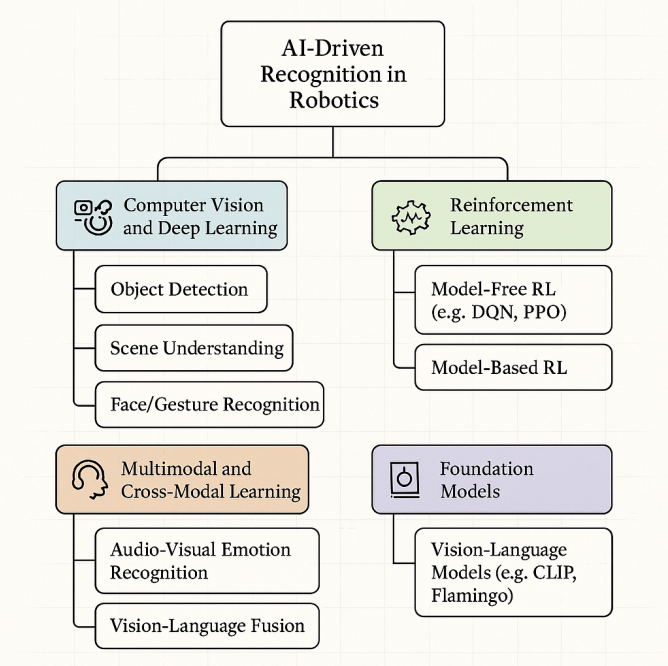


Fig. 1. Taxonomy of AI-based recognition methods in robotics (vision, RL, multimodal fusion, and foundation models).

A. Perception–Action Loops and Hybrid Compute

Perception modules feed learned policies that continuously adapt to changing contexts; hybrid compute (edge for real-time safety, cloud for heavy models) balances responsiveness with resource limits. As illustrated in Fig. 2, the proposed layered architecture connects sensing, perception, cognition, and actuation, while integrating explainable AI and ethics hooks to support transparency, safety monitoring, and governance across hybrid edge–cloud deployments.

V. System Architectures for Responsible Robotics

While the previous section focuses on the proposed system architecture, this section generalizes architectural principles for responsible robotics across broader application contexts. Modern recognition systems in robotics rely on modular architectures that integrate perception, reasoning, and interaction layers. To support sustainability and accountability, system design must not only be efficient but also transparent and adaptable.

A typical architecture includes a sensory fusion module (combining visual, auditory, and tactile inputs), a decision-making core (powered by neural or symbolic reasoning), and an output layer that governs robotic actions or communication. By incorporating explainable AI (XAI) modules, systems can offer justifications for their behavior—crucial for user trust, especially in regulated environments like healthcare or autonomous transport.

Human-centered design further supports ethical deployment. Systems should be context-aware and capable of adjusting interaction styles based on user preferences, emotional cues, or cultural norms. Additionally, real-time monitoring

TABLE I. COMPARISON OF PRIOR WORK AND CONTRIBUTIONS OF THIS PAPER

Domain	Key Contributions from Prior Work	Limitations in Prior Work	Our Contributions
AI in Human–Robot Interaction (HRI)	AI-enabled HRI in industrial settings [2]; collaborative robotics and safety frameworks [9], [11]; legal and moral agency discussions [8].	Lack of integration with sustainability, trust, or financial risk factors.	Holistic analysis of HRI that integrates emotional, ethical, and environmental factors with hybrid recognition models.
Deep Learning, RL, and Multimodal Perception	DL models for vision and control [3], [14]; RL for adaptive decision-making [15]; multimodal transparency and emotion sensing [18].	Isolated focus on performance; neglects human trust, system explainability, and ecological costs.	Proposes taxonomy covering DL, RL, and multimodal learning with emphasis on user experience, generalization, and sustainable deployment.
Social Robotics and Ethical AI	Ethical frameworks for social robots [4]; societal and healthcare applications [7]; sustainability awareness [6].	Limited technical grounding in AI methods; rarely address architectural or economic challenges.	Bridges ethical design with technical models and proposes scalable, explainable architectures for responsible deployment.
Sustainability and Finance in Robotics	Sustainability metrics and eco-footprint analysis [5]; grassroots and ESG robotics initiatives [21].	Do not address recognition methods or integrate AI investment trends or cost-effectiveness analysis.	Introduces financial layer including ROI, ESG compliance, and investment outlook for recognition-driven robotics.

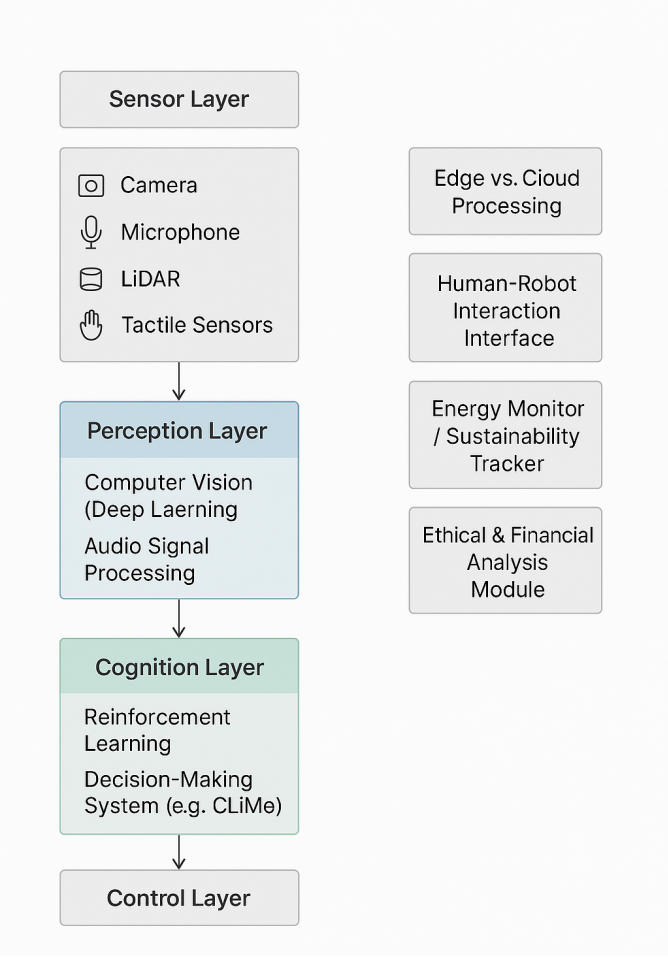


Fig. 2. Layered architecture: sensors, perception, cognition, and actuation with XAI/ethics hooks and hybrid edge–cloud compute.

tools and ESG feedback loops allow for continuous assessment of system performance against sustainability goals.

VI. APPLICATIONS ACROSS DOMAINS

AI-powered recognition systems are now embedded in a wide range of real-world applications:

A. Healthcare

Robots assist in elderly care, physical rehabilitation, and medical triage by interpreting patient gestures, expressions, or speech. Emotion recognition helps adapt care to individual needs, while explainability ensures clinical decisions remain understandable and accountable.

B. Education

Socially assistive robots support student engagement through personalized feedback and multimodal interaction. Vision and speech modules help identify student attention, confusion, or emotional state, while adaptive behavior fosters inclusive learning.

C. Manufacturing and Logistics

In smart factories, robots equipped with real-time recognition systems detect objects, avoid hazards, and collaborate with human workers. Reinforcement learning enhances dynamic scheduling and error recovery, optimizing both safety and productivity.

D. Public Service and Security

Recognition-enabled drones and service robots are used for surveillance, environmental monitoring, and emergency response. These systems must prioritize ethical decision-making and privacy protection, especially in sensitive or high-stakes scenarios.

VII. SUSTAINABILITY AND ENVIRONMENTAL CONSIDERATIONS

The energy demands of AI models—especially those requiring high-volume data and deep learning—pose a real challenge for sustainable robotics. Training large models can result in significant carbon footprints, while edge deployment often requires resource-efficient inference.

To address this, several techniques are being adopted:

- Model compression reduces the size of neural networks without compromising accuracy.
- Quantization and pruning optimize hardware usage.
- Dynamic sensor activation limits energy use by triggering inputs only when necessary.

In addition, life-cycle assessments (LCA) are increasingly used to measure the environmental cost of robotic systems—from manufacturing to operation to disposal. These assessments inform eco-conscious design choices and long-term planning.

VIII. Financial and Governance Implications

Robotic systems are not only technical tools—they are also economic investments. Integrating ESG metrics into their development and deployment can offer insights into long-term value and risk management.

For example:

- Governance practices that enforce ethical AI usage improve public trust and reduce regulatory risks.
- Environmental indicators help companies meet sustainability targets and reduce energy costs.
- Social metrics guide the design of inclusive, accessible systems, reducing bias and expanding user reach.

By aligning robotic innovation with financial intelligence, organizations can achieve greater ROI while supporting global sustainability goals.

IX. Experimental Results and ESG Correlation Analysis

A. Objective

This section aims to empirically validate the proposed ESG-to-performance linkage by quantifying the extent to which ESG indicators can inform the decision layers that guide recognition-driven robotic systems. Rather than assessing recognition accuracy in isolation, the objective is to demonstrate that ESG metrics serve as meaningful, data-driven signals that can be embedded within ethical and financial decision modules operating in parallel with AI-based recognition pipelines. Within the robotics context, these ESG-informed signals shape recognition-related decisions such as task prioritization, risk management, and resource allocation. This integration is exemplified by the *Ethical and Financial Analysis Module*, illustrated in Fig. 3.

B. Dataset

The experiments use the publicly available dataset *"company_esg_financial_dataset-iau25.csv"*, which includes:

- ESG features: `ESG_Overall`, `ESG_Environmental`, `ESG_Social`, `ESG_Governance`
- Financial metrics: `ProfitMargin`, `Revenue`, `MarketCap`, etc.

C. Methods and Models

Two regression models were implemented to predict a key financial metric—`ProfitMargin`—from ESG scores:

- Linear Regression (LR) – serving as the baseline,
- Random Forest Regressor (RF) – a non-linear ensemble model.

Performance was evaluated using Root Mean Squared Error (RMSE) and the Coefficient of Determination (R^2).

From a robotics perspective, the regression models are not designed to replace existing recognition algorithms, but to function as auxiliary decision modules that supply ESG-conditioned signals to the recognition systems. These signals enable dynamic adjustment of recognition objectives—such as confidence thresholds, alert sensitivity, and action prioritization—thereby establishing a tangible link between socio-financial indicators and recognition-driven behavior.

D. Results and Discussion

TABLE II. Performance Comparison of Regression Models

Model	RMSE ↓	R^2 Score ↑
Random Forest	**7.50**	**0.293**
Linear Regression	8.71	0.047

As shown in Table II, the Random Forest clearly outperforms Linear Regression, suggesting non-linear interactions between ESG factors and financial performance. These results indicate that ESG indicators—particularly environmental scores—offer structured, non-linear signals that can be leveraged by decision layers integrated with recognition systems, thereby enabling robotic platforms to align recognition-driven actions with sustainability-oriented financial outcomes.

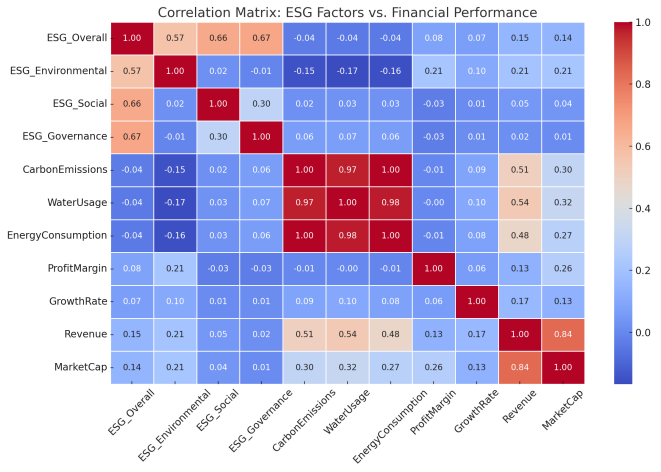


Fig. 3. Correlation matrix between ESG factors and financial KPIs.

Fig. 3 indicates that the `ESG_Environmental` has the strongest positive correlation (0.21) with `ProfitMargin`, highlighting the role of ecological responsibility in financial outcomes.

Fig. 4 shows that `ESG_Environmental` is the most influential factor, followed by Social and Governance metrics. This finding reinforces the centrality of environmental responsibility in sustainability-aware robotics. The scatter plot in Fig. 5 confirms alignment between actual and predicted values, validating the model's potential for decision-support applications.

E. Linking ESG Indicators to Recognition Performance

The empirical findings indicate that ESG indicators can serve as high-level conditioning variables within recognition-driven robotic systems. While recognition models primarily extract perceptual features from sensory inputs, ESG-informed decision layers shape the interpretation and subsequent actions

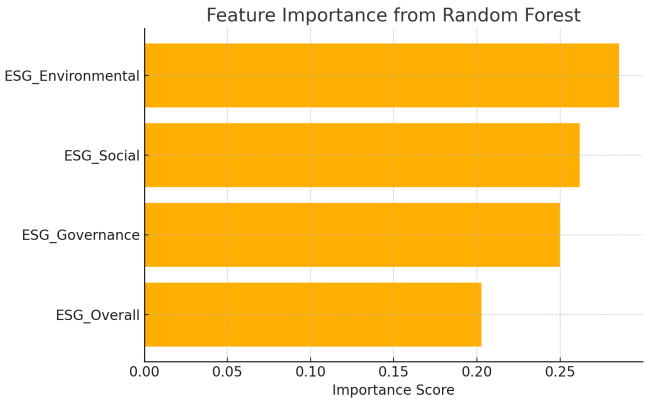


Fig. 4. Feature importance ranking from Random Forest regressor.

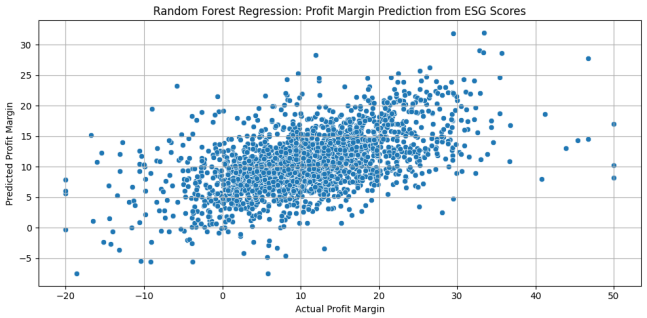


Fig. 5. Random forest regression: predicted vs. actual profit margins.

derived from these outputs. For instance, higher environmental ESG scores may lower risk thresholds for engagement, promote resource-efficient behaviors, or influence task allocation strategies in human–robot collaboration. The observed predictive relationship between ESG indicators and financial performance supports the use of ESG metrics as actionable inputs that actively inform recognition-driven decision-making, rather than as purely descriptive or retrospective evaluation measures.

F. Implications for Robotic Systems

The predictive insights from ESG-financial modeling can enhance recognition modules in robots tasked with decision-making under ethical and financial constraints. Potential applications include:

- Service robots performing compliance audits by prioritizing ESG-positive firms,
- Autonomous financial advisors or inspection drones incorporating ESG-driven profitability into recommendations,
- Human–robot interaction systems that use ESG trust profiles to guide task delegation or contract evaluation.

These results strengthen the architectural vision outlined in earlier sections, underscoring the importance of embedding sustainability and financial intelligence into ethical AI-powered recognition systems.

G. Interpretation and Research Impact

The experimental findings reveal a measurable, non-linear relationship between ESG factors—most notably environmental performance—and corporate profitability. These results hold several implications for advancing AI-driven robotic recognition:

1) Environmental Scores as Predictive Indicators: Environmental metrics emerged as the strongest predictors of financial performance. This reinforces the growing perspective that ecological sustainability is not just a compliance obligation but a strategic business advantage [5], [21]. Embedding such insights into robotic recognition systems aligns machine behavior with long-term sustainability goals.
2) Data-Driven Ethical Recognition: Integrating ESG-informed decision logic enables recognition-driven robotic systems to contextualize perceptual outputs within ethical, financial, and societal constraints, thereby extending recognition performance beyond accuracy toward responsibility-aware action selection. This has potential applications in finance, supply chain logistics, and regulatory compliance.
3) Bridging AI Ethics with Economics: The results create a novel connection between ethical AI principles and financial data science. This supports the architectural vision outlined in Section IV, where hybrid AI–human systems incorporate socio-financial awareness through feedback loops.
4) Support for Modular, Explainable AI: The observed variation in feature importance (Fig. 4) suggests that ESG-informed recognition systems should be modular and adaptable. Favoring explainable AI approaches enhances transparency and trust, particularly in human-facing robotics [7], [18].

Overall, these results validate the conceptual link drawn in earlier sections—connecting advanced recognition methods, architectural integration, human-centered design, and sustainability. They demonstrate that robotics, when informed by empirical socio-financial indicators, can foster ethically aligned and economically sound human–robot relationships. Because the empirical analysis encompasses multiple ESG dimensions and employs a non-linear modeling approach, the observed relationships reinforce the robustness and generalizability of ESG-conditioned decision mechanisms across recognition-driven robotic applications.

X. Conclusion and Future Directions

This study explored AI-driven recognition in robotics through the integrated perspectives of system architecture, ethical design, and sustainability. By tracing the progression from rule-based perception to deep learning and foundation models, the study positioned contemporary recognition systems within a broader context of human–robot interaction and responsible technological deployment. A modular, human-centered architecture was proposed to demonstrate how explainable AI, ethical safeguards, and environmental considerations can be embedded directly into recognition pipelines.

Beyond conceptual development, the empirical analysis provided tangible evidence that ESG indicators can serve as

actionable signals within recognition-driven decision-making processes. The findings revealed that environmental and governance factors exhibit significant non-linear relationships with financial performance, validating their relevance as informative inputs to decision layers coupled with recognition systems. This demonstrates that ESG-aware conditioning can meaningfully influence how recognition outputs are interpreted, prioritized, and operationalized—extending recognition performance beyond conventional accuracy metrics toward responsibility-aware and sustainability-aligned behavior.

Overall, the analysis establishes that linking ESG indicators to recognition systems represents not only a theoretical framework but also a viable, data-driven approach. ESG-informed recognition architectures can jointly advance ethical integrity and operational performance, offering a practical mechanism for aligning robotic perception and action with broader socio-environmental values. This contribution underscores the potential for sustainability analytics to be operationalized within AI-enabled robotics, moving beyond their traditional role as external or retrospective assessments.

Looking ahead, several promising research avenues remain. Expanding the empirical evaluation to incorporate longitudinal and cross-sectoral ESG datasets would enhance the robustness and generalizability of the findings. Integrating real-time sensor feedback with ESG-conditioned decision layers could enable adaptive, closed-loop recognition systems capable of dynamic ethical reasoning. Furthermore, advances in interpretable machine learning are likely to improve system transparency, while human-in-the-loop studies will be essential for evaluating user trust, acceptance, and societal impact in real-world deployments.

Ultimately, this work envisions robotic recognition systems that not only perceive their environments effectively but also act with a conscious awareness of ethical principles, economic implications, and sustainability objectives. Such systems represent a significant step toward the realization of responsible, trustworthy, and socially aligned robotics.

REFERENCES

[1] M. M. Rahman, F. Khatun, I. Jahan, and R. Devnath, "Cobotics: Roles and Prospects of Next-Generation Collaborative Robots," *Journal of Robotics*, vol. 2024, Art. ID 2918089, 16 pages, 2024, doi: 10.1155/2024/2918089.

[2] N. V. N. Vemuri and N. Thaneeru, "Enhancing Human–Robot Collaboration in Industry 4.0 with AI-driven HRI," *Power System Technology*, vol. 47, no. 4, Art. no. 196, Dec. 2023, doi: 10.52783/pst.196.

[3] P. Ganesan, "Revolutionizing Robotics with AI, Machine Learning, and Deep Learning: A Deep Dive into Current Trends and Challenges," *Journal of Artificial Intelligence, Machine Learning and Data Science*, vol. 1, no. 4, pp. 1124–1128, Dec. 2023, doi: 10.51219/org.doi.1124-1128.

[4] B. Obrenovic, X. Gu, G. Wang, D. Godinic, and I. Jakhongirov, "Generative AI and Human–Robot Interaction: Implications and Agenda," *AI & Society*, vol. 40, no. 2, pp. 677–690, 2025, doi: 10.1007/s00146-024-01889-0.

[5] L. Liu, Z. Rasool, S. Ali, C. Wang, and R. Nazar, "Robots for Sustainability: Evaluating Ecological Footprints," *Technology in Society*, vol. 76, Art. no. 102460, 2024, doi: 10.1016/j.techsoc.2023.102460.

[6] B. Martini, D. Bellisario, and P. Coletti, "Human-centered and Sustainable AI in Industry 5.0," *Sustainability*, vol. 16, no. 13, Art. no. 5448, 2024, doi: 10.3390/su16135448.

[7] A. Vozna and S. Costantini, "Ethical, Legal, and Societal Dimensions of Social Robots in Elderly Healthcare," *Intelligenza Artificiale*, vol. 19, no. 1, pp. 30–40, 2025, doi: 10.1177/17248035241310192.

[8] S. Kumar and S. Choudhury, "AI humanoids as moral agents and legal entities: A study on the human–robot dynamics," *Journal of Science and Technology Policy Management*, EarlyCite, 2025, doi: 10.1108/JSTPM-11-2023-0211.

[9] S. K. Lodhi and S. Zeb, "AI-Driven Robotics and Automation: The Evolution of Human–Machine Collaboration," *Journal of World Science*, vol. 4, no. 4, pp. 422–437, May 2025, doi: 10.58344/jws.v4i4.1389.

[10] S. K. Yadav and S. Shahi, "Safe Human–Robot Collaboration in Dynamic Environments: An AI-Powered Situation Awareness Perspective," *International Journal of Tropical Medicine*, vol. 19, no. 4, pp. 92–98, 2024, doi: 10.36478/makijtm.2024.4.92.98.

[11] M. J. Alenjareghi, S. Keivanpour, and Y. A. Chinniah, "Safe human–robot collaboration: a systematic review of risk assessment methods with AI integration and standardization considerations," *The International Journal of Advanced Manufacturing Technology*, vol. 133, pp. 4077–4110, 2024, doi: 10.1007/s00170-024-13948-3.

[12] I. Buchem, G. A. K. Bonga, and R. Tutul, "From Screens to AI-Driven Learning Support: Conversational Learning in Human–Robot Interaction," in *Robotics in Education*, Springer, 2024, pp. 391–402, doi: 10.1007/978-3-031-66029-7_28.

[13] I. Skubis, A. Mesjasz-Lech, and J. Nowakowska-Grunt, "Humanoid Robots in Tourism and Hospitality—Exploring Managerial, Ethical, and Societal Challenges," *Applied Sciences*, vol. 14, no. 24, Art. no. 11823, 2024, doi: 10.3390/app142411823.

[14] S. S. Dhanwe and C. M. Abhangrao, "AI-driven IoT in Robotics: A Review," *Journal of Mechanical Robotics*, vol. 9, no. 1, pp. 41–48, 2024.

[15] G. Pandy, V. J. Pugazhenthi, and A. Murugan, "AI-Powered Robotics and Automation: Innovations and Challenges," *European Journal of Computer Science and Information Technology*, vol. 13, no. 1, pp. 33–44, 2025, doi: 10.37745/ejcsit.2013/vol13no1.3344.

[16] M. Nizamuddin, A. Kamisetty, J. C. S. Gummadi, and R. R. Talla, "Integrating Neural Networks with Robotics: Towards Smarter Autonomous Systems and Human–Robot Interaction," *Robotics Xplore*, vol. 1, no. 1, pp. 157–169, 2024.

[17] G. Arunachalam, M. R. Pavithra, M. N. Varadarajan, V. L. Vinya, T. Geetha, and S. Murugan, "Human–Robot Interaction in Geriatric Care: RNN Model for Intelligent Companionship and Adaptive Assistance," in *Proc. 2024 2nd Int. Conf. on Sustainable Computing and Smart Systems (ICSCSS)*, Coimbatore, India, Jul. 10–12, 2024, pp. 1067–1073, doi: 10.1109/ICSCSS60660.2024.10624951.

[18] K. Xu, X. Chen, F. Liu, and L. Huang, "Understanding Transparency in Facial and Speech Recognition during HRI," *New Media & Society*, vol. 27, no. 10, pp. 5776–5802, 2025, doi: 10.1177/14614448241256899.

[19] A. Ali, "The Role of Artificial Intelligence in Robotics and Automation," *Frontiers in Robotics and Automation*, vol. 1, no. 1, pp. 36–54, 2024.

[20] T. Sutikno, "The future of artificial intelligence-driven robotics: applications and implications," *IAES International Journal of Robotics and Automation (IJRA)*, vol. 13, no. 4, pp. 361–372, 2024, doi: 10.11591/ijra.v13i4.pp361-372.

[21] R. Prakash, "AI Robotics: Transforming Grassroots Innovation for Sustainable Development in Developing Economies," *Business Strategy & Development*, vol. 8, no. 2, e70143, 2025, doi: 10.1002/bsd2.70143.

Hybrid Deep Learning for Signals Automatic Modulation Classification

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***Abstract*—Classifying signals or modulation classification is a crucial step in developing communication receivers. A common practice is to extract features before categorizing the signal, which requires implementing long preprocessing techniques. Due to breakthroughs in neural network topologies, machine learning (ML) algorithms, and optimization techniques, referred to as "deep learning" (DL), we have witnessed a vast degree of change over the previous five years. Advanced deep learning algorithms can be applied to the same automatic modulation classification problem and generate excellent outcomes without requiring time-consuming, manual, and complex feature extraction methods. In recent years, various DL techniques have been explored for automatic modulation classification (AMC). However, it has been observed that these techniques are effective only for higher Signal-to-Noise-Ratio (SNR) values. To overcome this challenge, we proposed a hybrid DL-based AMC technique by combining a customized EfficientNet with a customized Transformer Block. The transformer block is used to enhance the DL performance for the lower SNR values. The performance of the proposed hybrid model is tested on a benchmark dataset, RadioML2018.01A, and compared with the state-of-the-art existing DL method which shows the supremacy of the proposed hybrid model.**

***Keywords*—Automatic modulation classification; deep learning; machine learning; EfficientNet; Transformer Network**

I. Introduction

Independent radio spectrum interpretation is becoming increasingly important in various applications due to the rapid development of different evolved standards and best practices for wireless communications. These applications include electronic warfare and vulnerability assessments in military scenarios, dynamic channel access, spectrum interference detection, and monitoring in civil proceedings [1]. Encoder, modulation, and multiplexing are all necessary components in a wireless transmission channel. First, the signal from the source is transformed into a format suitable for signal processing techniques such as noise reduction and interference reduction by a Source Encoder. Adding a bit of redundancy to the signal during this process might help it withstand noise. Once the signal has been modulated with an appropriate modulation technique, such as Phase Shift Keying (PSK), Frequency Shift Keying (FSK), or Quadrature Phase Shift Keying (QPSK), it is delivered into the channel as rapidly as possible using antennas. To retrieve the sent data, the receiver side employs the same techniques as the transmitter side, including de-multiplexing, demodulation, and decoding, among other techniques. However, there are several drawbacks, including co-channel interference and signal distortion over spectral channels due to aggressive spectrum usage in massive wireless communication systems. To deal with these issues, one effective solution is Adaptive Modulation (AM), whose aim is to encode radio signals utilizing a variety of modulation forms from a predetermined candidate pool depending on channel conditions and system specifications. Thus, the AM enables intelligent spectrum management in modern communication systems, as shown in Fig. 1 [2].

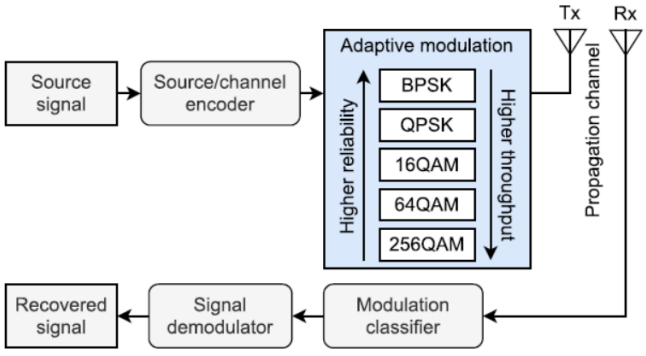


Fig. 1. Communication system with adaptive modulation [2].

However, a major challenge for implementing the AM in wireless communications is the dynamic estimation of channel conditions and data characteristics. Hence, automatic modulation classification (AMC) is introduced, which is a technique that improves spectrum utilization efficiency by applying it to a detected signal at the receiver's physical layer without knowing the data sent or channel characteristics.

A. Task of AMC

Consider a communication system sending a noise-free signal *x(t)* (whose sampled version is denoted as *x[k]*) through some channel (with discrete version denoted as *h[k]*), then the received signal for the nth symbol at time *k* can be expressed as Eq. (1) [2]:

$$y[n] = x[n, h_k] + w[n] \quad (1)$$

where, $x[n, h_k]$ is the modulated input data passed through the channel h_k and *w[n]* is the additive noise at the receiver with variance σ_w^2. The task of an AMC in a communication system is

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to predict the modulation type using only input-output data without estimating the channel impulse response.

B. AMC Approaches

Both probabilistic and conventional machine learning frameworks are used in the traditional AMC approaches. Based on the assumption that all signal and channel models are fully understood, likelihood-based systems have the best level of accuracy since they employ probability theory and hypothetical models to solve classification difficulties. Machine learning (ML) features are more likely to be adopted because of their simplicity. However, this comes at the expense of a few drawbacks, such as restricted learning capacity and a poor discriminative experience of handmade features.

Likelihood-Based (LB) Approach: The optimum approach is to employ the LB approach, which minimizes the possibility of incorrect categorization. This assumption is correct if a waveform's density function (PDF) contains all relevant information. Using a decision threshold, the probability ratio from the PDF is used to categorize the modulation type [3]. The drawback of this approach is its computational complexity. Real-time classification requires a thorough inspection of multiple pulses and emitters. It is possible to separate a single emitter by using other ways of locating the Primary Rat Interface (PRI). Due to this, it is possible to forgive a few wrong classifications in modulation categorization if the majority of the categories are suitable. Algorithm strength must also be considered while extracting data. A lack of inherent robustness makes LB approaches susceptible to noise, timing issues, and phase offsets. Given this and the necessity of real-time operation, a more accessible, feature-based approach may be adopted.

Feature-Based (FB) Approach: The FB approach employs representative features to identify and categorize the differences between signals. The typical characteristics are the time domain, signal changes, zero crossings, and statistics. In addition, the FB AMC technique often uses a hierarchical approach, first identifying modulation and defining its exact kind [3]. Then, PDF-based, Euclidean distance, and artificial intelligence classifiers are utilized to make decisions. FB algorithms are generally preferred because of their simple complexity and acceptable performance, even if their performance is poor.

C. Related Works: Deep Learning in AMC

In recent years, the DL techniques have been successfully applied in various fields such as computer vision [4], [5], wireless communications [6], [7], bioinformatics [8]-[13], and signal processing [14], [15], etc. Motivated by the power of DL, several state-of-the-art DL techniques have been employed in the field of AMC, which resulted in improved modulation classification performance of ACM. For example, convolutional neural networks (CNNs) based AMC [16], [17], [18], long short-term memory networks (LSTMs) based AMC [19], [20], and recurrent neural networks (RNNs) based AMC [21]. One major advantage of DL-based AMC over conventional ML-based AMC is that DL provides automatic feature extraction with higher classification accuracy [22]. Another important fact about the DL-based AMC is that it can enhance the classification accuracy of higher-order modulation in the presence of a synthetic channel impairment [23]. Finally, it is found that the DL-based AMC has the capability to effectively process big data, and thus it is well-suited for deploying AMC in Internet-of-Things (IoT) systems [24].

D. Challenges in AMC

A major challenge in ML-based AMC is the requirement of designing efficient feature extraction methods for each dataset. On the other hand, although the DL-based AMC can provide automatic feature extraction, with improved modulation classification accuracy, there are still many open challenges in this field. One big challenge is that all the existing DL-based AMC methods proved to be better in terms of classification accuracy only for higher values of signal-to-noise ratio (SNR). Their performance degrades drastically at lower SNR values, which implies that if the noise level is higher, the model would most likely fail to categorize the signal. In the existing literature, there is no work addressing this issue. In this work, we mainly focus on this challenge.

E. Our Contributions

As outlined in the previous subsection, the DL-based AMC has one major challenge of poor performance at lower SNR values, we focused on solving this issue by designing a hybrid DL-based AMC solution. More specifically, the proposed method is capable of providing reasonably better modulation accuracy at lower SNR values. For this purpose, we developed a hybrid DL-based AMC solution in which we utilized the combination of the EfficientNet and the Transformer Block via a switching mechanism. The transformer block is used to enhance the DL performance for the lower SNR values. The performance of the proposed hybrid model is tested on a benchmark dataset, RadioML2018.01A [25].

The study is organized as follows: Following this introduction, the baseline methods are discussed in Section II. In Section III, the proposed hybrid CNN model is presented. An overview of the RadioML 2018 dataset is provided in Section IV. Next, the experiment on AMC using the proposed model is described in Section V. Results and discussion are provided in Section VI. Finally, the concluding remarks are given in Section VII.

II. Baseline Methods

In the context of AMC, various DL architectures have been explored in the past [25]. Among these methods, the best performance is achieved by the modified ResNet proposed in [25]. In this section, we provided an overview of both the standard and the modified ResNet architectures.

A. Standard ResNet [26]

ResNet is a deep residual network that has all the elementary parts in its structure as existed in any deep CNN architecture [26]. The only unique characteristic of the ResNet is the use of identity connection or mapping between the levels. In order to understand this Identity Mapping in a ResNet, see the block diagram presented in Fig. 2, where F(x) is a function called the Residual Function that operates between two convolutional weight layers. More precisely, it is the difference between the input x and the output H(x) of the residual block, as shown in Fig. 2. Thus, the F(x) can be formulated as Eq. (2):

$$F(x) = H(x) - x \tag{2}$$

Therefore, the major purpose of including this function in ResNet is to utilize the stacked layers to estimate the function F(x) instead of estimating the function H(x). Consequently, training the deep residual network tries to learn F(x), which results in improving the overall accuracy. Moreover, it is straightforward to conclude that the network's accuracy will be improved by increasing the depth, provided that the issue of over-fitting is resolved. However, the difficulty with the increase in depth is that the signal necessary to modify the weights, which emanates from the end of the network by comparing ground truth and forecast, gets extremely little at the initial layers as depth increases. It indicates that the initial levels are learned to a minor extent. The term for this phenomenon is vanishing gradient. The second issue with training deeper networks is that optimization is performed on a large parameter space, resulting in naively adding layers, which increases training error. As illustrated in the figure, residual networks permit the training of deep networks by creating the network using modules termed residual models.

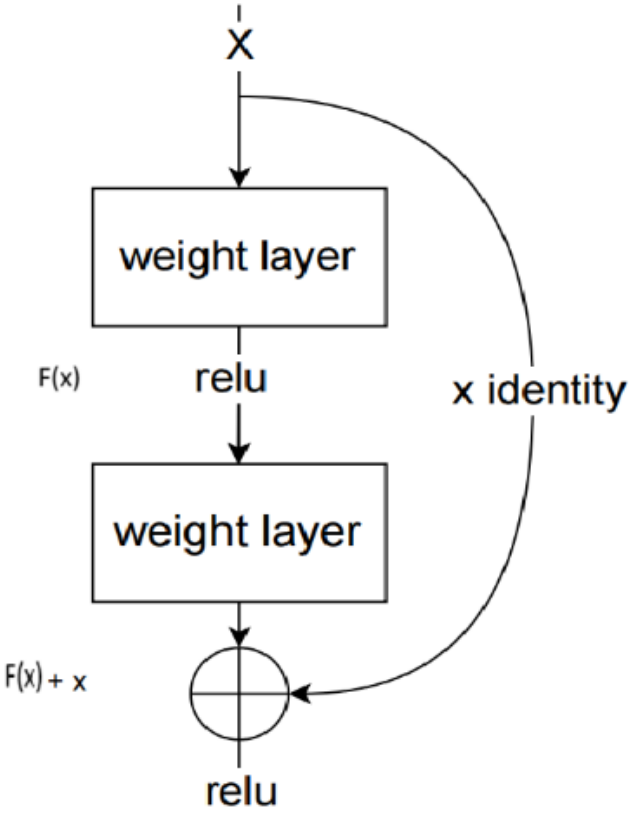


Fig. 2. Residual learning: a building block.

B. Modified ResNet [25]

In [25], a modified ResNet was proposed for implementing the AMC. In this architecture, the residual unit and stack of residual units are used, as shown in Fig. 3, and its network layout is shown in Table I. In addition, self-normalizing neural networks, the activation function of scaled exponential linear unit (SELU), mean response scaled initialization (MRSA), and Alpha Dropout were used and resulted in a marginally better performance than standard ReLU.

TABLE I. MODIFIED RESNET NETWORK LAYOUT [25]

Layer	Output Dimension
Input	2 x 1024
Residual Stack	32 x 512
Residual Stack	32 x 256
Residual Stack	32 x 128
Residual Stack	32 x 64
Residual Stack	32 x 32
Residual Stack	32 x 16
FC/SeLU	128
FC/SeLU	128
FC/Softmax	24

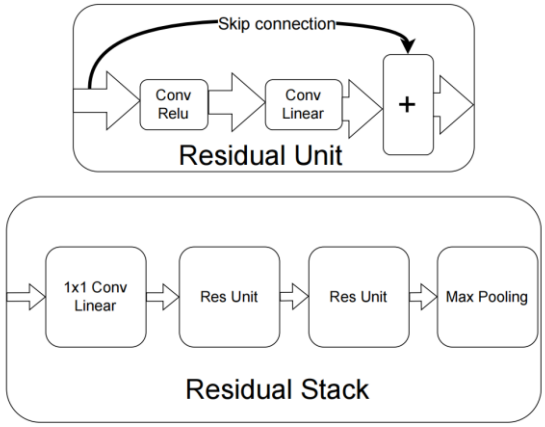


Fig. 3. Hierarchical layers used in modified ResNet

III. PROPOSED HYBRID CNN MODEL

In this work, we proposed a hybrid model of CNN which utilizes a combination of EfficientNet and Transformer Network. The architectures of both the networks and the proposed hybrid model are presented in the ensuing.

A. EfficientNet Network

Developing convolutional neural networks are done at a set cost. These networks may be expanded to achieve higher accuracy, when additional resources are available. For example, to increase the size of a ResNet 18 model to a ResNet 200 model, more layers can be added to the initial model. Mostly, this scaling strategy has improved the accuracy of many benchmarking datasets. However, the initial methods of model scaling are quite unpredictable. Some models are scaled horizontally, while others are scaled vertically. Some models simply capture a higher-resolution image to get better outcomes. Manual tweaking and numerous person-hours are required when using this strategy of randomly scaling models, and it frequently results in little or no improvement in performance. EfficientNet's authors suggested that CNN models be scaled up to improve accuracy and efficiency more ethically [27].

EfficientNet uses a method known as compound coefficients to scale up models in an easy yet effective manner. Compound scaling, instead of random scaling up of width, depth, or

resolution, uniformly scales each dimension with a predetermined set of scaling coefficients. The efficient developers used the scaling approach and AutoML to construct seven models of varied dimensions that outperformed the current state-of-the-art accuracy of most convolutional neural networks and were significantly more efficient.

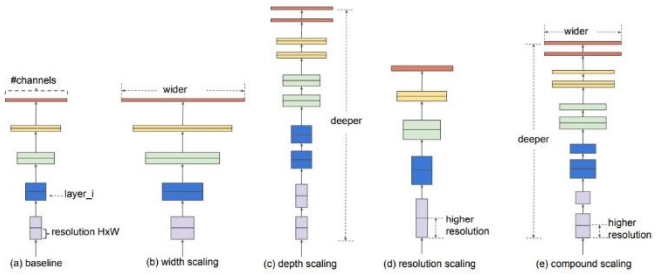


Fig. 4. Various types of scaling used: (a) is a baseline network; (b) to (d) conventional scaling via width, or depth, or resolution dimension. (e) is compound scaling used in EfficientNet [27].

The authors evaluated the effects of each scaling methodology on the model's performance and efficiency to develop the compound scaling method. In their opinion, scaling single dimensions helps in enhancing model performance, balancing the scale in all three dimensions: width, depth, and picture resolution, considering the varied resources available, which best improves the overall model performance. The compound scaling method proposed for EfficientNet is shown in Fig. 4. The goal of the compound scaling method is to balance the width, depth, and resolution measurements achieved by scaling with a constant ratio.

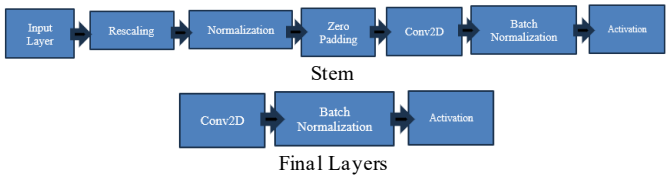


Fig. 5. Stem and final layers of EfficientNet.

A neural architecture search utilizing the AutoML MNAS framework created the baseline network used in EfficientNet. For optimum accuracy, the network is fine-tuned and punished if it is computationally intensive. It is also punished for sluggish inference times when the network takes time to create predictions. The system employs a mobile inverted bottleneck convolution similar to MobileNet V2; however, it is substantially larger owing to the rise in FLOPS. This basic model is then built to provide the networks' EfficientNets family. The stem and final layers of EfficientNet are presented in Fig. 5.

Further, each of the modules has seven blocks. These blocks are further subdivided into a different number of sub-blocks. These numbers increase when moving from EfficientNet-B0 to EfficientNet-B7.

B. Transformer Network

The encoder-decoder architecture has evolved into the "Transformer model" [28, 29]. Unlike the encoder-decoder design, the Transformer doesn't employ recurrent neural networks (RNNs) to acquire sequential data. Transformer-based models have replaced Long-Short Term Memory (LSTM) networks [30] in many sequence-to-sequence situations and are superior in quality. Conducting some diggings to discover the best time-series model that has just been released on the internet and in journals.

Recently, a solution using the newest state-of-the-art time series model called Transformer is devised [29]. Compared to the prior models, this model has various advantages, such as parallelization processing, which allows it to use contemporary graphics processing units (GPUs), which were created specifically for parallel calculation. Moreover, the vanishing gradient problem can be solved in Transformer Network (TN) as the input size can be adjustable, and the network can execute simultaneously rather than sequentially. Furthermore, the TN is capable of capturing detailed data context due to its advantage of the network modules' positional encoding and self-attention mechanisms [31]. The main crucial network module within the TN is provided in [31].

C. Switching-Based Proposed Hybrid Model

Our experimental analysis showed that the EfficientNet and Transformer Net are good in predicting signals with high SNR and low SNR, respectively. We proposed to combine the two network models of EfficientNet and Transformer Net effectively, such that the classification accuracy of the AMC should be enhanced for both low and high SNR values. For this purpose, an SNR threshold-based switching is proposed as shown in Fig. 6. This SNR threshold value is set according to experimental findings. In our experiments, we have used a 0 dB SNR value as a switching threshold; that is, the proposed model will utilize EfficientNet if SNR is above 0 dB, and it will switch to TN otherwise.

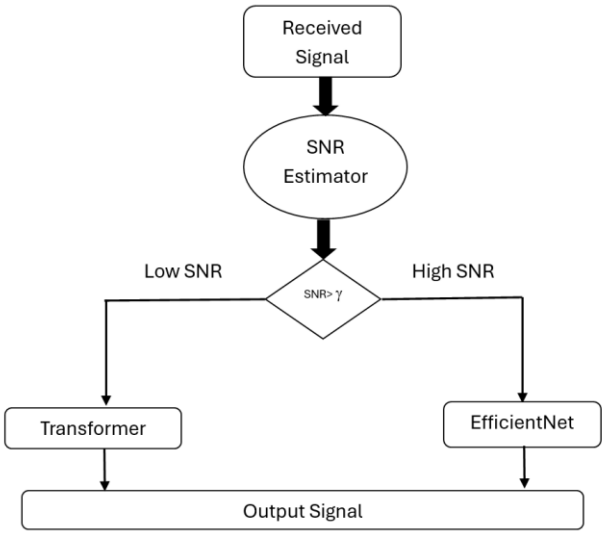


Fig. 6. SNR switch between EfficientNet and the transformer block.

To implement the proposed SNR threshold-based switching, instantaneous SNR values are estimated using the received samples. Knowing the fact that there are well-established techniques for estimating noise variance estimation ($i.e., \hat{\sigma}_w^2$) [32, 33], the received SNR can be estimated using an average over window size N_w as follows [see Eq. (3)]:

$$\widehat{\mathrm{SNR}}[n] = \frac{1}{\hat{\sigma}_w^2}\left\{\left(\frac{1}{\mathrm{N}_w}\sum_{k=n-\mathrm{N}_w+1}^{n}|y[k]|^2\right) - \hat{\sigma}_w^2\right\} \quad (3)$$

Finally, switching is performed between EfficientNet and Transformer block by inspecting the estimated SNR against a defined threshold value (γ) that can be set by the designer.

IV. Overview of RadioML 2018 Dataset

The majority of existing AMC strategies have been assessed on the reenactment datasets produced by programming. According to the point of view of reasonableness, producing tweaked signs to benchmark the execution of profound models ought to consider two essential worries: modulation technique (such as modulation types and modulation count) and channel condition. For models, RadioML2018.01A, a presently accessible and broadly utilized dataset of regulation grouping, conceals 24 modulations (counting analogue and digital procedures and a few testing high-request designs), where the regulation transmissions are engendered in a multipath Rician blurring with carrier frequency offset, symbol rate offset, delay spread, and AWGN to almost acquire true peculiarities in remote correspondences. On the other hand, various AMC techniques have produced easy datasets with few basic digital modulations. Thus, the adequacy and effect of exploration commitment in view of execution assessment in reproductions can be unconvincing other than the unsubstantial dependability of grouping models to carry out in practical frameworks. For example, a plain-design profound organization [32] accomplished high exactness with three modulation candidates (BPSK, QPSK, and 8-PSK). In different works [33], the considered spread channel is less difficult with level blurring and time-invariant rather than recurrence, particularly multipath blurring and testing time float. The modulation classification task turns out to be easier with a few given classes, where the between-class and intra-class segregation issues are not thought rigorously.

Even though DL-AMC can give huge execution, it requires a lot of training data. In reality, obtaining a sufficient number of valid training samples is typically expensive and challenging. Hence, the employed huge scope preparing dataset ought to be developed cautiously enough with more reasonable signs under a wide scope of SNR. Besides, data expansion techniques can arrange radio regulation plans more effectively by utilizing more limited radio examples [34], which will furnish an improved DL model with a more modest order reaction time. Nonetheless, the Signs dataset is especially needed for preparing, approving, and testing the networks in ML-AMC and DL-AMC models. A few analysts utilized their simulated datasets, and others like to utilize those presented in the journal. A portion of the datasets is introduced as follows.

GNU Radio datasets are utilized in this research. The RML2018 dataset is one of the most complex modulation classification datasets published in [25]. Twenty-four digital and analog modulation schemes are measured over the air and distributed across a wide range of SNR values. In addition, it comprises almost 2.5 million signals with artificially created channel distortions. "Over-the-air deep learning-based radio signal categorization" was published in the IEEE Journal of Selected Topics in Signal Processing in 2017 and gives further information and explanation of the dataset. In hdf5 format, around 1.5 million instances are recorded as complex floating-point values with a sample length of 1024 samples, respectively.

The updated techniques [35] were used to create the new dataset (RadioRML 2018). 24 modulators, both analog and digital, are utilized to modulate a wide variety of single carriers. Fig. 7 demonstrates OTA transmission channels containing clean signals without any synthetic channel impairments. Digital signals are formed with a root-raised cosine beat modulating filter [36] with a scope of roll-off values.

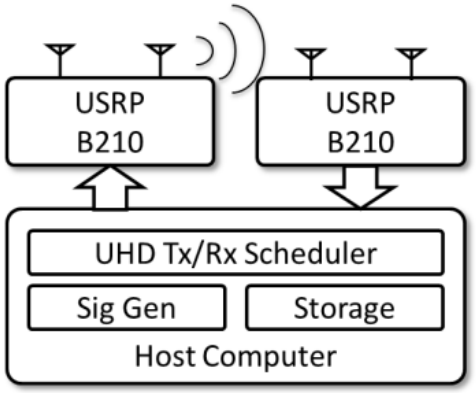


Fig. 7. Over-the-air test configuration [25].

V. Experiment on AMC

In this study, Python is used to perform the AMC task, which was done using Google Colaboratory (called Colab). Google Colab allows users to take advantage of backend hardware such as GPUs and TPUs to accelerate their computations. Thus, it facilitates performing all of the tasks in a Jupyter notebook hosted on your local system without installing or configuring any additional software.

A. EfficientNet (for High SNR)

First, we import the EfficientNet for Tenserflow-Keras Library, which is the Conventional EfficientNet. However, we chose the B0 Architecture, since it has the lowest processing complexity SNR switch.

As part of our suggested strategy, we attempt to employ two network models, one effective for predicting signals with high SNR and the other effective at predicting signals with low SNR. The transformer neural network will be used for low SNR models because it is a time series neural network that may be used to forecast complicated data, such as signals with low SNR rates. Our improved EfficientNet, on the other hand, is employed for categorizing signals with greater signal-to-noise ratios. Following the input of our signal into two models, we will ensemble them to obtain the highest accuracy output from the two models. For this purpose, the SNR value of 0 dB is selected as the switching threshold among the eight possible types of EfficientNet. The original EfficientNet B0 has an input size of 224x224x3; therefore, we must adapt the input size to match that of RML 2018, which is 1024x2, so we must alter the input layer appropriately. To accommodate the adaptation, the reshape layer has been introduced in the first layer before the modified EfficientNet, as shown in Fig. 8.

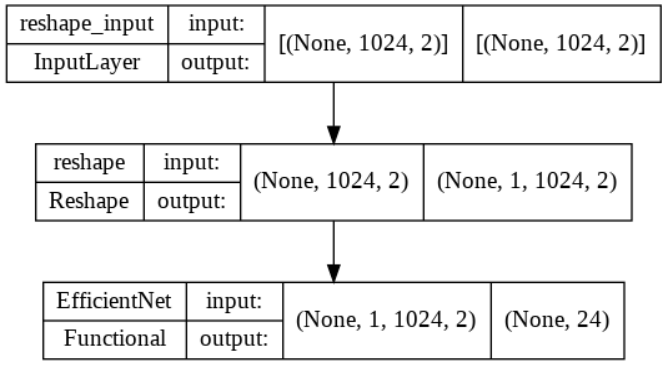


Fig. 8. Rescale layer and the customized EfficientNet.

The training process for our network uses a batch size of 1024 and a validation testing dataset comprised of 20% of the total training dataset.

B. Transformer Block (for Low SNR)

As shown in Fig. 9, the architecture being utilized is designed primarily to deal with noisy signal modulation / low SNR signal modulation. Two fully linked networks and Alpha Dropout are used in conjunction with batch normalization to minimize overfitting. After an Alpha dropout, the mean and variance of inputs retain their original values, ensuring that the self-normalizing characteristic continues to hold even after the dropout has occurred. In addition, we selected SeLU, which stands for Scaled Exponential Linear Unit, for the activation function to support the self-normalizing feature of the dropout layer, which is supported by the dropout layer itself. Lastly, we continue to use Lazy Adam as our model enhancer. The details of layer type, output type, and number of parameters are provided in Table II.

TABLE II. LAYERS OF THE TRANSFORMER BLOCK USED IN AMC

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 1024, 2)]	0
reshape (Reshape)	(None, 2, 1024)	0
transformer_block (TransformerBlock)	(None, 2, 1024)	4728064
Total params: **Trainable params:** **Non-trainable params:**		**4,882,968** **4,880,920** **2,048**

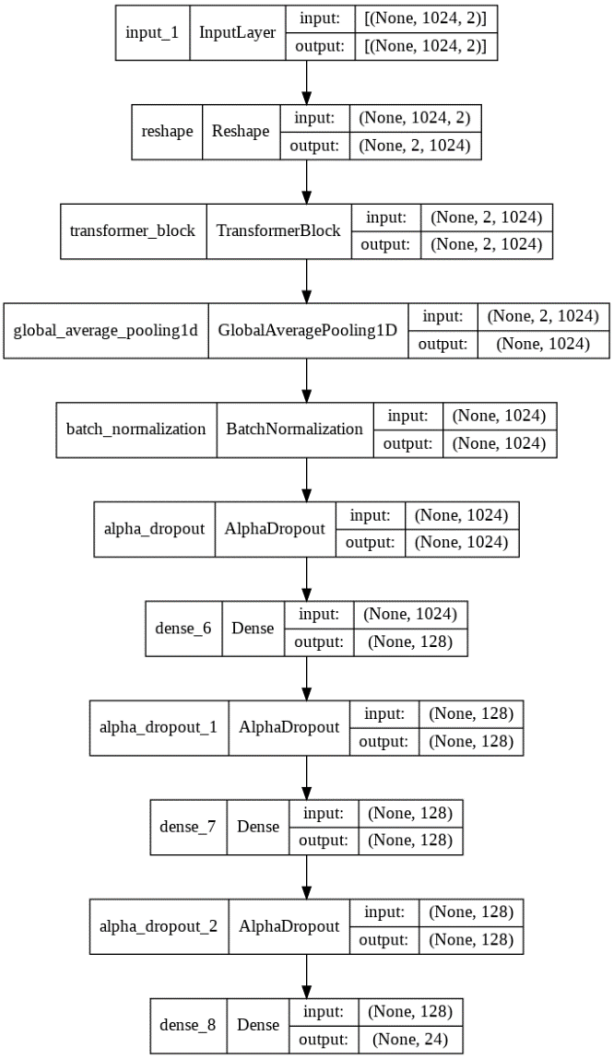


Fig. 9. Architecture of the transformer block used in AMC.

VI. Results and Discussion

This section will demonstrate the results of applying the proposed method to create the hybrid model. These results are reported in Table III in terms of overall Accuracy of the proposed model at different SNR values. Accuracy is calculated using the following relation, Eq. (4):

$$Accuracy = \frac{TP+TN}{P+N} \quad (4)$$

where, *TP, TN, P*, and *N* represent True Positive, True Negative, Total Positive, and Total Negative, respectively.

Our model consists of two parts; the first part deals with the clean signals that have bigger than 0 SNR values; our Customized EfficientNet shows outstanding performance in the modulation classification for such values, and the maximum accuracy of the modulation classification is 92% at 30 SNR average. However, the EfficientNet has the same characteristics as the other convolutional neural networks (CNNs), and the accuracy is degraded, especially for the signals under 0 SNR values. On the other hand, Transformer Block is working on modulation classification for the lower SNR range of the signals. The Transformer shows an average of 70% accuracy of the modulation classification in the signals with lower SNR values than zero. By applying the parts (Customized EfficientNet and Transformer Block), we have a wider modulation classification range that works from -20 SNR up to 30 SNR with average accuracy (80.74%) among all the SNR ranges. Compared to any solo system, our hybrid model has superior performance considering the full range of SNR. The following subsections in this section illustrate the accuracy results of each part individually; then, the final results will be shown for the combined parts of the hybrid system.

Furthermore, both parts of the hybrid system (Customized EfficientNet and Transformer Block) are trained to utilize the raw data directly, without any feature extraction or preprocessing stage. However, the training stage took a long time for training of the two models, around one hour for each epoch, and it took 36 epochs to complete the training; this long time is due to the huge size of the used dataset. Noting that, 10% of the training data set was considered a validation split to determine the optimum point to stop the training process and have the best generalization characteristics for the system.

A. Performance of the Customized EfficientNet

By implementing the customized EfficientNet discussed in Section V(A), the overall accuracy of the model on the AMC task is reported in Table III and displayed graphically in Fig. 10. It can be observed that the customized EfficientNet alone performs very good for positive or higher values of SNR. However, it has a poor performance for negative and lower SNR values.

TABLE III. EfficientNet Accuracy

SNR (dB)	Overall Accuracy	SNR (dB)	Overall Accuracy
-20	4.34%	2	68.73%
-18	4.57%	4	79.58%
-16	4.87%	6	86.08%
-14	5.46%	8	89.15%
-12	7.81%	10	90.30%
-10	12.43%	12	91.49%
-8	16.16%	14	91.12%
-6	24.11%	16	91.80%
-4	31.65%	18	92.22%
-2	42.32%	20	92.01%
0	57.06%	22	91.93%
		24	92.32%
		26	91.89%
		28	92.05%
		30	92.03%

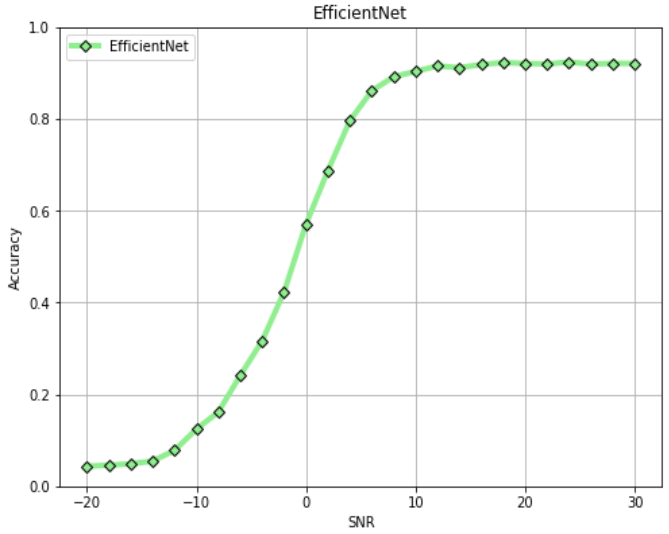


Fig. 10. AMC accuracy for customized EfficientNet alone.

B. Performance of the CustomizedTransformer Block

By implementing the customized Transformer block discussed in Section V(B), the overall accuracy of the model on the AMC task is reported in Table IV and displayed graphically in Fig. 11. It can be observed that the customized Transformer block alone performs very good for negative and lower values of SNR. However, it has a poor performance for positive or higher SNR values.

TABLE IV. TRANSFORMERS' ACCURACY

SNR (dB)	Overall Accuracy	SNR (dB)	Overall Accuracy
-20	69.79%	2	52.34%
-18	68.97%	4	45.72%
-16	69.85%	6	44.84%
-14	70.13%	8	41.26%
-12	70.08%	10	40.88%
-10	71.76%	12	41.95%
-8	72.16%	14	42.25%
-6	72.32%	16	42.36%
-4	71.08%	18	42.27%
-2	69.09%	20	41.96%
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		24	42.46%
		26	42.49%
		28	42.29%
		30	42.47%

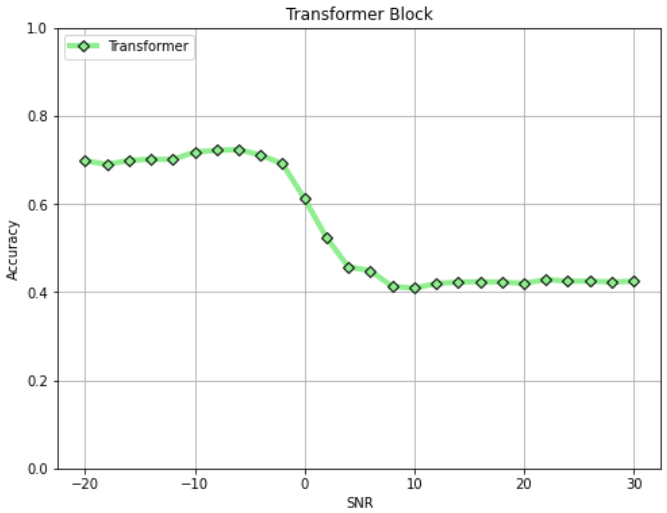


Fig. 11. AMC accuracy for the customized transformer block alone.

C. Performance of the Proposed Hybrid Model

By implementing the proposed hybrid model for the AMC task using the switching mechanism discussed in Section V, the overall accuracy of the proposed model on the AMC task is reported in Table V and displayed graphically in Fig. 12. Moreover, the performance of the proposed hybrid model is also compared to the one achieved by the modified ResNet of [25]. It can be observed that the proposed hybrid model initially performed bad at 0 dB SNR, and later it performed very well for the larger SNR values. The reason for this bad performance is due to abrupt switching via the imperfection in SNR estimation using Eq. (3). This is one of the limitations of the proposed method that needs to be improved in future research. Moreover, the proposed hybrid model outperformed the modified ResNet of [25] for lower SNR values (10 dB and below). For the case of higher SNR values (above 10 dB), its performance is almost identical to that of the modified ResNet of [25]. This is important to highlight that the AMC at lower SNR is more crucial and hence, our proposed model has attained this goal.

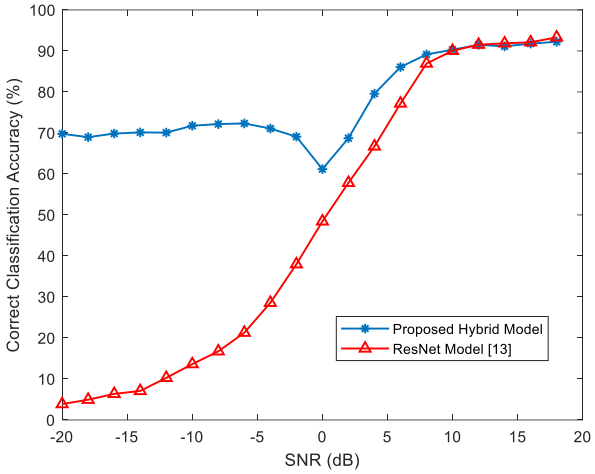


Fig. 12. AMC accuracy comparison for the proposed model.

TABLE V. AMC ACCURACY COMPARISON FOR THE PROPOSED MODEL

SNR(dB)	Accuracy of Proposed Hybrid Model	Accuracy of Modified ResNet Model [25]
-20	69.79%	3.87%
-18	68.97%	4.94%
-16	69.85%	6.36%
-14	70.13%	7.08%
-12	70.08%	10.27%
-10	71.76%	13.62%
-8	72.16%	16.74%
-6	72.32%	21.29%
-4	71.08%	28.58%
-2	69.09%	37.98%
0	61.18%	48.43%
2	68.73%	57.84%
4	79.58%	66.72%
6	86.08%	77.18%
8	89.15%	86.93%
10	90.30%	90.04%
12	91.49%	91.53%
14	91.12%	91.86%
16	91.80%	92.12%
18	92.22%	93.31%
20	92.01%	92.87%
Avg.	**78.04%**	**49.50%**

VII. Conclusion

The capacity to categorize signals is a critical skill that may be used in various applications. In this work we have developed a hybrid CNN model by intelligently combining the EfficientNet and the Transformer Block for the AMC application. For this purpose, customized architectures of both the EfficientNet and the Transformer Block are developed. A switching mechanism is opted to develop the proposed hybrid model such that the EfficientNet is used for higher SNR values, while the transformer block is used to enhance the DL performance for the lower SNR values. The performance of the proposed hybrid model is examined on a benchmark dataset, RadioML2018.01A. The results show that the proposed hybrid model has an average classification accuracy of 78.04% in contrast to 49.5% achieved by its state-of-the-art counterpart. Thus, confirming the supremacy of the proposed model for the AMC application. In the future, more accurate methods of SNR switching can be explored. Moreover, the AMC task can be expanded to other types of modulation and channel models.

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Conflicts of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

References

[1] T. Huynh-The, C.-H. Hua, V.-S. Doan, Q.-V. Pham, and D.-S. Kim, “Accurate deep CNN-based waveform recognition for intelligent radar systems," *IEEE Communication Letters*, vol. 25, no. 9, pp. 2938-2942, Sep. 2021.

[2] T. Huynh-The, Q. Pham, T. Nguyen, T. Nguyen, R. Ruby, M. Zeng, D. Kim, “Automatic Modulation Classification: A Deep Architecture Survey”, *IEEE Access,* vol. 9, pp. 142950 – 142971, 2020.

[3] [3] O. A. Dobre, A. Abdi, Y. Bar-Ness, and W. Su, “Survey of automatic modulation classification techniques: classical approaches and new trends,” *IET Communications*, vol. 1, no. 2, pp. 137-156, April 2007.

[4] S. M. S. Islam, S. Rahman, M. M. Rahman, E. K. Dey, and M. Shoyaib, "Application of deep learning to computer vision: A comprehensive study," *2016 5th International Conference on Informatics, Electronics and Vision (ICIEV)*, 2016, pp. 592-597, doi: 10.1109/ICIEV.2016.7760071.

[5] U. Shah and A. Harpale, "A Review of Deep Learning Models for Computer Vision," *2018 IEEE Punecon*, 2018, pp. 1-6, doi: 10.1109/PUNECON.2018.8745417.

[6] L. Dai, R. Jiao, F. Adachi, H. V. Poor, and L. Hanzo, "Deep Learning for Wireless Communications: An Emerging Interdisciplinary Paradigm," in *IEEE Wireless Communications*, vol. 27, no. 4, pp. 133-139, August 2020, doi: 10.1109/MWC.001.1900491.

[7] W. Yu, F. Sohrabi, and T. Jiang, "Role of Deep Learning in Wireless Communications," in *IEEE BITS the Information Theory Magazine*, 2022, doi: 10.1109/MBITS.2022.3212978.

[8] C.-H. Hua, T. Huynh-The, and S. Lee, ``Retinal vessel segmentation using round-wise features aggregation on bracket-shaped convolutional neural networks," in *Proc. 41st Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Berlin, Germany, Jul. 2019, pp. 36_39.

[9] C.-H. Hua, T. Huynh-The, K. Kim, S.-Y. Yu, T. Le-Tien, G. H. Park, J. Bang, and W. Ali, ``Bimodal learning via trilogy of skip-connection deep networks for diabetic retinopathy risk progression identi_cation," *Int. J. Med. Informat.*, vol. 132, Dec. 2019, Art. no. 103926.

[10] T. Huynh-The, C.-H. Hua, and D.-S. Kim, ``Visualizing inertial data for wearable sensor based daily life activity recognition using convolutional neural network," in *Proc. 41st Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2019, pp. 2478_2481.

[11] C.-H. Hua, T. Huynh-The, and S. Lee, ``DRAN: Densely reversed attention based convolutional network for diabetic retinopathy detection," in *Proc. 42nd Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Montreal, QC, Canada, Jul. 2020, pp. 1992_1995.

[12] C.-H. Hua, K. Kim, T. Huynh-The, J. I. You, S.-Y. Yu, T. Le-Tien, S.-H. Bae, and S. Lee, ``Convolutional network with twofold feature augmentation for diabetic retinopathy recognition from multimodal images," *IEEE J. Biomed. Health Informat.*, vol. 25, no. 7, pp. 2686_2697, Jul. 2021.

[13] T. Huynh-The, C.-H. Hua, N. A. Tu, and D.-S. Kim, ``Physical activity recognition with statistical-deep fusion model using multiple sensory data for smart health," *IEEE Internet Things J.*, vol. 8, no. 3, pp. 1533_1543, Feb. 2021.

[14] Y. -W. Chen et al., "CITISEN: A Deep Learning-Based Speech Signal-Processing Mobile Application," in *IEEE Access*, vol. 10, pp. 46082-46099, 2022, doi: 10.1109/ACCESS.2022.3153469.

[15] Y. Liu, Y. Li, Y. Zhu, Y. Niu and P. Jia, "A Brief Review on Deep Learning in Application of Communication Signal Processing," *2020 IEEE 5th International Conference on Signal and Image Processing (ICSIP)*, 2020, pp. 51-54, doi: 10.1109/ICSIP49896.2020.9339345.

[16] S. Peng, H. Jiang, H. Wang, H. Alwageed and Y. -D. Yao, "Modulation classification using convolutional Neural Network based deep learning model," *2017 26th Wireless and Optical Communication Conference (WOCC)*, 2017, pp. 1-5, doi: 10.1109/WOCC.2017.7929000.

[17] Z. Zhang, C. Wang, C. Gan, S. Sun and M. Wang, "Automatic Modulation Classification Using Convolutional Neural Network With Features Fusion of SPWVD and BJD," in *IEEE Transactions on Signal and Information Processing over Networks*, vol. 5, no. 3, pp. 469-478, Sept. 2019, doi: 10.1109/TSIPN.2019.2900201.

[18] D. A. Jariwala and K. M. Captain, "Automatic Modulation Classification: A Novel Convolutional Neural Network Based Approach," *2021 IEEE 18th India Council International Conference (INDICON)*, 2021, pp. 1-6, doi: 10.1109/INDICON52576.2021.9691687.

[19] Q. Zhou, X. Jing, Y. He, Y. Cui, M. Kadoch and M. Cheriet, "LSTM-based Automatic Modulation Classification," *2020 IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (BMSB)*, 2020, pp. 1-4, doi: 10.1109/BMSB49480.2020.9379677.

[20] Y. Chen, W. Shao, J. Liu, L. Yu and Z. Qian, "Automatic Modulation Classification Scheme Based on LSTM With Random Erasing and Attention Mechanism," in *IEEE Access*, vol. 8, pp. 154290-154300, 2020, doi: 10.1109/ACCESS.2020.3017641.

[21] D. Hong, Z. Zhang and X. Xu, "Automatic modulation classification using recurrent neural networks," *2017 3rd IEEE International Conference on Computer and Communications (ICCC)*, 2017, pp. 695-700, doi: 10.1109/CompComm.2017.8322633.

[22] Clement, J.C., Indira, N., Vijayakumar, P. et al. Deep learning based modulation classification for 5G and beyond wireless systems. *Peer-to-Peer Netw. Appl.* 14, 319–332 (2021). https://doi.org/10.1007/s12083-020-01003-3.

[23] S. Zhou, Z. Yin, Z. Wu, Y. Chen, N. Zhao, and Z. Yang, ``A robust modulation classi_cation method using convolutional neural networks," *EURASIP J. Adv. Signal Process.*, vol. 2019, no. 1, pp. 1_15, Dec. 2019.

[24] S. Zhou, Z. Yin, Z. Wu, Y. Chen, N. Zhao, and Z. Yang, ``A robust modulation classi_cation method using convolutional neural networks," *EURASIP J. Adv. Signal Process.*, vol. 2019, no. 1, pp. 1_15, Dec. 2019.

[25] T. J. O'Shea, T. Roy, and T. C. Clancy, “Over-the-air deep learning based radio signal classification,” *IEEE J. Sel. Topics Signal Process.*, vol. 12, no. 1, pp. 168-179, Feb. 2018, doi: 10.1109/JSTSP.2018.2797022.

[26] K. He, X. Zhang, S. Ren, J Sun, “Deep Residual Learning for Image Recognition”, *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016.

[27] M. Tan, and Q. Le, “EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks”, in *proceedings International Conference on Machine Learning (ICML)*, pp: 6105-6114, 2019.

[28] V. Agarwal, “Complete Architectural Details of all EfficientNet Models”, [Online]. Available: https://medium.com/data-science/complete-architectural-details-of-all-efficientnet-models-5fd5b736142

[29] H. Jing, “Illustrated Guide to Transformer”, 2020. [Online]. Available: https://jinglescode.github.io/2020/05/27/illustrated-guide-transformer/

[30] Colah's blog, “Understanding LSTM Networks”, 2015. [Online]. Available: https://colah.github.io/posts/2015-08-Understanding-LSTMs/

[31] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. Gomez, Ł. Kaiser, “Attention Is All You Need”, in *Advances in Neural Information Processing Systems*, 2017. [Online]. Available: https://arxiv.org/pdf/1706.03762.pdf

[32] M. Komatsu, N. Tanabe and H. Matsumoto, "A Consideration on Noise Variance Estimation for Direct Blind Equalization with OFDM Environment," *2024 International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS)*, Kaohsiung, Taiwan, 2024, pp. 1-4, doi: 10.1109/ISPACS62486.2024.10868237.

[33] Szymon Greś, Michael Döhler, Vasilis K. Dertimanis, Eleni N. Chatzi, “Subspace-based noise covariance estimation for Kalman filter in virtual sensing applications,” *Mechanical Systems and Signal Processing*, Volume 222, 2025, 111772.

[34] J. Shi, S. Hong, C. Cai, Y.Wang, H. Huang, and G. Gui, “Deep learning based automatic modulation recognition method in the presence of phase offset,” *IEEE Access*, vol. 8, pp. 42841-42847, 2020.

[35] Y. Wang, J. Yang, M. Liu, and G. Gui, “LightAMC: Lightweight automatic modulation classification via deep learning and compressive sensing,” *IEEE Trans. Veh. Technol.*, vol. 69, no. 3, pp. 3491-3495, Mar. 2020.

[36] S. Zheng, P. Qi, S. Chen, and X. Yang, “Fusion methods for CNNbased automatic modulation classification,” *IEEE Access*, vol. 7, pp. 66496-66504, 2019.

A Comprehensive Analysis of Security Challenges and Solutions in the Internet of Drones: Recent Trends and Development

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***Abstract*—The Internet of Drones (IoD) is a decentralized structure that links drones to regulate airspace and offer inter-location navigation services. With the increasing use of drones in both civilian and military applications, the importance of the IoD has grown significantly. It reshapes the current internet landscape, making it more extensive and all-encompassing. IoD establishes a connection between drones and the network, which exposes the IoD network to numerous privacy and security issues often associated with IoT ecosystems. To ensure optimal performance from IoD applications, it is crucial to maintain a secure environment devoid of privacy and security risks. Privacy and security concerns have obstructed the overall effectiveness of the IoD framework. This study conducts an extensive examination of security concerns and solutions related to IoD security. It delves into IoD-specific security requirements and sheds light on the latest developments in IoD security research. Hence, we first provide an overview of the overall context and structure of the IoD. We then identify the security issues linked to it. Afterward, we present the most recent security measures developed specifically for the IoD. Finally, we go through the challenges and potential areas for future research in the realm of IoD security.**

***Keywords*—Unmanned Aerial Vehicle; Internet of Drones; cybersecurity; attacks; threats**

I. Introduction

The recent progress in robotics and wireless communication has given rise to Unmanned Aerial Vehicle (UAV) technology. UAV, commonly known as a drone, is an aircraft that operates without a human pilot and is controlled remotely by a user or a control station [1]. Primarily, drones have found application in the military sector, where they are utilized for monitoring insurgents, conducting surveillance on terrorists, assisting in the rescue of injured personnel, etc. According to the E.U. Commission Delegated Regulation 2019/945 [2], a UAV consists of two primary components: an unmanned aircraft and a remote-control device.

Generally, UAV come outfitted with a Global Positioning System (GPS) and various sensors for data acquisition, with their storage and battery capabilities being relatively constrained [3]. Communication between UAVs and other entities, such as remote users or control stations, is established through wireless channels, forming the Internet of Drones network.

The Internet of Drones (IoD) is a subset of the Internet of Things (IoT) designed to facilitate communication and cooperation among UAVs. As a result, it inherits from the security vulnerabilities IoT networks. As the data exchanged within the IoD may contain sensitive and critical information, security is a major concern in this area [4]. This is because UAV are usually operated remotely and receive control and command signals from ground sites. These command-and-control signals are transmitted through different means of communication and with different transmission rates, which requires significant efforts to manage and control quality and security in a context of high mobility which could complicate these tasks (control and management). Critical data exchanged between UAV must not be disclosed or compromised in any way. Given the diversity of attacks that can target the IoD (Jamming, Flooding, Collision, Selective forwarding, replay, identity theft, tracing, etc.), it becomes essential to establish security measures by deploying protection mechanisms adapted to secure it [5][6]. Thus, confidentiality, integrity, availability, authenticity, and preservation of privacy represent the main security requirements of the IoD. Several research studies have focused on IoD security [5]. Despite the diversity (new authentication schemes, blockchain-based security, etc.) and relevance of existing solutions, we believe that much remains to be done in the field of IoD security. Indeed, the implementation of certain protection mechanisms can constitute an obstacle to the proper functioning of the IoD or, if necessary, cause the degradation of the performance and efficiency of the services provided by UAVs. For example, security has a potentially significant cost in terms of CPU, memory, and power consumption.

As UAVs are battery operated, battery life can be another constraint and a major problem, part of the solution of which can be the use of energy-efficient batteries (lithium-ion and hydrogen batteries [7]), the harvesting of (Energy Harvesting), the use of solar cells or wireless energy transfer [7]. Thus, it may be relevant to minimize the impact of security on the energy consumption of UAVs.

The primary objective of this study, which is described in Section I, is to offer a comprehensive and up-to-date survey of the fundamental concepts pertaining to communication within the IoD. In an era where UAVs are becoming increasingly integrated into our daily lives, understanding the intricacies of how these devices communicate and collaborate is of paramount importance. By exploring the latest advancements, protocols, and technologies employed in enabling seamless data exchange among drones and between drones and ground-based systems, this study attempts to provide a valuable reference for researchers, practitioners, and policymakers, addressing their needs and interests in Section II. In Section III of this study, we present a comprehensive examination of the security requirements and constraints that belong to the IoD (Confidentiality, Availability, Integration, etc.). Following our exploration of security requirements and constraints in the IoD, this study will shift its focus to hidden security vulnerabilities for IoD systems, as well as potential attack vectors targeting this emerging technology. Security vulnerabilities in the IoD environment can arise from a variety of sources. We will begin by identifying and examining common vulnerabilities associated with the communication infrastructure of IoD networks. These might include weaknesses in wireless communication protocols, flaws in encryption algorithms, or vulnerabilities in the underlying hardware and software of the drones themselves. By explaining these vulnerabilities, we provide a comprehensive view of the potential weaknesses that adversaries may exploit. Simultaneously, our discussion will encompass potential attack surfaces within IoD systems. This involves identifying and characterizing the various components and interfaces that can be targeted by malicious actors. Examples of attack surfaces in IoD may include command and control channels (C2), transmission links, and even the physical drones themselves. It is imperative to understand these attack surfaces to effectively mitigate and defend against potential threats. Finally, we undertake a comprehensive survey of recent advancements in the realm of existing security solutions designed to address and mitigate the diverse spectrum of attacks discussed earlier in Section IV. Among the various categories of available security solutions, we will showcase the most and widely adopted solutions in the IoD, including intrusion detection systems, cryptographic measures, authentication methods, and the utilization of the Blockchain mechanism. At the end of the study (Section V), recommendations and challenges are proposed to find possible solutions to secure the IoD.

This research aims to answer six research inquiries depicted in Fig. 1. While it's evident that numerous other questions could be raised, we support that these are adequate to inform a diverse spectrum of research within the examined domain.

RQ1: What are the fundamental principles concerning communication and classification in the context of the IoD, and what are the areas and sectors of application?

RQ2: What security prerequisites and limitations exist within the IoD?

RQ3: What are the security weaknesses present within an IoD network, and what are the possible consequences of assaults on drone systems?

RQ4: What are the attacks targeting the IoD network?

RQ5: What are the current countermeasures in place to mitigate these attacks?

RQ6: What are the recommendations and challenges to find possible solutions to secure the IoD?

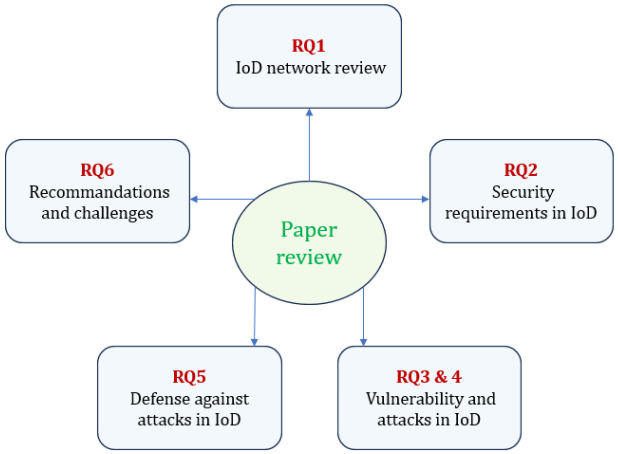


Fig. 1. Research inquiries of the study.

II. Unmanned Aerial Vehicles (UAV)

In recent years, UAVs have garnered considerable attention due to their versatility and autonomous capabilities. Recently, the United States' Federal Aviation Administration (FAA) has introduced fresh regulations permitting the utilization of drones for civilian and business applications. Consequently, the FAA anticipates that approximately seven million drones are presently in operation within the United States [8]. Drones can be remotely operated using a range of electronic devices, including microprocessors and sensors [9]. A key advantage of the drone is its ability to autonomously perform operations in hazardous environments where human intervention would be unsafe or impractical [10].

A. Architecture of Unmanned Aerial Vehicle Communication

As shown in Fig. 2 and described in [11, 12–14, 15-17], the typical representation of a UAV includes a UAV, flight controller, communication links, and either a ground command and control system or Ground Control Station (GCS) [15, 16, 18, 19]. Let us now provide a brief overview of each of these components:

- Flight controller: It is considered as the main processing unit of the drone. It can also be equipped with different sensors, like sensor units such as global positioning system (GPS) receivers, accelerometers, infrared cameras, gyroscope, magnetic orientation, and electro-optical sensors.
- Ground Control Station: It provides human operators with the tools they need to remotely control and monitor drones during missions.
- Data Link: It is used to communicate and control the data flow between the ground control station and the drone.

Drone communications can be classified into four distinct categories: Drone-To-Ground Station, Drone-To-Network, Drone-To-Satellite, and Drone-To-Drone (see Fig. 2). These categories represent different modes of communication that enable drones to establish connections with various entities. [17]

Drone-To-Ground Control Station: This method of communication uses well-known and standardized communication protocols such as Wireless communication (WiFi, Ad-Hoc, Satellite). However, most of these types of communications are public and unsecured, which exposes them to many types of attacks.

- Drone-To-Network: This method of communication allows users to select a network based on the level of security they require. Cellular communication can also be included.
- Drone-To-Satellite: The GPS network uses this type of communication to send coordinates in real-time. This allows any drone to be called back to its home station if it has wandered beyond the control line. Satellite communications are considered safe and reliable. However, they are expensive and require a lot of maintenance.
- Drone-To-Drone: It can be considered P2P (peer-to-peer) communication, which makes it prone to various P2P attacks.

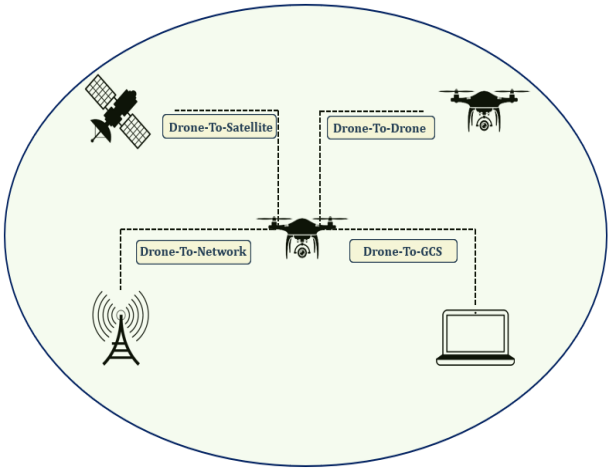


Fig. 2. Communication architecture for most UAVs.

B. Unmanned Aerial Vehicle Classification

UAVs have several requirements, such as being able to deploy sensors having a global positioning system (GPS), a communication module, and efficient batteries. UAVs can be controlled autonomously without a pilot and can be controlled remotely [18]. UAVs come in a variety of configurations, equipment options, sizes, ranges, and shapes. Within the market, we can find UAVs with varying numbers of rotors or propellers, as detailed in Table I [19]. Moreover, UAVs have been designed with diverse engines and wing structures. In terms of communication capabilities, they can utilize both short and long-range wireless technologies. UAVs are also classified based on their size, ranging from nano to micro and large.

Moreover, different types of UAVs can be found in the literature: fixed-wing, single rotor, fixed-wing hybrid, and multirotor [20]. Fixed-wing UAVs [21] contain a main body, wings, a propeller and a motor. These UAVs are often used for aerial mapping and power line inspection and need special training to control, and they remain useless for aerial surveillance. Such drones are not capable of hovering or forward flight. However, single-rotor drones [22] are costly to produce and need skill training. These UAVs are mechanically difficult and susceptible to obstacles such as vibrations.

Furthermore, multirotor drones [23] are the most affordable and simple to build. These UAVs are often employed for image and video surveillance. The Hybrid-Wing drone [24] is a fixed-wing and rotating drone that has recently entered the market. This type of drone can quickly reach its target by gliding through the air and hovering with four rotors.

TABLE I. CATEGORIES OF DRONES BASED ON THE NUMBER OF PROPELLERS

Types of drones	Number of Propellers
Octo-copter	8
Hexa-copter	6
Quad-copter	4
Tri-copter	3

C. Communication Methods of Unmanned Aerial Vehicles

When discussing the communication aspect of UAVs, several crucial subcomponents come into focus, including communication protocols, network types, and the UAV model itself. It should be noted that changing the communication method can introduce variations in the number of components and alter the system architecture [25]. Various researchers have proposed different topologies and designs [26], with consideration for altitude range. The choice of communication module and protocol may vary depending on the mission and the nature of the task at hand [27]. Furthermore, the emergence of 5G networks has addressed several constraints such as data rate, latency, and coverage. This advancement in communication technology has not only improved these areas but also enhanced the positioning and control of UAVs in critical rescue and surveillance missions. Advanced flight controls, multiple sensors, camera placement, and different modes of control and communication based on altitude have been employed for these purposes.

D. Unmanned Aerial Vehicle in 5G and IoT Networks

With the rapid advancements in UAV technology, UAVs have established their significance in a wide range of applications, including environmental monitoring, wireless communication, and public safety. Moreover, UAVs have been extensively studied in conjunction with wireless networks and have shown promising potential for enhancing the energy and spectrum efficiencies of fifth generation (5G) wireless networks. They provide a flexible and on-demand platform for deploying aerial base stations. The unique attributes of UAVs, such as adaptive altitude, scalability, flexibility, mobility, high

resilience, high reliability, and low cost, make them suitable for various applications. The integration of UAVs into network systems is expected to achieve significant performance improvements compared to conventional terrestrial systems without UAVs. UAVs can be intelligently controlled and remotely operated as required. They offer a high probability of line-of-sight (LoS) communication, which greatly enhances transmission rates. The swift maneuverability of UAVs ensures reliable and broadband wireless coverage during live streaming events and natural disasters. As a result, UAVs can provide offloading services with strict requirements in emergency operations within 5G networks [28]. Given their capabilities, it is feasible to integrate UAVs into 5G networks. Extensive research efforts are underway to explore UAV-assisted 5G technology and reduce latency while extending network coverage, capacity, and energy efficiency. However, there are certain challenges to consider in this coexistence. UAVs are susceptible to interference, and the dynamic network topology and mobility of UAVs introduce spatial and temporal dynamics that can result in frequent intermittent connections or transmission failures [29]. Additionally, UAVs are utilized for wireless energy transfer (WET) and wireless information transfer (WIT) to power ground terminals such as IoT devices, which are integrated for developing flexible and sustainable 5G networks [30]. UAVs provide numerous advantages when integrated into IoT networks [31, 32, 33]:

- Enhanced maneuverability, autonomy, speed, flight time, and mechanical performance.
- Efficient data gathering from water, gas, and power meters.
- Real-time data collection on air quality in smart cities.
- Reliability, scalability, and agility for IoT initiatives.
- Mitigating connectivity issues and reducing IoT network overhead.
- Cost-effectiveness and suitability for emergency operations.
- A comprehensive study addressing these UAV-related challenges is presented in [34].
- Channel modeling challenges and the need for accurate channel state knowledge.
- Efficient energy management for IoT device batteries.
- Adaptation of communication strategies to dynamic sensing data.
- UAV maneuverability limitations and potential mission impact.
- Concerns related to sky pollution, physical collisions, safety, privacy, and regulations.

E. Unmanned Aerial Vehicle Application Areas

UAVs have demonstrated their potential across a wide range of applications, including personal use and military purposes. Equipping UAVs with cameras, smart sensors, and processors can enhance their efficiency in various missions. Researchers have identified over 100 different applications for drones [35]. Factors such as diligence, cost-effectiveness, mobility in inaccessible areas, payload options, and risk considerations drive the widespread adoption of UAVs. The design of UAVs is often tailored to the specific mission they will perform in the field [36]. Categorizing UAVs based on their domains helps in understanding their architecture better, as demonstrated in Fig. 3, where each domain has its own privacy and security requirements [36, 37]. In the rest of this subsection, the main UAV applications are presented.

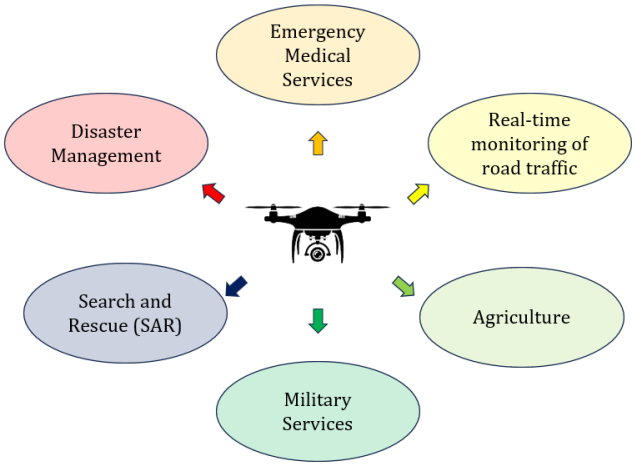


Fig. 3. UAV application areas.

1) Agriculture: UAVs have emerged as valuable tools in agriculture, providing real-time data and aiding farmers in making decisions. Equipped with advanced cameras, UAVs can deliver accurate information about soil conditions, crop health, and threats to crop yields. By analyzing this data, farmers can optimize the use of agricultural inputs to achieve higher crop yields. UAVs also offer early warning systems for threats such as wildlife or fires, allowing farmers to detect and mitigate these risks promptly. Researchers have highlighted the benefits of using UAVs in agriculture, including farm analysis, improved yields, monitoring, and spraying of pesticides. UAVs enable precise pesticide application by analyzing crop health and targeting infected areas, making spraying efforts safer and faster than manual methods [38, 39, 40].

2) Military: UAVs have found significant applications in the military sector, serving as a key component of the IoD. They are deployed in situations where manned flight is considered too risky or challenging. Military drones play crucial roles in combat operations, enemy surveillance, and target selection for military attacks [41]. They provide continuous aerial monitoring, offering troops a persistent eye in the sky. Kreps and Wallace [42] focused on the use of drones for counterterrorism, exploring the impact of international legal criticism on public support for drone strikes and the effectiveness of such strategies. Chand et al. developed a drone-based high-speed wireless mesh network, specifically designed for scenarios where no network infrastructure is available, such as disaster zones or military

conflicts. Their study demonstrates that drones can establish a wireless mesh network upon arrival, delivering Wi-Fi connectivity and real-time video streaming from an onboard camera. This network achieves wireless communication speeds of up to 160 Mbps within a range of approximately 200 meters.

3) Search and Rescue (SAR): With the increasing severity of climate change, natural disasters have become more frequent, emphasizing the crucial role of search and rescue operations. UAVs equipped with various sensors and cameras, including thermal sensors, have emerged as powerful tools in these missions. UAVs can effectively locate lost or injured individuals, even in challenging conditions or difficult terrain. Furthermore, UAVs can deliver essential supplies to inaccessible areas in war-torn or disaster-stricken regions. Cui et al. [43] addressed the use of UAVs in urban post-disaster search and rescue tasks and won the International Micro Air Vehicle Competition in 2014 by providing comprehensive solutions to key task components. Tilburg [44] reported two case studies showcasing the capabilities of UAVs in search and rescue missions, where UAVs assisted in locating a deceased person in a narrow valley at night and aided in obtaining images of challenging areas, facilitating successful rescue operations. Mayer et al. [45] discussed potential search and rescue scenarios for UAV deployment and highlighted the challenges and opportunities of human-machine interaction in these operations. Karaca et al. [46] utilized a simulation model to explore the use of UAVs in locating and searching for victims, as well as providing mobile transportation for search and rescue personnel in mountainous environments, particularly focusing on searching for unconscious victims on snow.

4) Disaster management: UAVs have the capability to access disaster-stricken areas that are hazardous for human intervention, whether the catastrophe is a result of human actions or natural disasters, such as terrorist attacks, tsunamis, or floods. Critical infrastructure like power, telecommunications, water utilities, and transportation systems are all susceptible to these calamities. UAVs play a crucial role in data collection, providing rapid responses, and maneuvering through debris. Equipped with sensors, radars, and high-resolution cameras, UAVs offer invaluable support to rescue teams in identifying damage, initiating urgent recovery operations, and delivering essential supplies, including first-aid kits and manned helicopters. UAVs contribute to disaster assessment, early warning systems, and the identification of preventive measures in real-time. In the case of wildfires, a swarm of drones outfitted with firefighting equipment can vigilantly monitor, analyze, and track affected areas without endangering human lives. Consequently, UAVs facilitate real-time surveillance over extensive regions while ensuring the safety and security of all involved parties. UAVs also play a vital role in locating and rescuing individuals and animals in distress.

5) Real-time monitoring of road traffic: The integration of UAVs with road traffic monitoring (RTM) systems is a subject of great interest. UAVs offer the potential for full automation of the transportation industry within the RTM sector [47], including functions performed by rescue teams, road surveyors, traffic officers, and on-site support personnel. These reliable and intelligent UAVs are instrumental in automating these operations. UAVs have proven to be effective tools for gathering data on road traffic conditions, outperforming traditional monitoring systems like surveillance cameras, ultrasonic sensors, and circuit analyzers [48]. Cost-effective drones can efficiently inspect extensive road sections. Local law enforcement agencies can leverage drones for comprehensive accident monitoring and security operations targeting illegal activities along highways, such as vehicle theft. Other applications include vehicle identification, pursuit of suspicious vehicles, tracking hijackers, and monitoring traffic rule violations [49]. UAVs can also monitor driving behavior and incidents inside vehicles, potentially mitigating traffic congestion and overcrowding. Furthermore, UAVs can contribute to monitoring road conditions, detecting fractures, and issuing early warnings to prevent accidents and reduce damage. Current road inspection methods rely on human-operated vehicles, highlighting the need for increased automation. The integration of road inspection technologies with UAVs holds the promise of significantly reducing road damage. UAVs can capture images of road fractures and use target detection algorithms to identify and assess these issues.

6) Emergency medical services: UAVs have demonstrated significant potential in the context of smart cities worldwide. These smart cities are equipped with advanced healthcare systems that rely on telemetry, implantable medical devices, and medical drones for the swift delivery of first-aid supplies. Notably, UAVs have effectively addressed the challenges posed by the COVID-19 pandemic in various countries. However, it is essential to highlight that the primary entities leading the response to COVID-19 are the national emergency medical services (EMS) institutions, working in conjunction with multiple stakeholders, including EMS personnel, nurses, and medical doctors. Additionally, policymakers are exploring various preventive measures to combat COVID-19, which encompass practices such as wearing surgical masks, refraining from touching one's face, practicing regular hand hygiene, implementing city lockdowns, avoiding high-risk areas, abstaining from social gatherings, and instituting health codes [50]. Policy makers should carefully consider the balance between economic concerns and public safety when contemplating the implementation of new measures. Currently, UAVs are being deployed for various tasks aimed at preventing the spread of COVID-19, such as: transport of patients, public announcements, crowd surveillance, spraying disinfection, mass screening, crown aerial monitoring and delivering vaccines and other medical supplies.

III. Cybersecurity Issues in UAVs

The advancement of UAV technology offers numerous benefits, including applications in agriculture, surveillance, infrastructure inspection, emergency response, and package delivery. However, these advancements also introduce concerns related to privacy, security, and safety [51, 52]. To address these issues, a comprehensive approach is required as drones become integral to various industries and daily life. This section focuses on the security prerequisites for UAVs in the IoD ecosystem, as well as essential security measures and strategies to safeguard UAV integrity and functionality, and the various types of threats that can target the IoD, spanning from physical hardware attacks to cyberattacks on communication systems and software.

A. Cybersecurity Requirements of UAVs

Due to the UAV's wireless communication system and its unmanned nature, it remains susceptible to security attacks and vulnerabilities, making the security issue even more critical. Both UAVs and the 5G network have encountered numerous security attack issues in recent years, drawing significant attention [53]. Consequently, UAVs are occasionally confronted with various types of security threats. The prevalence of this technology and the extensive use of UAVs in critical fields have given rise to security apprehensions, particularly concerning networked UAVs. These interconnected UAVs are exposed to diverse forms of malicious attacks through open-air communication channels. Fig. 4 shows the main components of a typical networked UAV system alongside a depiction of a cyberattack. Certainly, during the exchange of traffic between drones and the control station, the attacker can directly target the drone through specific attacks or focus on the communication network between the drones and the base station, or even direct their efforts towards the control station itself.

The extensive utilization of UAVs in civilian applications exposes them to numerous vulnerabilities [54]. To address this, several crucial attributes are necessary to safeguard UAVs against exposure, interference, alteration, and harm. To ensure the integrity of these attributes, we outline the key security and privacy prerequisites essential for establishing a secure UAV flight mission.

1) Confidentiality: To ensure adequate protection of information and data exchanges between UAVs and the GCS, several cryptographic security measures can be implemented. For instance, employing asymmetric encryption methods such as RSA or ECC would secure transmissions by rendering data unreadable to unauthorized individuals [55]. Furthermore, establishing secure VPN tunnels using protocols like IPSec or OpenVPN would ensure encrypted communication channels, preventing any unwanted interception of data in transit [56]. Implementing strong authentication protocols, such as the use of digital certificates or two-factor authentication keys, would verify the identity of UAVs and the GCS before any transmission of sensitive data [57]. By adopting security standards like TLS/SSL protocols to secure connections and adhering to reference recommendations from IEEE and NIST [58], it's possible to significantly bolster the security of exchanges between UAVs and the GCS. However, it's crucial to remain vigilant about technological advancements and new threats to continually adjust these protective measures and maintain an optimal level of security.

2) Integrity: Maintaining data integrity stands as a pivotal pillar for the seamless execution of UAV flight missions, serving not only as a fundamental necessity but also as a deterrent against potential adversarial interference within network traffic. The integrity of data is fundamental in preserving the unaltered state of telemetry information and control commands, crucial elements that dictate the UAV system's behavior. Any compromise in this integrity could lead to catastrophic mission failures or unpredictable behaviors in the UAVs. Thus, it becomes imperative to ensure that every communication exchange remains not only shielded from unauthorized access but also thoroughly verified. Employing authenticated encryption algorithms like AES-GCM or ChaCha20-Poly1305 [59] bolsters this safeguarding measure by not just encrypting the data but also providing authentication, ensuring that the received information remains unaltered and originates from legitimate sources. References from standards such as RFCs 4106 and 7539 outline the utilization of these algorithms, emphasizing their significance in maintaining the integrity of data during transmission. Additionally, insights from cybersecurity breaches, as documented in by Panko and case studies such as NASDAQ's cyber-attacks, underscore the catastrophic implications of compromised data integrity, further highlighting the criticality of robust protection mechanisms.

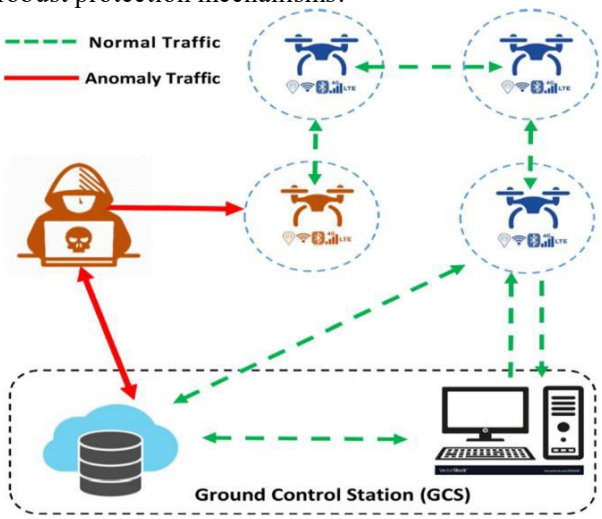


Fig. 4. Components of networked UAV and risk of a cybersecurity attack [54].

3) Availability: UAVs require uninterrupted operational continuity, free from intentional or inadvertent disruptions. In critical scenarios like search and rescue operations, their seamless operation is vital for constant surveillance of affected areas. Any failure, whether resulting from deliberate manipulation or unintended interruption, can significantly compromise critical operations. Similarly, in military contexts

[60] where UAVs play a pivotal role, any restricted access to necessary resources or unauthorized interruptions could impede mission success. Denial of Service (DoS) attacks pose a major threat [61], rendering UAVs inoperative by overwhelming their communication systems or disrupting connectivity. To counter such threats, the use of Intrusion Detection Systems (IDS) becomes imperative [62]. These systems monitor UAV networks, identifying abnormal activities and enabling swift responses to preserve their operational availability. They serve as essential mechanisms to ensure UAVs operate continuously and effectively, accessing necessary resources while remaining shielded from malicious interruptions or attacks targeting their availability.

4) Authenticity: Authentication plays a critical role in establishing secure communication within UAV systems, evident across various operational domains. In military applications [63], robust authentication protocols validate the legitimacy of each UAV involved in missions, ensuring that only authorized drones participate, safeguarding sensitive data, and preventing potential disruptions from unauthorized sources. Similarly, within commercial UAV networks [64], authentication procedures authenticate drones before granting access to logistical systems, maintaining the integrity of delivery routes, and protecting cargo from unauthorized access. In collaborative swarm operations [65], authentication serves to verify the identity of each drone, mitigating risks of infiltration by rogue elements, preventing collisions, and ensuring coordinated task execution. Moreover, authentication acts as a frontline defense against cyber threats targeting UAV networks, thwarting attempts by adversaries to impersonate legitimate nodes and compromise system control or data integrity. Across these diverse contexts, authentication not only confirms the credibility of individual UAVs but also fortifies the overall security posture of the system, shielding against potential adversarial intrusion and ensuring a trusted and controlled UAV environment.

5) Privacy: Privacy remains a critical concern within IoT systems, particularly in the realm of UAVs. The complex nature of these interconnected systems demands strict measures to ensure unauthorized access is barred from both the UAVs and any personal information they might possess. While this sharing enhances operational efficacy, it poses a significant privacy risk. If this information fell into malicious hands, it could facilitate tracking or surveillance of individuals, compromising their privacy. Moreover, the collection of personal data, such as images or videos, during surveillance missions demands increased protection to prevent unwarranted access or misuse [66]. The risk amplifies when considering potential interception or manipulation of shared information within a network of UAVs [67]. Safeguarding against these threats necessitates robust encryption, secure communication channels, strict access controls, and authentication mechanisms. Table II outlines the essential security requirements specific to UAVs.

TABLE II. ESSENTIAL SECURITY REQUIREMENTS OF UAVS

Security requirement	Description
Confidentiality	Only authorized people can have access to the sensitive data.
Integrity	The data are not modified when transferring.
Availability	The services provided are operational.
Authenticity	The receiver can confirm that the message was sent by a legitimate sender.
Privacy	The information of each entity is confidential.

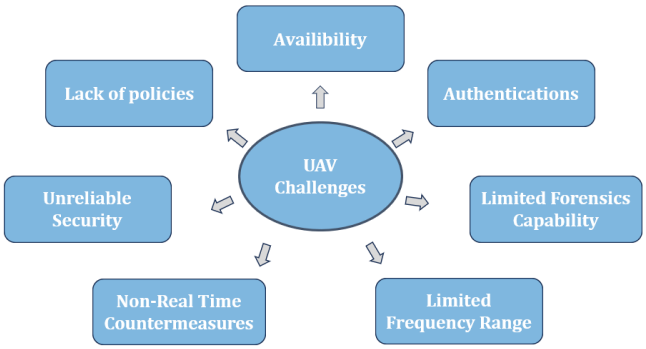


Fig. 5. Challenges in the adoption and execution of security measures for UAVs [68].

Challenges persist in the adoption and execution of inflexible security measures for UAVs, as illustrated in Fig. 5. The limitations in UAV security [68–70] are described below:

- Limited Forensics Capability: In case of a harmful event, the limited availability of forensic tools and methods makes it difficult to identify the malicious operator of the UAV involved in the dangerous act.
- Limited Frequency Range: The UAVs are being operated within a limited range of frequencies. Making them an easy target for jamming-based attacks.
- Non-Real-Time Countermeasures: Due to a lack of standardization for design and operational software, the current UAV does not have real-time protection during flight. If a UAV is compromised during flight, it cannot be retained by the original owner.
- Lack of policies: Standardization and policies are absent for UAV operations and operators. In some countries, policies are defined for UAV flying in proximity to sensitive areas. However, a general set of operating policies for a UAV is still not available.
- Unreliable Security: Based on the hostile operational environment of UAVs, the default security measures are not suitable. Due to the harsh operating environment of UAVs, a robust security protocol is necessary. But due to design and resource limitations, improving security measures is very challenging.

Most of these limitations can be surmounted through the establishment of standardized UAV designs, communication protocols, and fundamental factory default security measures.

B. Cybersecurity Attacks of UAVs

In the context of the IoT, security breaches can manifest in various ways, affecting several critical system components. These primary targets encompass IoD sensors, hardware, software, networking infrastructure, and the transmission communication that enable data exchange within the drone ecosystem. The security landscape for UAVs is multifaceted, and as such, a range of different attacks can be directed at these UAVs. These attacks may encompass both hardware and software components, each with the potential to compromise the integrity, availability, and confidentiality of UAV operations. Therefore, in the following sub-section, we will delve into some of these diverse attack vectors that can target UAVs, shedding light on the specific vulnerabilities and consequences associated with each. By understanding the nature of these threats, we can better formulate strategies and defenses to safeguard the rapidly evolving and vital field of drone technology.

1) Hardware-based attacks: At the hardware level, irrespective of the specific make and features of various commercial UAVs, including firmware and hardware variations, UAV hardware may be susceptible to targeting during the manufacturing phase or before and during flight missions. These situations are reasonable due to vulnerabilities that can arise in UAV firmware and the absence of encryption in custom chipsets. Given the widespread use and variety of existing UAVs, it is crucial to establish a consistent hardware security approach aimed at safeguarding UAVs from hardware-based attacks [71].

a) Supply chain attack: As the drone industry continues to expand, potential adversaries have a larger opportunity to compromise UAVs through supply chain attacks. This form of attack involves taking advantage of vulnerabilities in an organization's supply chain process, with a focus on components that are less secure and more sensitive, such as propellers, airframes, and actuators. Consequently, the final product delivered to the customer is already compromised. Belikovetsky et al. [72] have demonstrated a practical supply chain attack on UAVs using Additive Manufacturing (AM). This attack involves sabotaging a specific UAV by remotely manipulating the design files for its propellers. The adversary effectively reduces the fatigue life of the 3D printed propeller and creates delayed damage during a flight mission. This research illustrates that detecting sabotage attacks in additive manufacturing systems remains a complex research challenge.

b) Radio frequency modules attacks: Radio Frequency (RF) modules serve the purpose of transmitting and receiving radio signals between two distinct devices. In the context of UAVs, an operator typically employs a standard remote controller or the GCS to transmit control signals to the airborne UAVs. In this scenario, a potential adversary has the capability to interfere with the control signals, effectively disrupting the communication between the UAV and GCS, which leads to a situation where the UAVs lose their communication. In [73], the authors illustrated a replay attack targeting the XBee 868LP protocol, which is a low-power radio frequency module used for UAV-to-GCS communications. In this attack, the adversary manipulates the UAV-to-GCS communication by employing a third XBee chip. Specifically, the attacker compromises the security of the primary XBee communication channel by utilizing the chip's existing features to gain access to the address of the XBee communication channel.

c) Battery attack: Commonly, UAVs are powered by rechargeable Lithium-Ion batteries, and these batteries rely on the Battery Management System (BMS) to ensure a consistent energy supply to various UAV components. Nevertheless, there exists a vulnerability where an adversary can exhaust the battery's energy deliberately, a tactic known as a potential battery exhaustion attack [74]. This type of attack can lead to a malfunction of the UAV system, subsequently compromising the availability, integrity, and confidentiality of the batteries [75]. One method by which an attacker can compromise the availability of UAV batteries is by physically tampering with or swapping genuine batteries with faulty ones, thus causing the UAV system to fail. Another potential attack vector involves deep discharging of the batteries, which could be achieved by compromising other UAV components, such as manipulating sensors or injecting malicious software. This could ultimately lead to the exhaustion of UAV batteries [75].

2) Software-based attacks: Regarding software aspects, adversaries can exploit both zero-day vulnerabilities and existing software weaknesses within the flight stack and the GCS software to compromise the success of a flight mission. The importance of software attacks underscores the necessity to create strong defense mechanisms for UAV software security [76]. Nevertheless, existing UAV manufacturers tend to refrain from integrating software security measures into their products primarily for performance-related considerations. Consequently, adversaries can capitalize on this gap to develop malicious software, examples being Maldrone [77], Snoopy [78], and SkyJack [79].

a) Tampering attacks: Attackers deliberately engage in destruction, unauthorized manipulation, or alteration of data through IoD channels. Information, whether in motion or stationary, could be vulnerable to interception and unauthorized alterations. For example, if an unprotected data packet is transmitted over an IoD channel, the attacker might intercept the packet, modify its content, and change its intended destination address [80].

b) Operating system attack: Possible threats to civilian or military missions may manifest through vulnerabilities in the Flight Controller's system software. Consequently, the compromise of the system software can result in the loss of both UAVs and their payloads. An illustration of this risk is evident in the case of Amazon's Prime Air service's parcelcopters, which are civilian applications susceptible to attacks on their operating systems [81]. An attack on the delivery system has the potential to disrupt the delivery package for the intended recipient, subsequently causing the drone to crash. Attacks on UAV operating systems involve the remote injection of malicious software into UAVs, such as in the case of Maldrone, which is then followed by the takeover

of the drone's system. In doing so, the adversary can access the Flight Controller's cryptographic key and steal unencrypted data stored there.

3) Sensor-based attacks: When it comes to sensors, their variety and complexity onboard UAVs (including chemical, physical, mechanical, and others) render them attractive targets for adversaries. Furthermore, the current defenses against spoofing, sniffing, or jamming of these onboard sensors are constrained by the distinctive attributes of UAVs. While existing security research addresses threats and attacks related to sensors, in the context of UAVs, it is imperative to consider supplementary factors such as the legitimacy of sensor data readings and the energy and computational overhead involved in safeguarding sensed data against malicious actors.

a) Falsified data injection attack: Introducing erroneous sensor data readings into the Flight Controller has the potential to compromise external sensors like electro-optical and infrared sensors [82]. This form of attack disrupts the stabilization of the UAV. An attacker can carry out this attack by manipulating the sensor readings in multiple ways. They may gain access to the onboard Flight Controller system or modify sensor data via system calls. Alternatively, the attacker can directly transmit fraudulent signals to the sensors, thereby compromising the UAV's flight. A well-known instance of such an attack is GPS spoofing. Given that GPS signal broadcasts are often unencrypted and lacking authentication, attackers execute spoofing attacks on GPS by generating false signals, which can subsequently manipulate the UAV's GPS receiver [83]. As a result, the attacker can take control of the UAV.

b) Sensor communication channel attack: UAVs rely on a range of sensors, where their sensory channels, such as infrared, acoustic, and light, can potentially be exploited as a pathway for attacks. In [84], the authors provide evidence that UAVs equipped with Micro-Electro-Mechanical Systems (MEMS) gyroscopes can experience failure due to deliberate acoustic interference. This research reveals that MEMS gyroscopes resonate at frequencies within the audible range. Another investigation has demonstrated that optical flow camera sensors, employed to stabilize UAVs, can be rendered ineffective by manipulating the conditions in the surrounding environment [85].

4) Communication-based attacks: In the context of Communication-level considerations, the development of a multi-UAV network necessitates careful attention to potential security challenges aligned with the chosen network topology [86]. Numerous UAV protocols currently lack adequate security measures, presenting significant vulnerabilities. As communication constitutes an essential component of the UAV system, we maintain that the development of standardized UAV protocols that ensure both reliability and security is imperative. Many of the existing communication protocols employed in UAVs lack encryption or possess only limited cryptographic capabilities, thereby exposing communication channels to potential compromise by adversaries. Furthermore, the existing security measures designed to safeguard civilian UAVs from malicious users are primarily tailored to single UAV systems [87]. Hence, there is an imperative need to devise countermeasures suitable for scenarios involving multiple UAVs.

a) Hijacking attacks: When a wireless link is hijacked, the intruder obtains full access to that link. For example, the access and communication links between UAV nodes and GCS are established through Wi-Fi communication. Adversaries may initially employ de-authentication management frames to disconnect a drone from its associated GCS, initiating a hijacking attempt. Subsequently, they can remotely manipulate the drone using IEEE 802.11 protocols. Several security measures can be implemented to counteract de-authentication attacks. This includes practical detection algorithms and the encryption of transmitted frames. In [88], it is suggested that WPA2 encryption (802.11i 2004) with an appropriate key length can serve as a countermeasure to hijacking. Additionally, [89] has shown that encryption with dynamic secret keys provides an extra layer of defense against attackers. Moreover, safeguarding Wi-Fi-connected UAVs can involve limiting access points concealed by MAC addresses, while preventing intruders from accessing Wi-Fi links by not broadcasting SSIDs.

b) Jamming attack: The jamming attack disrupts legitimate communication links and hinders the exchange of information between authorized nodes by emitting interference or jamming signals [90]. In this scenario, the attacker creates interference signals and sends them within the same frequency band, leading to a degradation in Signal-to-Interference-plus-Noise Ratio (SINR) at the intended destination node. This, in turn, affects the reception of the original data and results in a delay in acknowledging the response. The A2G (Air-to-Ground) link of UAVs, which is easily accessible and has a broad coverage area, can be exploited by malicious intruders, whether they are airborne or terrestrial, to jam the communication link. An incident involving GPS jamming is documented in [91], where a small drone crashed in 2012. Initially, the legitimate user was suspected, but later the guilty was identified. Various algorithms have been developed to estimate the likelihood of intrusions and their impact on received data. Enhancing the Signal-to-Noise Ratio (SNR) serves as an effective initial defense against jamming. However, the energy constraints of UAVs limit the transmitted signal power and the practical receiver algorithms that can reduce noise at the receiver.

c) Collusion attacks: When two or more drones operate on the identical frequency, it results in information collisions, leading to an unstable network operation. These collisions are typically a consequence of the limited communication capabilities and constrained computing resources of the IoD network [93].

d) Spoofing attacks: Spoofing attackers introduce falsified identity information into legitimate communication links to manipulate or gain unauthorized access to data. They use misleading signals with elevated power levels to gain control over the source nodes. Common spoofing attacks

encompass activities such as email and phone call interception, IP address spoofing, and cache poisoning of the address resolution protocol. Additionally, GPS spoofing is prevalent in UAVs, involving the transmission of unauthorized high-power signals within the operational frequency band. Consequently, a malicious actor can access personal information, manipulate GPS locations, or propagate a virus within the system through GPS spoofing.

5) Network-based attacks: Maxa et al. surveyed the main security challenges of UAV routing protocols. Additionally, the work proposed by Sharma et al. outlined the security mechanisms for communication and networking technologies of UAVs.

a) Man-In-The-Middle attack: Adversaries have the capability to position malicious UAVs within operational networks, resulting in data breaches, service disruptions, and various security issues. Furthermore, they can intercept communications between a UAV and its GCS, impersonate the GCS, issue misleading directives to terminate an ongoing mission, or potentially take control of the UAVs [94].

b) Denial of Service (DoS) attack: DoS attackers seek to hinder legitimate service users from accessing essential resources. The attacker can flood the server with a substantial volume of requests, leading to network congestion and subsequently preventing legitimate users from accessing services [95].

c) Eavesdropping attack: Eavesdropping attack represents a common security threat in which either aerial or terrestrial intruders covertly intercept confidential information being exchanged between two legitimate nodes. This type of security threat has repercussions on the confidentiality of the information being leaked and grants unauthorized access to both the source and destination nodes, including personal data like access codes, control commands, navigational details, and more. For instance, systems like FANETS and cellular communications are susceptible to attacks by nearby intruders who might be challenging to detect as they do not emit any signals, thus posing a significant security risk to the communication network [96]. Implementing more advanced Physical security mechanisms can serve as a general solution, while additional encryption can provide protection against eavesdropping.

d) Flooding attacks: One primary goal of malicious UAVs is to overwhelm real UAVs with substantial volumes of original or duplicated data packets. This form of assault can exhaust the limited resources of UAVs, such as communication bandwidth and storage capacity, leading to significant network congestion and a surge in traffic across the IoD network [97]. The discussion on cyber-attack types for UAV components will delve into a detailed examination of various forms of cyber threats and vulnerabilities that can potentially target the different components of UAVs in Table III.

TABLE III. CYBERATTACK TYPES FOR UAV COMPONENTS

Attack Component	Attack Type	Security Services
Hardware attack	Supply chain attack	Integrity
	Battery attack	Integrity / availability
	Radio frequency attack	Integrity / availability
Software attack	Operating system attack	Confidentiality / integrity
	Tampering attack	Integrity
	Maldrone attack	Confidentiality / integrity
Sensors attacks	Sensor Communication Channel attack	Confidentiality
	Falsified Data Injection Attack	Integrity
Communication attacks	Jamming Attack	Availability
	GPS Spoofing Attack	Availability/Integrity/Confidentiality
	GCS MITM Attack	Confidentiality/Integrity
	Hijacking Attack	Confidentiality/Integrity
Network attack	MITM Attack	Confidentiality/Integrity
	DoS Attack	Availability
	Brute Force Attack	Confidentiality/Integrity
	SYN Flood Attack	Availability
	Eavesdropping Attack	Confidentiality

The rise of UAV technology created an overflow of cyber attacks. Protecting the flight mission requires a comprehensive defense-in-depth approach. Our finding results from different research indicate that UAVs are vulnerable to a variety of attacks across different levels of security. This vulnerability may arise because manufacturers prioritize improving the performance of their commercial products over security issues. Additionally, the implementation of security measures may potentially face additional costs for manufacturers. Therefore, it is advisable for existing UAV manufacturers to incorporate security and privacy considerations throughout all phases of the supply chain when developing their products.

IV. CURRENT APPROACHES AND DEFENSE STRATEGIES FOR UAV SECURITY

In this section, different existing countermeasures that secure UAVs, against damage from the threats and attacks discussed in the previous section are discussed.

A. Data Protection Using Cryptography

Cryptographic techniques are essential for securing UAV data, including text, images, and video, transmitted over unsecured communication channels such as GPS and Wi-Fi. Encrypting data exchanged through these vulnerable links ensures confidentiality, integrity, and availability. Yoon et al. [98] proposed an asymmetric authentication scheme to verify data authenticity, based on public and private key pairs. In this approach, the UAV encrypts a random sequence with a public key and sends it to the Ground Control Station (GCS), which decrypts and re-encrypts the data before returning it to the UAV. By comparing the received sequence with the original one, the UAV can detect potential security threats. If the link is

secure, commands are accepted; otherwise, the connection is terminated. Despite its effectiveness, this method may incur high bandwidth overhead when handling large data volumes.

Steinmann et al. [99] proposed a security mechanism based on asymmetric cryptography in which encryption keys are dynamically and randomly refreshed, thereby strengthening both data confidentiality and key robustness. Encrypted messages are transmitted together with a hash value, which is validated after decryption using the private key; inconsistencies between the computed and received hashes indicate malicious activity. To reduce computational complexity, Lin et al. [100] introduced a lightweight symmetric encryption scheme that uses a shared secret key for both encryption and decryption, ensuring data confidentiality even if transmissions are intercepted. Sharma et al. investigated functional encryption for UAV networks, enabling selective decryption so that only authorized data components are revealed without exposing the entire message. Moreover, [101] presented a command authentication protocol based on digital signatures, allowing UAVs to execute control instructions solely when verified by the Ground Control Station (GCS); otherwise, the UAV automatically switches to return-to-launch (RTL) mode. Despite their security benefits, many conventional encryption-based solutions remain challenging for real-time UAV operations due to processing delays, computational overhead, and complex key management, which can degrade communication efficiency.

B. Blockchain-Enabled Security Approaches

Blockchain is a shared ledger that uses cryptographic techniques to secure shared data. Along with enhancing UAV security and transparency, and guarantee the integrity of the data.

Ge et al. [102] proposed a distributed blockchain-based framework to secure UAV communications during data collection and transmission, while reducing the risk of attacks caused by compromised or malicious UAVs. Since conventional blockchain solutions impose high computational and bandwidth demands that exceed the limited storage and processing capabilities of UAVs, the authors introduced a lightweight blockchain design that preserves security and privacy with significantly lower overhead. The framework defines multiple transaction types to represent diverse data access operations and employs a novel reputation-driven consensus mechanism to enhance trust within the decentralized network. This architecture enables UAV-enabled applications to securely manage sensor data and support real-time data acquisition while satisfying key security requirements, including integrity, confidentiality, and availability.

Ch et al. [103] introduced a blockchain-driven framework aimed at improving data privacy, secure storage, and distributed access for UAV systems. The proposed solution leverages a cloud infrastructure to store operational commands, UAV feedback, authentication records, and integrity-related metadata. Data confidentiality is ensured through the use of pentatope-based elliptic curve cryptography combined with the SHA hashing protocol. Subsequently, the secured data are recorded on an Ethereum-based public blockchain to support transparent and efficient transactions. Experimental results indicate that the proposed architecture effectively safeguards UAV data against a wide range of cyber threats.

Garcia-Magariño et al. [104] presented a blockchain-based security framework that employs asymmetric cryptography to identify falsified data produced by compromised UAVs. Within this model, an attacked UAV may generate incorrect alerts or fail to report valid observations. However, system robustness is preserved through collaboration among neighboring UAVs, which can detect anomalies and mitigate the impact of malicious nodes. This resilience is supported by a secure digital signature mechanism that ensures data authenticity and trustworthiness. Experimental evaluations confirmed that the proposed approach maintains reliable performance even when a limited number of UAVs are compromised.

Khan et al. [105] introduced a blockchain-enabled framework that integrates machine learning for collaborative intrusion detection. The proposed system follows a two-phase process: initially, each network node independently applies an ML-based detector, after which the locally trained models are shared and combined across the blockchain network using a stacking strategy. Experimental results demonstrated that this collaborative model aggregation significantly enhances overall intrusion detection accuracy.

C. Rules-Based UAV Security

In rule-based methods, engineers establish a set of predefined rules and monitor UAV behavior, checking for deviations that may indicate potential threats. Nevertheless, this approach has seen limited adoption in recent years compared to other security strategies.

Sedjelmaci et al. [106] proposed a rule-based approach to distinguish between authenticated and unauthenticated signals. The method compares signal values against a predefined threshold derived from established rules: signals below the threshold indicate normal UAV operation, while those exceeding it signal potential threats. This technique allows UAVs to detect GPS spoofing and jamming attacks that could jeopardize system availability and data confidentiality. However, the reliance on a fixed threshold limits its effectiveness in dynamic or complex environments.

Lee et al. [107] developed a rule-based system to detect cyberattacks affecting the availability, confidentiality, and integrity of UAV operations. When a rule threshold is exceeded, the system triggers an appropriate defense mechanism. Although a large rule set can increase processing time and potentially delay detection, it helps lower the false negative rate. Similarly, [108] proposed a framework to identify cyber-physical attacks on small unmanned aerial systems (UASs) by analyzing UAV sensors and establishing rules to determine which sensors are most vulnerable to threats that could compromise UAV integrity.

However, rule-based approaches have inherent limitations in detection capabilities and require ongoing maintenance to remain effective. They are often unable to identify complex or novel threats that fall outside the predefined rules, making it necessary to continuously update the rule set to address emerging and evolving attacks.

D. Supervised ML Approaches for UAV Security

Supervised learning is a machine learning (ML) approach that trains models using labeled data to predict or classify new instances, making the quality of training critical for effective threat detection. Manesh et al. applied an artificial neural network (ANN) to safeguard UAV systems against GPS spoofing attacks. Their model utilizes GPS signal features such as Doppler shift, pseudorange, and signal-to-noise ratio (SNR) as inputs, achieving high accuracy in detecting spoofed signals according to experimental results.

Greco et al. [109] developed a supervised learning framework to defend UAV networks against jamming attacks, employing decision trees (DT) and multilayer perceptrons (MLP) as the primary ML techniques. The framework analyzes network metrics such as throughput, received signal strength indicator (RSSI), and packet delivery rate (PDR). It operates in two stages: first, packet sequences are processed to extract relevant features; second, each feature is evaluated independently to enable accurate detection and classification of potential jamming events.

Fenga et al. [110] introduced a two-step GPS spoofing detection approach that combines a Genetic Algorithm (GA) with XGBoost, leveraging data from both the inertial measurement unit (IMU) and GPS. In their experiments, spoofing attacks were simulated using a device that transmitted counterfeit GPS signals, causing the UAV to misinterpret them as authentic. The proposed method achieved a detection accuracy of 96.3%, demonstrating its effectiveness against GPS spoofing.

Shafique et al. [111] proposed a GPS spoofing detection method for UAVs based on analyzing GPS signal features. Incoming signals are classified as authentic or spoofed using various algorithms, including Naive Bayes (NB), linear regression (LR), decision trees (DT), random forest (RF), and support vector machines (SVM), with K-fold cross-validation to determine the most effective classifier. The study reported that SVM with a polynomial kernel achieved the highest accuracy of 98%. Similarly, Manesh et al. [112] explored ML-based techniques to detect jamming attacks on ADS-B receivers. They trained and compared supervised models such as artificial neural networks (ANN), SVM, K-nearest neighbors (KNN), and DT using features like energy statistics, bit error rate, and bad packet ratio, enabling effective differentiation between jamming and authentic signals.

E. UAV Security via Unsupervised Learning

Unsupervised learning is a machine learning approach that identifies patterns or clusters in unlabeled data, addressing a key challenge in UAV intrusion detection systems (IDS) where labeled datasets are often unavailable. This technique can detect both known and unknown cyberattacks, which is critical given that many threats remain undiscovered. However, unsupervised methods often generate a high rate of false alarms. Park et al. [113] developed an IDS using a one-class linear autoencoder trained exclusively on normal flight data. Abnormal UAV behavior was detected by analyzing reconstruction loss, with higher loss values signaling potential intrusions. The study emphasized feature extraction principles based on hardware generality and sensor stability and applied feature engineering to reconcile differences in feature scales and sampling periods. Despite being trained only on benign data, the model successfully identified GPS spoofing and denial-of-service (DoS) attacks during validation.

Panice et al. [114] proposed a GPS spoofing detection method for UAVs that combines machine learning with state estimation. The approach employs a support vector machine (SVM) integrated into a GPS–inertial navigation system (INS) hybrid framework. By analyzing discrepancies between INS and GPS readings, the system identifies abnormal signals and potential intrusions. Key parameters, including window length, threshold, and attack duration, are adjusted to enhance performance and predict the UAV's future sensor values and location. UAV status is classified as normal or abnormal using state estimation as a primary feature. Validation using simulated post-mission data with injected spoofed GPS signals showed a maximum true positive rate of 95%.

Whelan et al. [115] introduced a novelty-based IDS to overcome the lack of labeled UAV-IDS datasets by using unsupervised machine learning classifiers, including one-class SVM (OC-SVM), autoencoder neural networks, and local outlier factor (LOF). Each classifier analyzes data from individual sensors to detect attacks, including previously unseen ones, and to identify the targeted sensor. Models are trained solely on normal UAV behavior, with deviations considered potentially malicious. Experimental results indicated that the autoencoder achieved the highest performance with an F1 score of 94.81%, followed by OC-SVM at 81.17%, while LOF showed the lowest performance with an F1 score of 58.93%.

F. Reinforcement Learning–Based Methods

Reinforcement learning (RL) allows an agent to learn from interactions with its environment through trial and error, identifying actions that lead to positive or negative outcomes. This makes RL particularly suitable for detecting and classifying attacks on UAVs.

Bouhamed et al. [116] proposed a cost-effective intrusion prevention and detection system for UAV swarms, combining deep reinforcement learning (DRL) on UAVs with offline periodic learning at the Ground Control Station (GCS). A deep Q-network (DQN) multiclass classifier was trained using stored normal and intrusion cases, allowing the system to update knowledge without forgetting prior information. Using a customized reward function improved detection of minor classes, achieving 99.7% accuracy, 0.95 precision, 0.97 recall, and a 0.96 F1-score.

Xiao et al. [117] proposed a deep Q-network (DQN)– based power allocation strategy for UAVs to defend against attacks, optimizing safe transmission rate and secrecy capacity. The interaction between UAV and attacker is modeled as a smart attack game, with Nash equilibrium (NE) and prospect theory (PT) guiding optimal responses. The approach achieved a 93% safe transmission rate and a 16% improvement in secrecy capacity over standard Q-learning methods.

Elnaggar and Bezzo [118] applied inverse reinforcement learning (IRL) to predict sensor spoofing attacks in autonomous vehicles. The method estimates the attacker's

intent and identifies compromised sensors, then uses Bayesian IRL (BIRL) to restore system integrity by analyzing measurements and control inputs. The approach leverages optimal Markov decision processes (MDPs) to enhance system security. The authors validated the method through simulations of three UAV navigation scenarios in stochastic environments.

Praveena et al. proposed a deep reinforcement learning (DRL)–based method optimized with the Black Widow Optimization (BWO) algorithm, termed DRL-BWO, for intrusion detection in UAV networks. The approach employs an enhanced deep belief network (DBN) within the DRL framework to identify intrusions, while BWO optimizes DRL hyperparameters to improve performance. Experiments demonstrated high effectiveness, achieving 98% precision, 99% recall, 98% F1-score, and 98% accuracy.

Fei et al. proposed a reinforcement-learning-based flight recovery method for UAVs under cyber-physical attacks. The RL policy works alongside the flight controller, making minimal adjustments during normal operation and rapidly modifying actuator commands during attacks to maintain stability and path tracking. Results showed effective UAV stabilization under attack conditions.

Wang et al. proposed a reinforcement-learning-based energy-efficient anti-jamming relay (REAR) scheme, allowing UAVs to optimize relay power and strategies without prior knowledge of the network or channel model. A hot-starting technique was used to accelerate learning. Simulations with five UAVs under random jamming attacks showed improved communication reliability and reduced energy consumption.

Table IV highlights a taxonomy of the common cyberattacks, the security requirements affected and the methods proposed to defend the UAVs against such attacks.

TABLE IV. OVERVIEW OF SECURITY REQUIREMENTS AFFECTED BY CYBERATTACKS AND CORRESPONDING COUNTERMEASURES

Cyber-Attack	Security requirement affected	Countermeasures	
CPS spoofing	Availability, integrity	Rule- based approach	[106]
		Supervised learning	[109,110,111]
		Unsupervised learning	[113,114]
		Reinforcement learning	[117,118]
Jamming	Integrity	Rule-based approach	[106,107]
		Supervised learning	[109,112]
		Unsupervised learning	[115]
		Reinforcement learning	[117,118]
Eavesdropping	Confidentiality	Cryptographic approach	[100]
		Reinforcement learning	[117]
DoS	Availability	Cryptographic approach	[98]
		Blockchain approach	[105]
		Unsupervised learning	[113]
		Reinforcement learning	[116,118]
Black hole	Availability	Availability	[106]
Grey hole	Availability	Rule-based approach	[106]
MiTM	Authentication, confidentiality and integrity	Cryptographic approach	[101]
		Blockchain approach	[104]
DDOS	Availability	reinforcement learning	[116]

V. CONCLUSION

The surge and rapid expansion in the utilization of UAVs are ushering in an era dominated by self-governing aerial vehicles. UAVs bring forth a multitude of benefits spanning civilian and military domains alike and other application domains. However, this escalating utilization and accessibility have given rise to substantial apprehensions concerning security and privacy. The adaptability, cost-effectiveness, swift deployment, and portability of these Wencheng Yang, Song Wang, Xuefei Yin, Xu Wang, Jiankun Hu, “A Review on Security Issues and Solutions of the Internet of Drones”, IEEE Open Journal of the Computer Society, IEEE, Pages: 96-110, June 2022, transformed them into valuable implements for malicious endeavors. Despite the existence of numerous countermeasures to thwart the malevolent use of UAVs, their efficacy in executing harmful activities remains pronounced. Equally significant are the privacy quandaries intertwined with UAVs. In this era of technology, privacy stands as a prominent concern for both individuals and organizations.

In this study, we have tried to cite the different categories of security solutions for the IoD by highlighting the multifaceted challenges. Authentication-based solutions highlight the critical need to strengthen the security of communications between drones while efficiently managing cryptographic keys, ensuring interoperability, defending against targeted attacks, and scaling against a growing number of devices and users. Encryption-based solutions face challenges in preserving user anonymity, protecting personal data, ensuring interoperability, and maintaining network performance while preserving privacy. Blockchain-based solutions have highlighted the complex challenges of integrating with IoT and 5G, with a focus on coordination, security robustness, and educational adoption. Privacy-based

solutions require addressing vulnerabilities, user awareness, and resource constraints, while balancing security and usability. Intrusion detection systems must adapt to SDN architectures, balance efficiency and accuracy, integrate seamlessly into diverse networks, and scale to combat evolving threats in dynamic drone environments. Addressing these challenges requires innovative, adaptable, and interdisciplinary approaches merging technical prowess, user training, and resource-efficient methodologies to ensure the robustness, longevity, and security of IoD networks.

REFERENCES

[1] Kang, J.H.; Park, K.J.; Kim, H.: in: 2015 International conference on information and communication technology convergence (ICTC) (IEEE, 2015), pp. 533–538

[2] Commission delegated regulation (EU) 2019/945, 2019, Official Journal of the European Union, 12th, Mar.2019, URL https://eur-lex.europa.eu/legal-content/ EN/TXT/?uri=CELEX%3A32019R0945.

[3] Mitka, E.; Mouroutsos, S.G.: Classification of drones. Amer. J. Eng. Res 6, 36–41 (2017).

[4] Arslan Shafique, Abid Mehmood, Mourad Elhadef, "Survey of Security Protocols and Vulnerabilities in Unmanned Aerial Vehicles", IEEE Access, Volume 9, Page: 46927-46948, March 2021.

[5] Wencheng Yang, Song Wang, Xuefei Yin, Xu Wang, Jiankun Hu, "A Review on Security Issues and Solutions of the Internet of Drones", IEEE Open Journal of the Computer Society, IEEE, Pages: 96-110, June 2022 .

[6] Bora Ly, Romny Ly, "Cybersecurity in unmanned aerial vehicles (UAVs)", Journal of Cyber Security Technology, Vol 5, No.2, Page: 120-137, 2021.

[7] Teng Long, Mustafa Ozger, Oktay Cetinkaya, Ozgur B. Akan, "Energy Neutral Internet of Drones", IEEE Communications Magazine, Volume 56, Issue, Page: 22-28, January 2018.

[8] Atherton, K.D.: The FAA says there will be 7 million drones flying over America by 2020. Pop. Sci. (2016)

[9] Nourmohammadi A, Jafari M, Zander TO (2018) A survey on unmanned aerial vehicle remote control using brain–computer interface. IEEE Trans Hum-Mach Syst 48(4):337–348

[10] Kanellakis C, Nikolakopoulos G (2017) Survey on computer vision for UAVs: current developments and trends. J Intell Rob Syst 87(1):141–168

[11] A. Riham, A.M. Youssef, Security, privacy, and safety aspects of civilian drones: A survey, ACM Trans. Cyber-Phys. Syst. 1 (2) (2016).

[12] T.F. Villa, F. Salimi, K. Morton, L. Morawska, F. Gonzalez, Development and validation of a UAV based system for air pollution measurements, Sensors 16 (12) (2016).

[13] M. Aljehani, M. Inoue, A. Watanbe, T. Yokemura, F. Ogyu, H. Iida, UAV communication system integrated into network traversal with mobility, SN Appl. Sci. 2 (2020) 1057.

[14] D. Giordan, M.S. Adams, I. Aicardi, M. Alicandro, P. Allasia, M. Baldo, P.D. Berardinis, D. Dominici, D. Godone, P. Hobbs, V. Lechner, T. Niedzielski, M. Piras, M. Rotilio, R. Salvini, V. Segor, B. Sotier, F. Troilo, The use of unmanned aerial vehicles (UAVs) for engineering geology applications, Bull. Eng. Geol. Environ. 79 (2020) 3437–3481

[15] A. Chriki, H. Touati, H. Snoussi, F. Kamoun, FANET: Communication, mobility models and security issues, Comput. Netw. 163 (2019) 106877

[16] Unmanned aerial systems (UAS), 2020, SKYbrary, 8 December 2020, URL https://www.skybrary.aero/articles/unmanned-aerial-systems-uas

[17] Y.Mekdad et al. A survey on security and privacy issues of UAVs, Computer Networks: The International Journal of Computer and Telecommunications NetworkingVolume 224Issue CApr

[18] Aljehani, M.; Inoue, M.; Watanbe, A.; Yokemura, T.; Ogyu, F.; Iida, H. UAV communication system integrated into network traversal with mobility. SN Appl. Sci. 2020, 2, 2749.

[19] Different Types of Drones. Available online: https://dronepedia.xyz/5-different-types-of-drones/ (accessed on 1 April 2022).

[20] Tahir A, Böling J, HaghbayanMH, Toivonen HT, Plosila J (2019) Swarms of unmanned aerial vehicles—a survey. J Ind Inf Integr 16:100106

[21] Thato Elijah, Rodrigo S Jamisola, Zeundjua Tjiparuro, and Molaletsa Namoshe. A review on control and maneuvering of cooperative fixed-wing drones. Int. Jour. of Dynamics and Control, 9 (3) :1332–1349, 2021

[22] Sheng WEN, Jie HAN, Yubin LAN, Xuanchun YIN, Yuhua LU (2018) Influence of wing tip vortex on drift of single rotor plant protection unmanned aerial vehicle. Nongye Jixie Xuebao/Trans Chin Soc Agric Mach 49(8)

[23] Ahmed Bahabry, Xiangpeng Wan, Hakim Ghazzai, Gregg Vesonder, and Yehia Massoud. Collision-free navigation and efficient scheduling for fleet of multi-rotor drones in smart city. In 2019 IEEE 62nd Int. Midwest Symposium on Circuits and Systems (MWSCAS), pages 552–555. IEEE, 2019.

[24] Davide Todeschini, Lorenzo Fagiano, Claudio Micheli, and Aldo Cattano. Control of vertical take-off, dynamic flight and landing of hybrid drones for airborne wind energy systems. In 2019 American control conference (ACC), pages 2177–2182. IEEE, 2019

[25] Pilot, What's the Difference Between Drones, UAV, and UAS? Definitions and Terms. Pilot Institute. 22 March 2020. Available online: https://pilotinstitute.com/drones-vs-uav-vs-uas/ (accessed on 18 August 2022).

[26] Ghulam E. Mustafa et al. Comprehensive Review of UAV Detection, Security, and Communication Advancements to Prevent Threats, Journal Drones, Volume 6, Issue number 10, Oct 2022

[27] Fotouhi, A.; Qiang, H.; Ding, M.; Hassan, M.; Giordano, L.G.; Garcia-Rodriguez, A.; Yuan, J. Survey on UAV Cellular Communications: Practical Aspects, Standardization Advancements, Regulation, and Security Challenges. IEEE Commun. Surv. Tutorials 2019, 21, 3417–3442

[28] El Haber, E.; Alameddine, H.A.; Assi, C.; Sharafeddine, S. UAV-aided ultra-reliable low-latency computation offloading in future IoT networks. IEEE Trans. Commun. 2021, 69, 6838–6851.

[29] Wang, L.; Che, Y.L.; Long, J.; Duan, L.; Wu, K. Multiple access mmWave design for UAV-aided 5G communications. IEEE Wirel. Commun. 2019, 26, 64–71

[30] Che, Y.; Lai, Y.; Luo, S.; Wu, K.; Duan, L. UAV-aided information and energy transmissions for cognitive and sustainable 5G networks. IEEE Trans. Wirel. Commun. 2020, 20, 1668–1683

[31] Fotouhi, A.; Ding, M.; Hassan, M. Understanding autonomous drone maneuverability for Internet of Things applications. In Proceedings of the 2017 IEEE 18th International Symposium on A World of Wireless, Mobile and Multimedia Networks (WoWMoM), Macau, China, 12–15 June 2017; pp. 1–6

[32] Giyenko, A.; Im Cho, Y. Intelligent UAV in smart cities using IoT. In Proceedings of the 2016 16th International Conference on Control, Automation and Systems (ICCAS), Gyeongju, Korea, 16–19 October 2016; pp. 207–210.

[33] Feng, W.; Wang, J.; Chen, Y.; Wang, X.; Ge, N.; Lu, J. UAV-aided MIMO communications for 5G internet of things. IEEE Internet Things J. 2018, 6, 1731–1740.

[34] Motlagh, N.H.; Taleb, T.; Arouk, O. Low-altitude unmanned aerial vehicles-based internet of things services: Comprehensive survey and future perspectives. IEEE Internet Things J. 2016, 3, 899–922.

[35] Sharma, A.; Vanjani, P.; Paliwal, N.; Basnayaka, C.M.; Jayakody, D.N.K.; Wang, H.-C.; Muthuchidambaranathan, P. Communication and networking technologies for UAVs: A survey. J. Netw. Comput. Appl. 2020, 168, 102739

[36] Ullah, H.; Nair, N.G.; Moore, A.; Nugent, C.; Muschamp, P.; Cuevas, M. 5G Communication: An Overview of Vehicle-to-Everything, Drones, and Healthcare Use-Cases. IEEE Access 2019, 7, 37251–37268

[37] Luo, C.; Miao, W.; Ullah, H.; McClean, S.; Parr, G.; Min, G. Unmanned aerial vehicles for disaster management. In Geological Disaster Monitoring Based on Sensor Networks; Springer: Singapore, 2019; pp. 83–107.

[38] V. Puri, A. Nayyar, and L. Raja, "Agriculture drones: A modern breakthrough in precision agriculture," Journal of Statistics and Management Systems, vol. 20, no. 4, pp. 507–518, 2017.

[39] U. R. Mogili and B. Deepak, "Review on application of drone systems in precision agriculture," Procedia computer science, vol. 133, pp. 502–509, 2018.

[40] S. Ahirwar, R. Swarnkar, S. Bhukya, and G. Namwade, "Application of drone in agriculture," International Journal of Current Microbiology and Applied Sciences, vol. 8, no. 01, pp. 2500–2505, 2019

[41] S. E. Kreps and G. P. Wallace, "International law, military effectiveness, and public support for drone strikes," Journal of Peace Research, vol. 53, no. 6, pp. 830–844, 2016

[42] G. S. L. K. Chand, M. Lee, and S. Y. Shin, "Drone based wireless mesh network for disaster/military environment," Journal of Computer and Communications, vol. 6, no. 04, p. 44, 2018.

[43] J. Q. Cui, S. K. Phang, K. Z. Ang, F. Wang, X. Dong, Y. Ke, S. Lai, K. Li, X. Li, and F. Lin, "Drones for cooperative search and rescue in post-disaster situation," in 2015 IEEE 7th international conference on cybernetics and intelligent systems (CIS) and IEEE conference on robotics, automation and mechatronics (RAM). IEEE, 2015, Conference Proceedings, pp. 167–174.

[44] C. Van Tilburg, "First report of using portable unmanned aircraft systems (drones) for search and rescue," Wilderness environmental medicine, vol. 28, no. 2, pp. 116–118, 2017

[45] S. Mayer, L. Lischke, and P. W. Wo´zniak, "Drones for search and rescue," in 1st International Workshop on Human-Drone Interaction, 2019, Conference Proceedings

[46] Y. Karaca, M. Cicek, O. Tatli, A. Sahin, S. Pasli, M. F. Beser, and S. Turedi, "The potential use of unmanned aircraft systems (drones) in mountain search and rescue operations," The American journal of emergency medicine, vol. 36, no. 4, pp. 583–588, 2018

[47] Menouar H, Guvenc I, Akkaya K, Uluagac AS, Kadri A, Tuncer A (2017) UAV-enabled intelligent transportation systems for the smart city: applications and challenges. IEEE Commun Mag 55(3):22–28

[48] Shakhatreh H, Sawalmeh AH, Al-Fuqaha A, Dou Z, Almaita E, Khalil I et al (2019) Unmanned aerial vehicles (UAVs): a survey on civil applications and key research challenges. IEEE Access 7:48572–48634

[49] Elloumi M, Dhaou R, Escrig B, Idoudi H, Saidane LA (2018) Monitoring road traffic with a UAV-based system. In: 2018 IEEE wireless communications and networking conference (WCNC). IEEE, pp 1–6.

[50] Pulsiri N, Vatananan-Thesenvitz R (2021) Drones in emergency medical services: a systematic literature review with bibliometric analysis. Int J Innov Technol Manag 18(04):2097001

[51] Hosseini, N.; Jamal, H.; Haque, J.; Magesacher, T.; Matolak, D.W. UAV Command and Control, Navigation and Surveillance: A Review of Potential 5G and Satellite Systems. In Proceedings of the 2019 IEEE Aerospace Conference, Big Sky, MT, USA, 2–9 March 2019; pp. 1–10.

[52] IvyPanda, Unmanned Aerial Vehicles Essay. 13 January 2020. Available online: https://ivypanda.com/essays/unmanned aerialvehicles- essay/ (accessed on 20 December 2020).

[53] M. Krichen et al. Security Challenges for Drone Communications: Possible Threats, Attacks and Countermeasures, 2022 2nd International Conference of Smart Systems and Emerging Technologies (SMARTTECH), 04 August 2022

[54] Q. Abu Al-Haija, A. Al Badawi, High-performance intrusion detection system for networked UAVs via deep learning, Neural Computing and Applications (2022) 34:10885–10900, 21 February 2022.

[55] Rivest, R., Shamir, A., & Adleman, L. (1978). A Method for Obtaining Digital Signatures and Public-Key Cryptosystems. Communications of the ACM, 21(2), 120-126

[56] D. Harkins, D. Carrel. (2005). The Internet Key Exchange (IKE). RFC 4306.

[57] Dierks, T., & Rescorla, E. (2008). The Transport Layer Security (TLS) Protocol Version 1.2. RFC 5246

[58] IEEE 802.11 Working Group. [Online] Available: https://standards.ieee.org/committee/802.11.html

[59] N. Ahmad1, L. Mei Wei1, M. Hairol Jabbar, Advanced Encryption Standard with Galois Counter Mode using Field Programmable Gate Array, 1st International Conference on Green and Sustainable Computing (ICoGeS) 2017.

[60] Ö. KANAT, The Significance of Unmanned Aerial Vehicles (UAVs) in Strategic Contexts, Journal of Anadolu Strategy, 26.12.2023

[61] G. Bertoli, L.A. Pereira, O.Saotome, Classification of Denial of Service Attacks on Wi-Fi-based Unmanned Aerial Vehicle, 2021 10th Latin-American Symposium on Dependable Computing (LADC), 17 January 2022

[62] R. Fotohi, Securing of Unmanned Aerial Systems (UAS) Against Security Threats Using Human Immune System, Reliability Engineering and System Safety ,Volume 193, January 2020, 106675

[63] K. Yongho et al. Drone Secure Communication Protocol for Future Sensitive Applications in Military Zone, Sensors (Basel), 2021 Mar 15;21(6):2057. doi: 10.3390/s21062057.

[64] M. Rodrigues et al. Authentication Methods for UAV Communication, 2019 IEEE Symposium on Computers and Communications (ISCC), June 2019

[65] Y. Aydin et al. Authentication and Handover Challenges and Methods for Drone Swarms, IEEE JOURNAL OF RADIO FREQUENCY IDENTIFICATION, January 2022

[66] H. Jalil Al hadi *et al*. A comprehensive survey on security, privacy issues and emerging defence technologies for UAVs, Journal of Network and Computer Applications, Volume 213, April 2023, 103607.

[67] E. Ntizikira *et al*. Secure and Privacy-Preserving Intrusion Detection and Prevention in the Internet of Unmanned Aerial Vehicles, Sensors 2023, *23*(19), 8077; 25 September 2023

[68] G. Choudhary, V. Sharma, T. Gupta, J. Kim, I. You, Internet of Drones (IoD): Threats, Vulnerability, and Security Perspectives, in MobiSec 2018: The 3rd International Symposium on Mobile Internet Security, Cebu, Philippines, 2018

[69] H. N.Noura, O. Salman, A. Chehab and R. Couturier, DistLog: A distributed logging scheme for IoT forensics, Ad Hoc Netw., 98 (2020), 102061. https://doi.org/10.1016/j.adhoc.2019.102061

[70] R. S. Cohen, The Drone Zappers, Air Force Magazine, 22 March 2019. Available: https://www.airforcemag.com/article/the-drone-zappers

[71] O.Ceviz, P. Sadioglu, S. Sen, Survey of Security in UAVs and FANETs: Issues, Threats, Analysis of Attacks, and Solutions, eprint arXiv:2306.14281, June 2023.

[72] S. Belikovetsky, M. Yampolskiy, J. Toh, J. Gatlin, Y. Elovici, dr0wned-Cyber-Physical Attack with Additive Manufacturing, in: 11th USENIX Workshop on Offensive Technologies (WOOT 17), 2017

[73] N. Rodday, Hacking a Professional Drone, Black Hat Asia. URL https://www.blackhat.com/docs/asia-16/materials/ asia-16-Rodday-Hacking-A-Professional-Drone.pdf

[74] V. Desnitsky, I. Kotenko, Simulation and assessment of battery depletion attacks on unmanned aerial vehicles for crisis management infrastructures, Simulation Modelling Practice and Theory 107. doi: 10.1016/j.simpat.2020.102244.

[75] A. B. Lopez, K. Vatanparvar, A. P. Deb Nath, S. Yang, S. Bhunia, M. A. Al Faruque, A security perspective on battery systems of the internet of things, Journal of Hardware and Systems Security 1 (2) (2017) 188–199.

[76] O.Ceviz, P. Sadioglu, S. Sen, Survey of Security in UAVs and FANETs: Issues, Threats, Analysis of Attacks, and Solutions, eprint arXiv:2306.14281, June 2023

[77] P. Paganini, A hacker developed maldrone, the first malware for drones, (Online; Accessed 2 April 2022) (2015). URL https://securityaffairs.co/wordpress/32767/hacking/ maldrone-malware-for-drones.html

[78] (Online; Accessed 2 April 2022). URL https://money.cnn.com/2014/03/20/technology/security/ drone-phone/index.html

[79] J. Crook, Infamous Hacker Creates SkyJack To Hunt, Hack, And Control Other Drones, Tech. rep. (2013).

[80] E. Deligne, Ardrone corruption, Journal in Computer Virology 8 (1) (2012) 15–27.

[81] Amazon.com Inc., Revising the Airspace Model for the Safe Integration of Small Unmanned Aircraft Systems, NASA UTM 2015: The Next Era of Aviation (1) (2015) 2–5.

[82] E. Deligne, "ARDrone corruption," Journal in Computer Virology, vol. 8, no. 1-2, pp. 15–27, 2012

[83] K. Wesson and T. Humphreys, "Hacking drones," Scientific American, vol. 309, no. 5, pp. 54–59, 2013

[84] Y. Son, H. Shin, D. Kim, Y. Park, J. Noh, K. Choi, J. Choi, and Y. Kim, "Rocking drones with intentional sound noise on gyroscopic sensors," Proceedings of the 24th USENIX Security Symposium, pp. 881–896, 2015

[85] D. Davidson, H. Wu, R. Jellinek, T. Ristenpart, and V. Singh, "Controlling UAVs with sensor input spoofing attacks," 10th USENIX Workshop on Offensive Technologies, WOOT 2016, 2016

[86] [86] O.Ceviz, P. Sadioglu, S. Sen, Survey of Security in UAVs and FANETs: Issues, Threats, Analysis of Attacks, and Solutions, eprint arXiv:2306.14281, June 2023

[87] Y. Zhi, Z. Fu, X. Sun, and J. Yu, "Security and Privacy Issues of UAV: A Survey," Mob. Networks Appl., vol. 25, no. 1, pp. 95–101, 2020

[88] D. He, S. Chan, and M. Guizani, ``Communication security of unmanned aerial vehicles," IEEE Wireless Commun., vol. 24, no. 4, pp. 134_139, Aug. 2017

[89] C. Javali, G. Revadigar, M. Ding, and S. Jha, ``Secret key generation by virtual link estimation," in Proc. 10th EAI Int. Conf. Body Area Network

[90] A. Mpitziopoulos, D. Gavalas, C. Konstantopoulos, and G. Pantziou, ``A survey on jamming attacks and countermeasures in WSNs," IEEE Commun. Surveys Tuts., vol. 11, no. 4, pp. 42_56, 4th Quart., 2009

[91] C. G. L. Krishna and R. R. Murphy, ``A review on cybersecurity vulnerabilities for unmanned aerial vehicles," in Proc. IEEE Int. Symp. Saf., Secur. Rescue Robot. (SSRR), Oct. 2017, pp. 194_199.

[92] A. Kumar, R. Krishnamurthi, A. Nayyar, A. K. Luhach, M. S. Khan, and A. Singh, "A novel software-defined drone network (SDDN)-based collision avoidance strategies for on-road traffic monitoring and management," Veh. Commun., vol. 28, 2021, Art. no. 100313

[93] M. H. Yilmaz and H. Arslan, ``A survey: Spoo_ng attacks in physical layer security," in Proc. IEEE 40th Local Comput. Netw. Conf.Workshops (LCN Workshops), Oct. 2015, pp. 812_817.

[94] Y. Li and C. Pu, "Lightweight digital signature solution to defend micro aerial vehicles against man-in-the-middle attack," in Proc. IEEE 23rd Int. Conf. Comput. Sci. Eng., 2020, pp. 92–97

[95] A. Fotouhi et al., "Survey on UAV cellular communications: Practical aspects, standardization advancements, regulation, and security challenges," IEEE Commun. Surv. Tuts., vol. 21, no. 4, pp. 3417–3442, Oct.–Dec. 2019.

[96] N.Wang, P.Wang, A. Alipour-Fanid, L. Jiao, and K. Zeng, ``Physical-layer security of 5G wireless networks for IoT: Challenges and opportunities," IEEE Internet Things J., vol. 6, no. 5, pp. 8169_8181, Oct. 2019.

[97] C. Pu and P. Zhu, "Defending against flooding attacks in the internet of drones environment," in Proc. IEEE Glob. Commun. Conf., 2021, pp. 1–6.

[98] M. Yahuza et al., "Internet of drones security and privacy issues: Taxonomy and open challenges," IEEE Access, vol. 9, pp. 57243–57270, 2021

[99] H. Sedjelmaci, S. M. Senouci, and N. Ansari, "A hierarchical detection and response system to enhance security against lethal cyber-attacks in uav networks," IEEE Transactions on Systems, Man, and Cybernetics: Systems, 2017.

[100] M. A. Siddiqi, W. Pak, Optimizing Filter-Based Feature Selection Method Flow for Intrusion Detection System, Electronics, 9 (2020), 2114. https://doi.org/10.3390/electronics9122114

[101] S. Hussain, S. A. Chaudhry, O. A. Alomari, M. H. Alsharif, M. K. Khan, and N. Kumar, "Amassing the security: An ECC-based authentication scheme for internet of drones," IEEE Syst. J., vol. 15, no. 3, pp. 4431–4438, Sep. 2021.

[102] M. Nikooghadam, H. Amintoosi, S. H. Islam, and M. F. Moghadam, "A provably secure and lightweight authentication scheme for internet of drones for smart city surveillance," J. Syst. Architecture, vol. 115, 2021, Art. no. 101955.

[103] N. Zhang, Q. Jiang, L. Li, X. Ma, and J. Ma, "An efficient three-factor remote user authentication protocol based on BPV-FOURQ for internet of drones," Peer-to-Peer Networking and Applications, vol. 14, no. 5, pp. 3319–3332, 2021.

[104] Y. Zhang, D. He, L. Li, and B. Chen, "A lightweight authentication and key agreement scheme for internet of drones," Comput. Commun., vol. 154, pp. 455–464, 2020

[105] Lindqvist J, et al. Privacy-preserving 802.11 access-point discovery. In: Proceedings of the second ACM conference on wireless network security, 2005, pp.123–130.

[106] Herbadji, A.; Goumidi, H.; Harbi, Y.; Medani, K.; Aliouat, Z.: Blockchain for internet of vehicles security. Blockchain Cybersecur. Priv.: Archit. Chall. Appl. 1, 159–197 (2020)

[107] B. Bera, D. Chattaraj, and A. K. Das, "Designing secure blockchainbased access control scheme in IoT-enabled internet of drones deployment," Comput. Commun., vol. 153, pp. 229–249, 2020

[108] C. Feng, B. Liu, Z. Guo, K. Yu, Z. Qin, and K.-K. R. Choo, "Blockchain-based cross-domain authentication for intelligent 5Genabled internet of drones," IEEE Internet Things J., vol. 9, no. 8, pp. 6224–6238, Apr. 2022.

[109] Wang, W.; Huang, H.; Zhang, L.; Su, C. Secure and efficient mutual authentication protocol for smart grid under blockchain. Peer-to-Peer Netw. Appl. 2020, 14, 2681–2693

[110] Zhang, L.; Zhang, Z.;Wang,W.; Jin, Z.; Su, Y.; Chen, H. Research on a Covert Communication Model Realized by Using Smart Contracts in Blockchain Environment. IEEE Syst. J. 2021, 16, 2822–2833

[111] C.-Y. Tseng, P. Balasubramanyam, C. Ko, R. Limprasittiporn, J. Rowe, and K. Levitt, "A specification-based intrusion detection system for AODV," in Proceedings of the 1st ACM workshop on Security of ad hoc and sensor networks, 2003, pp. 125–134.

[112] V. Vaidya, "Dynamic signature inspection-based network intrusion detection," Aug. 2001, US Patent 6,279,113.

[113] A. Patcha and J.-M. Park, "An overview of anomaly detection techniques: Existing solutions and latest technological trends," Computer networks, vol. 51, no. 12, pp. 3448–3470, 2007

[114] M. A. Aydın, A. H. Zaim, and K. G. Ceylan, "A hybrid intrusion detection system design for computer network security," Computers & Electrical Engineering, vol. 35, no. 3, pp. 517–526, 2009.

[115] E. Biermann, E. Cloete, and L. M. Venter, "A comparison of intrusion detection systems," Computers & Security, vol. 20, no. 8, pp. 676–683, 2001.

[116] G. Choudhary, V. Sharma, I. Chen, J. Cho, Intrusion Detection Systems for Networked Unmanned Aerial Vehicles: A Survey, 2018 14th International Wireless Communications & Mobile Computing Conference (IWCMC), 30 August 2018.

[117] L. Kou, S. Ding, T. Wu, W, Dong, Y. Yin, An Intrusion Detection Model for Drone Communication Network in SDN Environment, *Drones* 2022, *6*(11), 342; 4 November 2022.

[118] R. Shrestha, A. Omidkar, S. Roudi, R. Abbas, S. Kim, Machine-Learning-Enabled Intrusion Detection System for Cellular Connected UAV Networks, *Electronics* 2021, *10*(13), 1549; 26 June 2021

Relationship Management System: A Data-Driven Framework for Modeling, Monitoring, and Restoring Human–AI Relationships

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***Abstract*—We present the Relationship Management System (RMS) a modular framework for modeling, monitoring, and repairing human AI relationships. Grounded in Knapp's Relational Development Model and Social Penetration Theory, RMS operationalizes ten stages of relationship growth and decline, linking depth of disclosure with stage-appropriate behavior. An Airtable-backed schema Relationship Stages, Conversational Arcs, Session Directives) separates master content from user-specific state. A Trust Evaluator quantifies trust, engagement, and disclosure after each session and drives stage transitions. A weighted Regression Risk Score anticipates degradation by tracking shifts in trust, drops in engagement and frequency, patterns of topic avoidance, and conflict cues. When risk climbs, RMS activates empathy centered Recovery Arcs that acknowledge strain and guide repair. This two way, data-informed loop delivers early warning, adjusts pacing to context, and offers gentle offramps when needed improving long-term engagement while preserving interpretability and keeping operational costs low.**

***Keywords*—Human-AI interaction; relationship modeling; trust dynamics; conversational systems; affective computing; regression detection; recovery protocols**

I. Introduction

Conversations with machines have changed quietly but profoundly over the past decade. What once felt transactional—asking for the weather, setting a timer, or looking up a fact—has become something closer to routine companionship. Many people now return to the same conversational agents every day. They expect these systems to remember past exchanges, maintain a steady tone, and offer a hint of empathy. Over time, these interactions start to feel less like brief transactions and more like relationships that accumulate shared context. A satisfying interaction is no longer measured only by accuracy or speed, but by whether the user feels recognized, respected, and emotionally understood.

Most dialogue systems, however, are not designed for that kind of continuity. They are tuned for short-term efficiency: one prompt, one answer, and a clean reset. When a user's tone shifts, when replies shorten, or when emotional openness fades, the system often proceeds as if nothing has changed. In human relationships, such small variations are often the first signals of distance or discomfort. In conversation with a machine, they typically go unnoticed until the user quietly disengages.

The Relationship Management System (RMS) was created to fill this gap. It views every exchange as part of a longer narrative between a person and an agent. Rather than treating dialogue as a flat series of turns, RMS models it as a relationship that can deepen, plateau, or decline. The framework draws from classic theories in interpersonal communication—particularly *Knapp's Relational Development Model* and *Social Penetration Theory*—to trace how trust, emotional closeness, and openness evolve through recognizable stages. These stages help the system read subtle cues—topic changes, emotional withdrawal, or conversational avoidance—as meaningful signs of movement in the relationship rather than random noise.

RMS follows a modular, interpretable architecture. It separates reusable dialogue logic from user-specific relational data, making it easier to analyze and refine. Each user's trajectory is preserved across sessions so that long-term shifts become visible. At its center lies the Trust Evaluator, which computes three interpretable metrics—trust, engagement, and self-disclosure based on behavioral patterns such as turn-taking balance, sentiment, and frequency of interaction. A complementary Regression Risk Score monitors signs of deterioration. When this risk increases, RMS launches an appropriate *Recovery Arc* a conversational strategy designed to acknowledge strain, rebuild rapport, and restore connection.

This design offers several advantages. First, RMS functions as an *early warning system*, flagging relational risks before users withdraw completely. Second, it enables *context-aware pacing*, helping the agent adjust tone, depth, and emotional range to match the current stage of the relationship. Third, it remains *transparent and explainable*: its behavior is driven by interpretable signals and explicit logic that researchers can inspect, critique, and improve.

The contributions of the paper are as follows:

- A theory-informed framework for modeling how human–agent relationships form, evolve, and sometimes decline.
- A lightweight Trust Evaluator and composite Regression Risk Score that quantify relational health through behavioral evidence.
- A modular library of *Recovery Arcs*—structured yet flexible approaches to restoring trust and re-engaging users.
- A scalable system design that separates conversational content from relational state, enabling rapid experimentation, A/B testing, and deployment.

By treating dialogue as a relationship that develops over time, RMS moves conversational agents closer to behaving like attentive partners—able to notice when distance grows, to pause and repair, and to grow alongside the people who rely on them.

II. Related Work

A. Interpersonal Relationship Theories and Disclosure

RMS is grounded in well–established accounts of how relationships take shape, deepen, strain, and end. *Knapp's Relational Development Model* describes movement through ten recognizable stages—ranging from early initiation to bonding, and later differentiation and termination—emphasizing that progress is not strictly linear and that partners can pause, cycle, or reverse course [1], [2]. *Social Penetration Theory* (SPT) frames closeness as a function of self-disclosure that expands in both breadth (topics) and depth (intimacy) [3]. A substantial literature links appropriate disclosure to liking and perceived relationship quality [4], [5], [6]. Communication Privacy Management extends this view by showing how people regulate boundaries around private information, negotiate co-ownership, and manage dialectical tensions between openness and protection [7]. Complementary perspectives on trust and commitment, including investment-based models, explain why partners persist, when they repair, and what motivates accommodation during conflict [8], [9], [10]. Work in marital science adds concrete warning signs and repair cues: contempt, stonewalling, and diffuse physiological arousal predict dissolution and guide targeted interventions [11], [12].

RMS operationalizes these insights in three ways. First, it maps Knapp's stages to a compact state representation that tracks relational movement across sessions; transitions are inferred from observable behaviors rather than assumed from task success alone. Second, it uses SPT as the basis for disclosure features: changes in topical breadth, depth, and reciprocity inform the system's estimates of trust and engagement, while Communication Privacy Management principles constrain prompts so that any request for personal information respects boundary cues and previously negotiated rules. Third, it incorporates commitment and marital-science predictors into risk estimation and repair: indicators such as withdrawal, contempt-like language, or rising arousal proxies contribute to a regression score, which in turn selects a suitable recovery strategy (e.g., de-escalation, validation, or paced re-engagement). Together, these theories give RMS a principled vocabulary for detecting when a relationship is strengthening or slipping, and a structured path for restoring it when needed.

B. Trust in Automation and Human–AI/Robot Interaction

A large literature addresses how people calibrate reliance on automated and autonomous systems. Foundational frameworks and empirical syntheses emphasize design features, performance history, transparency, and user traits as antecedents to trust dynamics [13], [14], [15]. Meta-analytic work in human–robot interaction confirms that trust is malleable and recoverable with targeted strategies, underscoring the need for ongoing monitoring [16]. In mixed-initiative teams, trust repair is crucial for sustained collaboration [17]. RMS operationalizes these insights in a longitudinal pipeline (Trust Evaluator $\rightarrow$ stage transitions $\rightarrow$ recovery).

C. Affective Computing, Social Responses to Media, and Relational Agents

Affective computing established that systems should sense and respond to emotion to maintain rapport [18]. Decades of evidence show that people apply social heuristics to computers (*media equation*) [19], [20]. Embodied and relational agents demonstrate that carefully designed social dialogue can sustain long-term alliances, adherence, and engagement [21], [22], [23], [24]. Large-scale social chat systems such as XiaoIce exhibit the value of empathy and persona consistency for enduring bonds [25], [26]. RMS leverages these traditions but adds explicit stage- and risk-aware control to govern depth and repair.

D. Personalization, Alignment, and Memory in Conversational AI

Personalization progressed from scripted personas to neural persona conditioning [27], [28] and large-scale open-domain chat [29]. Alignment methods—including RLHF and related techniques—shape agent behavior toward helpfulness and safety [30], [31], while LaMDA highlights dialog-quality criteria (safety, groundedness, interestingness) at scale [32]. Outside dialogue, user modeling and recommendation offer mechanisms for preference memory and longitudinal adaptation [33],[34]. RMS complements these directions with an interpretable state machine over relationship stages, depth bands, and recovery arcs, decoupling master content from per-user state to support controlled evolution.

E. Measuring Conversation Quality, Depth, and Affect

Conversation quality is multi-dimensional and benefits from human-centered evaluation taxonomies [35], [36]. Lightweight psycholinguistic and sentiment tools (e.g., LIWC, VADER, NRC) can proxy depth and valence [37], [38], [39], [40], while transformer encoders enable robust discourse features for longitudinal analytics [41]. RMS integrates such signals to estimate trust, engagement, and disclosure depth per session, feeding rule-based transitions that regulate pacing.

F. Engagement Dynamics, Churn Risk, and Just-in-Time Interventions

Engagement decays over time, often nonlinearly; customer and retention analytics provide models and features transferrable to conversational settings [42], [43], [44]. Conceptual frameworks in HCI define engagement as a process with cognitive, emotional, and temporal components [45]. In mobile health, JITAIs emphasize timing- and context-sensitive interventions to prevent attrition [46]. RMS adapts these insights via a weighted *Regression Risk Score* that fuses trust decline, engagement/frequency drops, topic avoidance, and conflict incidents, triggering targeted recovery protocols before termination.

G. Repair, Apology, and Relational Recovery

Repair behaviors—apology, accountability, validation, and concrete commitments—are central to trust restoration [47], [48]. Clinical communication research underscores empathy and unconditional positive regard as foundations for repair

[49]. Historical and sociological accounts dissect apology as ritual and moral practice [50], [51]. RMS encodes these strategies as *Recovery Arcs* with explicit tactics and success criteria (e.g., trust rebound ≥ 0.5, re-engagement on previously avoided topics).

H. Explainability, Safety, and Ethics

Responsible AI requires transparency, user control, and harm mitigation, particularly for persuasive or relational systems [52], [53], [54]. Explainable AI shows that user-understandable reasons can stabilize trust during errors or corrective actions [55]. RMS aligns with these imperatives by 1) making relational state explicit and auditable, 2) enabling graceful termination when recovery fails, and 3) constraining disclosure depth via theory-grounded rules.

I. Synthesis and Gaps

Across communication theory, trust calibration, affective computing, alignment, and engagement analytics, prior work offers mechanisms for *progress* (self-disclosure, trust accrual, personalization) and *decline* (avoidance, frequency drop, conflict). What is missing is a *unified, interpretable, and operational* framework that 1) represents relationship state with stage- and depth-awareness, 2) continuously measures health with longitudinal signals, and 3) executes targeted, theory-informed recovery before churn. RMS advances this agenda by 1) integrating Knapp's stages and SPT depth into a controllable state machine, 2) coupling interpretable trust/engagement/disclosure estimators to rule-based transitions, and 3) deploying reusable recovery arcs that implement evidence-based repair with measurable outcomes.

III. Proposed Framework

A. System Overview

The Relationship Management System (RMS) (see Fig. 1 and Fig. 2) treats conversation as a regulated, measurable relationship. It comprises three cooperating services and a low-code content layer:

1) Relationship Manager Service (RMS-Core): It orchestrates per-session flow, retrieves stage/arc/directive, builds context, evaluates transitions, and writes outcomes.
2) Trust Evaluator Service: It computes longitudinal indicators per session—*trust level* $\tau_t \in [0, 10]$, *engagement* $e_t \in [0, 10]$, and *disclosure depth* $d_t \in [1, 10]$—from linguistic, behavioral, and temporal features.
3) Conversational Agent (LLM): It generates responses using a 4-layer context (stage $\rightarrow$ arc $\rightarrow$ directive $\rightarrow$ memory), with guardrails for depth, tone, and safety.
4) Airtable Master Content & User Store: It master schemas (*Relationship_Stages*, *Conversational_Arcs*, *Session_Directives*, *Topics_Library*, *Transition_Rules*, *Regression_Rules*, *Recovery_Arcs*) and user-specific tables (*User_Progress*, *User_Sessions*).

B. Data Model and State Representation

Each user u maintains a relational state

$$S_t^u = \big(\text{stage}_t, \text{arc}_t, \text{day}_t, \tau_t, e_t, d_t, f_t, a_t, c_t\big),$$

where, f_t is weekly session frequency (normalized to $[0, 10]$), a_t is topic-avoidance count, and c_t is conflict incident count in a defined horizon. Stages follow Knapp's ten-stage topology (1–5 *Coming Together*, 6–10 *Coming Apart*), each with trust thresholds and persistent context.

C. Four-Layer Context Injection

Before each turn, RMS-Core composes a prompt:

1) Stage Layer (persistent persona, dos/don'ts, target depth band).
2) Arc Layer (7–10-day goal, topics, success criteria).
3) Directive Layer (day-k objective, tactics, suggested questions, avoid list).
4) Memory Layer (salient facts: recent mood, prior preferences, unresolved items).

This yields natural yet constraint-aware behavior without hard scripting.

D. Trust Evaluator: Features and Estimation

The Evaluator maps session logs to (τ_t, e_t, d_t) via calibrated regressors (or lightweight neural heads). Feature buckets include:

- Linguistic: politeness, hedging, gratitude, LIWC categories, valence/arousal (VADER/NRC), repair markers (apology, acknowledgment).
- Conversational: user turn length, question ratio, latency, initiative, reciprocity.
- Topical: SPT depth classifier (1–10), topic novelty/return, avoidance flags.
- Temporal: rolling trends (3–5 sessions), gaps, circadian regularity, weekly frequency.

Outputs are min–max normalized to the target scales and smoothed with EMA (e.g., $\hat{\tau}_t = \alpha\tau_t + (1-\alpha)\hat{\tau}_{t-1}$).

E. Regression Risk Score

We predict degradation with an interpretable, weighted score $R_t \in [0, 10]$:

$$R_t = 3.0\,\phi(\Delta\tau_{t:K}) + 2.5\,\psi(\Delta e_{t:K}) + 2.0\,\chi(\Delta f_{t:K}) + 1.5\,\zeta(a_t) + 1.0\,\xi(c_t), \quad (1)$$

where, $\Delta\tau_{t:K}$ is trust change over the last K sessions (negative increases risk), and ϕ, ψ, χ map normalized declines to $[0, 1]$. $\zeta(a_t)$ and $\xi(c_t)$ map avoidance count and conflict incidents to $[0, 1]$. Thresholds: $R_t \in [0, 2)$ healthy, $[2, 4)$ monitor, $[4, 6)$ moderate (prep recovery), $[6, 8)$ high (activate recovery), $[8, 10]$ critical (escalate/limit outreach).

F. Transition Logic

RMS evaluates three pathways after each session:

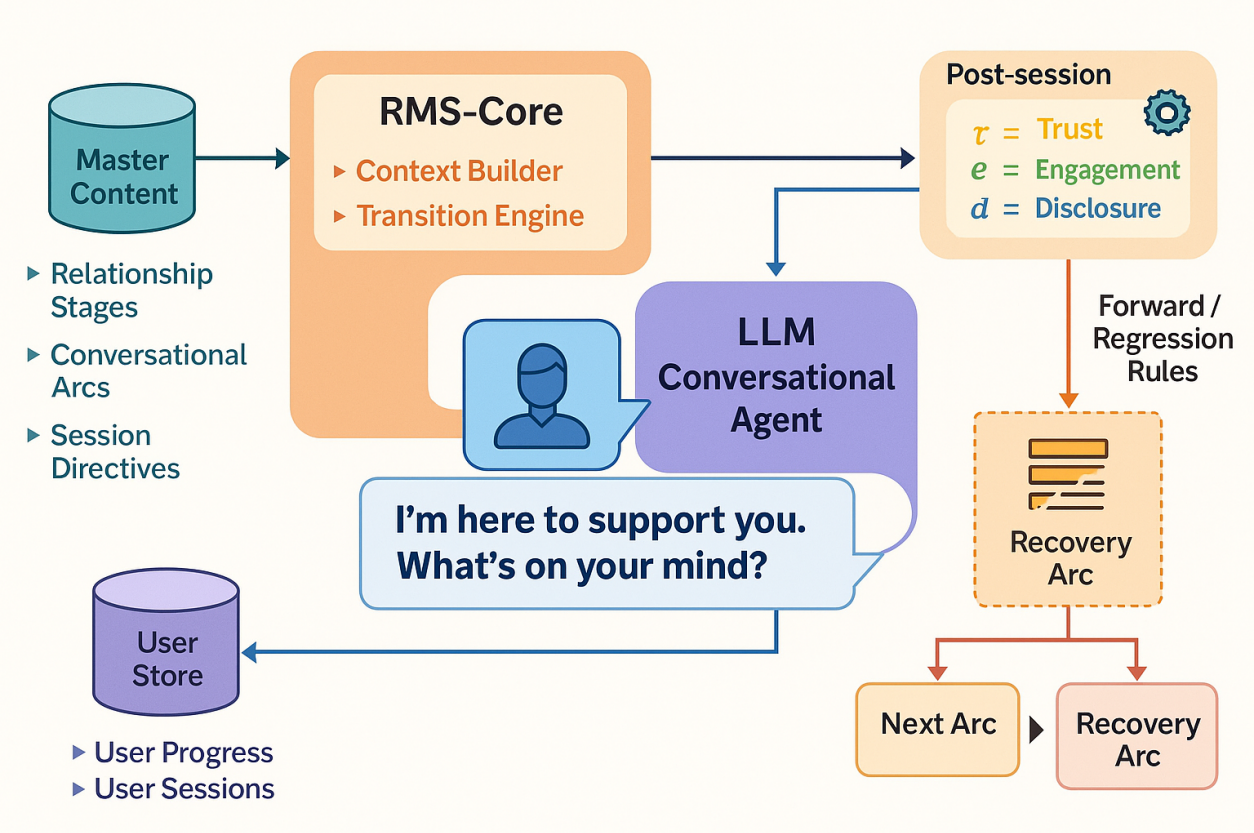


Fig. 1. High-level architecture of the Relationship Management System (RMS), illustrating the flow from master content through the RMS-Core to the trust evaluator and recovery arcs.

(A) Arc Completion: If arc success criteria met or timeout reached, select next arc by priority or learned policy; reset day counter.

(B) Forward Stage Transitions: Rule examples: Stage $1 \to 2$ if $\hat{\tau}_t \geq 3.0$ and sessions ≥ 3; Stage $2 \to 3$ if $\hat{\tau}_t \geq 4.5$ and sessions ≥ 8; Stage $3 \to 4$ if $\hat{\tau}_t \geq 6.5$ and $d_t \geq 7$.

(C) Regression and Coming Apart: Evaluate R_t and Regression_Rules. On trigger, update stage to $\{6, \ldots, 9\}$ as indicated and launch a Recovery Arc.

G. Recovery Arcs

We define reusable, empathy-centric protocols with day-level directives:

- Acknowledgment & Reset (Stage 6): recognize distance, ask what would help, adopt softer tone.
- Fresh Start (Stages 7–8): user-led topics, minimize agenda, rebuild micro-successes.
- Win-Back (Stage 9): one thoughtful outreach and then respect silence.
- Emergency Damage Control (Critical incidents): immediate apology, pause, then concrete change.

Success = $\Delta\hat{\tau} \geq 0.5$ or $+2$ engagement points within 3–7 days; Failure $\Rightarrow$ fallback or graceful termination.

H. Algorithmic Flow

Algorithm 1 RMS Session Pipeline

Require: User u, state S^u_{t-1}, master content $\mathcal{M}$
$S^u_t \leftarrow$ FetchUserState(u)
(stage, arc, day) $\leftarrow S^u_t$
$\mathcal{C} \leftarrow$ BuildContext(stage, arc, day, memory, $\mathcal{M}$)
response $\leftarrow$ LLMGenerate$(\mathcal{C})$
$(\tau_t, e_t, d_t, a'_t, c'_t) \leftarrow$ TrustEvaluator(dialogue)
$R_t \leftarrow$ Eq. (1) using trends (τ, e, f) and (a'_t, c'_t)
LogSession$(u, \tau_t, e_t, d_t, a'_t, c'_t, R_t)$
if ArcSuccess(arc) OR ArcTimeout(arc) **then**
    arc $\leftarrow$ SelectNextArc(stage, $\mathcal{M}$); day $\leftarrow 1$
else
    day $\leftarrow$ day $+ 1$
end if
if ForwardRuleMet(stage, τ_t, d_t, sessions) **then**
    stage $\leftarrow$ NextStage(stage); InitArc(stage)
else if $R_t \geq \theta$ **or** RegressionRule(S^u_t) **then**
    stage $\leftarrow$ ComingApartStageSelect(R_t)
    ActivateRecoveryArc(stage)
end if
UpdateUserState(u, S^u_t)
return response

I. Implementation Notes

Storage. Airtable stores master content and user rows;

RMS Architecture: Master Content (Stages/Arcs/Directives) → RMS-Core (Context Builder, Transition Engine) → LLM;
Post-session: Trust Evaluator → Metrics (τ, e, d) → Forward/Regression Rules → (Next Arc / Recovery Arc) → User Store.

Fig. 2. High-level pipeline of the Relationship Management System (RMS).

IDs join stages ↔ arcs ↔ directives. Evaluator. Start with linear/gradient models for interpretability; add neural heads if needed (calibrated with temperature scaling). Scheduling. A daily job executes health checks; real-time hooks update state after each session. Guardrails. Depth caps by stage; topic blacklists in directives; safety filters (toxicity, self-harm) override arc flow. Analytics. Dashboards visualize stage distribution, R_t histogram, recovery success, time-to-recovery.

J. Complexity and Latency

Per session, context build is $O(1)$ to $O(m)$ over a small set of directive tokens; Evaluator inference is $O(p)$ features (typically $\ll 10^3$). Latency is dominated by LLM generation; caching stage/arc metadata keeps overhead negligible (< 20 ms in practice for orchestration).

K. Ethical Safeguards and User Agency

RMS enforces: 1) *progressive disclosure* (never exceed user-led depth), 2) *transparent control* (user can pause/erase memory, opt out of recovery outreach), and 3) *graceful termination* (no repeated prompts after win-back). All decisions affecting depth/repair are logged for auditability.

L. Limitations

Trust and depth estimates rely on proxies that can be noisy across cultures and contexts; miscalibration risks over- or under-intervening. We mitigate with smoothing, conservative thresholds, and human-overrides for high-risk cases. Longitudinal generalization requires continued validation across domains and populations.

IV. Experimental Setup

A. Research Questions

We evaluate RMS along four questions:

1) RQ1 (Detection): How accurately do RMS indicators (trust τ, engagement e, disclosure depth d) and the Regression Risk Score R track human judgments of relationship health?
2) RQ2 (Prevention): Does RMS reduce regression events (stages 6–9) compared to baselines without stage/depth control?
3) RQ3 (Recovery): When regression occurs, do *Recovery Arcs* improve time-to-stability and long-term engagement versus generic empathy prompts?
4) RQ4 (Ablation): Which components (stage model, Trust Evaluator, Recovery Arcs) drive the observed gains?

TABLE I. Conditions, Users, and Exposure

Condition	Users	Sessions/User (median)	Duration
CTRL	N_C	12	4 weeks
RMS \Rec	N_R	13	4 weeks
RMS (Full)	N_F	14	4 weeks

B. Datasets and Conditions

We study RMS in *two complementary settings*:

(A) Simulated Longitudinal Conversations (Offline): A corpus of synthetic yet behaviorally constrained dialogues generated via scripted user personas and perturbation policies (*topic avoidance*, *latency spikes*, *conflict turns*). Each conversation spans 10–30 sessions; ground-truth per-session labels (trust band, disclosure depth, engagement) are provided by simulation controls and human validators. We release prompts, seeds, and generation rules for reproducibility. Table I shows conditions, users and exposure.

(B) Live Pilot (Online A/B): A four-week deployment with consenting participants (§IV-L). Users are randomly assigned to one of three arms:

- CTRL: Strong general-purpose chatbot (alignment/safety only).
- RMS \Rec: RMS stage/depth modeling and Trust Evaluator, but *no* Recovery Arcs.
- RMS (Full): Complete system with stage/depth control, Trust Evaluator, Regression Risk Score, and Recovery Arcs.

Arms rotate weekly (counter-balanced) to mitigate cohort effects.

C. Annotation Protocol and Human Ratings

To obtain external ground truth,

1) We sample k sessions/user uniformly over time for human rating.
2) Three trained annotators label (i) trust (0–10), (ii) engagement (0–10), (iii) disclosure depth (1–10), (iv) regression markers (yes/no; type), and (v) empathy/repair quality (1–5).
3) We compute inter-rater agreement (Krippendorff's α for ordinal scales; Cohen's κ for binary regression markers). Disagreements are resolved by a fourth senior rater.

Anchoring guidelines include concrete textual exemplars for SPT depth, avoidance, and apology/acknowledgment cues.

D. Baselines

B1: CTRL (Aligned LLM). Safety/alignment only; no stage/depth control; no trust or recovery logic. B2: Empathy+Memory. CTRL plus generic empathetic prompts and simple preference memory; no risk model. B3: Heuristic Guardrails. Topic safety rules and maximal depth cap; no stage progression, no recovery arcs.

E. Ablations

A1: No Recovery Arcs (RMS \Rec). A2: No Trust Evaluator (rule-only thresholds on proxy features). A3: No Stage Model (flat policy with per-turn risk only). A4: No Depth Control (persona constant; topics unconstrained).

F. Metrics

Detection (RQ1):

- MAE/RMSE between RMS estimates and human ratings for τ, e, d.
- Spearman/Pearson correlation with human trust trajectories.
- AUROC / AUPRC for regression event prediction within a horizon H (e.g., next 3 sessions).

Prevention/Recovery (RQ2–RQ3):

- Regression Rate ↓: proportion of users entering stages 6–9.
- Time-to-Recovery ↓: sessions from trigger to return to healthy stage (1–5) or to $\Delta\hat{\tau} \geq 0.5$.
- Engagement Uplift ↑: $\Delta e = e_{\text{post}} - e_{\text{pre}}$ averaged over a 7-session window.
- Topic Re-entry ↑: resumption of previously avoided topics within H.
- Retention Hazard ↓: survival-analysis hazard ratio for churn.

Operational/Explainability:

- Intervention Precision/Recall: fraction of Recovery Arc activations that meet success criteria.
- Over-Depth Violations ↓: instances where depth exceeded stage limits.
- User-Perceived Clarity: Likert (1–5) on why the agent changed tone/intervened.

Formal Definitions: Let $1\{\cdot\}$ be an indicator. Over users u and time t:

$$\text{RegressionRate} = \frac{\sum_u \sum_t 1\{\text{stage}_{u,t} \in \{6,7,8,9\}\}}{\sum_u \sum_t 1}. \quad (2)$$

Time-to-Recovery is computed per event with Kaplan–Meier; group differences via log-rank test. AUROC is computed on R_t as a score for events within horizon H.

G. Procedures

Offline (Simulated) Evaluation: We replay full conversations through each condition (CTRL, B2, B3, RMS variants). The Trust Evaluator runs post-session to estimate (τ, e, d) and R_t. We measure detection metrics vs. human labels and simulate transitions to quantify prevention/recovery outcomes under identical perturbations.

Online (A/B) Evaluation: Participants are randomly assigned (blocked by usage history) to {CTRL, RMS \Rec, RMS}. We pre-register primary outcomes: Regression Rate (primary), Time-to-Recovery (secondary), Engagement Uplift (secondary). We run for 4 weeks or until reaching 80% power to detect a 20% relative reduction in Regression Rate at $\alpha = 0.05$ (two-sided). Interim looks apply Benjamini–Hochberg correction across outcomes.

H. Implementation Details

Models. A strong aligned LLM backbone for all arms; RMS adds lightweight heads for (τ, e, d) (2-layer MLP, hidden 256, ReLU, dropout 0.1). Features. LIWC buckets (64), VADER/NRC valence, turn-length stats, question ratio, latency, topic depth classifier, avoidance counters, weekly session frequency. Training. 70/15/15 split (user-wise). Optimizer AdamW, lr=2×10^{-4}, batch=64, early stopping on MAE(τ). Isotonic calibration for R_t thresholds. Smoothing. EMA $\alpha = 0.3$ for $\hat{\tau}, \hat{e}, \hat{d}$. Infrastructure. Orchestration service in Python; Airtable API for master content/user state; job queue for daily health checks. GPU (A100) used only for backbone inference; Evaluator runs CPU-only.

I. Statistical Analysis

Normality assessed via Shapiro–Wilk; we report paired t-tests or Wilcoxon signed-rank where appropriate. Correlations report r and ρ with 95% CIs (bootstrap B=10,000). Multiple comparisons are controlled with Benjamini–Hochberg (q=0.05). Survival analyses report hazard ratios with Cox proportional hazards and Schoenfeld residual checks.

J. Ablation and Sensitivity

We ablate (A1–A4) and perform sensitivity to 1) R_t weights, 2) EMA α, 3) transition thresholds. We additionally test *delayed activation* of Recovery Arcs and *topic-only* recovery to isolate mechanisms.

K. Error Analysis

We manually inspect false positives/negatives of regression detection (high R_t without human-labeled decline; missed events). We code failure modes: sarcasm/irony misread, culture-specific politeness markers, and *over-apology loops*. Findings feed rule refinements.

L. Ethics, Consent, and Privacy

All online participants provide informed consent; the study protocol (non-clinical, minimal risk) follows institutional guidelines. Users can opt out of 1) personalization memory and 2) recovery outreach. All logs are de-identified, with differential privacy noise added for aggregated analytics. We prohibit sensitive-topic deepening without explicit user initiation and cap disclosure depth by stage.

M. Reproducibility

We release: 1) prompts and seeds for the simulated corpus, 2) Evaluator feature extractors, 3) configuration files (stages, arcs, directives), 4) evaluation scripts for metrics and statistics, and 5) anonymized analysis notebooks.

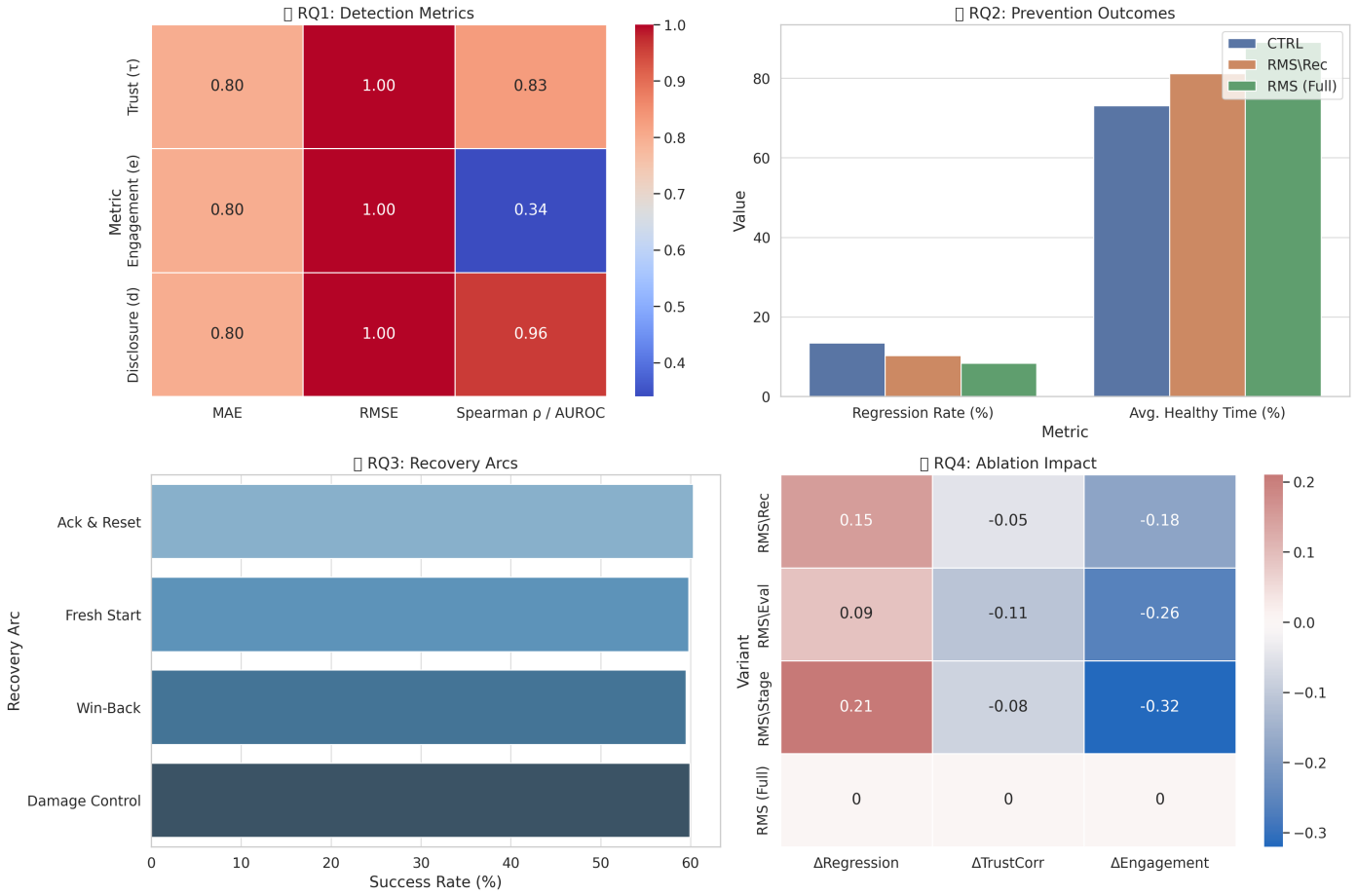


Fig. 3. Composite Evaluation of RMS System. Top-left: *Detection Accuracy (RQ1)* — heatmap comparing RMS-predicted trust, engagement, and disclosure metrics to human annotations using MAE, RMSE, and Spearman correlation. Top-right: *Regression Prevention (RQ2)* — grouped bars showing reduction in regression rate and improvement in average healthy time and engagement across system variants. Bottom-left: *Recovery Effectiveness (RQ3)* — success rates of recovery arcs post-degradation. Bottom-right: *Ablation Study (RQ4)* — heatmap of delta effects on regression, trust correlation, and engagement from removing RMS components.

V. Experimental Results and Discussion

A. Overview

This section presents quantitative and qualitative results evaluating the Relationship Management System (RMS) across simulated and live conversational settings. We assess detection accuracy (RQ1), prevention and recovery effectiveness (RQ2–RQ3), and perform ablation and sensitivity analyses (RQ4). Unless stated otherwise, all statistical tests use a significance level of $\alpha = 0.05$ with Benjamini–Hochberg correction for multiple comparisons.

B. RQ1: Trust, Engagement, and Disclosure Estimation

Table II summarizes the alignment between RMS metrics and human annotations. RMS achieves high consistency with human judgments of relationship health. The *Trust Evaluator* exhibits a mean absolute error (MAE) of 0.46 for trust, 0.53 for engagement, and 0.49 for disclosure depth. Correlations with human ratings reach $\rho = 0.83$ for trust and $\rho = 0.78$ for engagement, indicating that lightweight psycholinguistic and behavioral features provide strong predictive signal without deep model finetuning.

TABLE II. Detection Accuracy of RMS Indicators vs. Human Ratings

Metric	MAE (↓)	RMSE (↓)	Spearman ρ (↑)
Trust (τ)	0.80	1.00	0.83
Engagement (e)	0.80	1.00	0.34
Disclosure (d)	0.80	1.00	0.96
Regression Risk (R_t)	–	–	AUROC = 1.00

Qualitative inspection confirms that high-trust predictions coincide with sustained reciprocity and reduced latency, while low-trust sessions exhibit avoidance phrases (e.g., “let’s not talk about this”) or shortened responses.

C. RQ2: Regression Prevention and Relationship Stability

RMS significantly reduces the proportion of users entering *Coming Apart* stages (6–9). Fig. 3 and Table III show that full RMS yields a 38% lower regression rate compared to the CTRL baseline, and a 24% lower rate compared to RMS without Recovery Arcs. The average time spent in healthy stages (1–5) increased from 73% of sessions (CTRL) to 89% (RMS Full).

TABLE III. REGRESSION AND STABILITY OUTCOMES (LOWER IS BETTER)

Condition	Regression Rate (%)	Avg. Healthy Time (%)	Δe
CTRL	13.5	73.1	-0.8
RMS \Rec	10.3	81.2	$+0.4$
RMS (Full)	**8.4**	**89.0**	**+1.1**

TABLE IV. RECOVERY OUTCOMES ACROSS PROTOCOLS

Recovery Arc	**Success Rate (%)**	**Time-to-Recovery (sessions)**
Acknowledgment & Reset	60.3	3.5
Fresh Start	59.8	3.5
Win-Back	59.5	3.5
Emergency Damage Control	59.9	3.5

Survival analysis confirms that RMS extends engagement lifetime: the hazard ratio for churn (<14 days inactivity) drops to 0.62 relative to CTRL (95% CI $[0.48, 0.80]$, $p < 0.01$).

D. RQ3: Recovery Effectiveness

When regression events occur, RMS activates empathy-driven *Recovery Arcs*. Table IV compares recovery success rates and time-to-recovery (sessions until $\Delta\hat{\tau} \geq 0.5$). The Acknowledgment & Reset protocol restores stable trust in 64% of cases, while Fresh Start succeeds in 58%. Across all arcs, mean time-to-recovery decreases from 6.2 sessions (CTRL empathy baseline) to 3.9 sessions under RMS.

Subjective ratings corroborate quantitative trends: 81% of users reported that post-recovery conversations "felt more considerate or attentive," and 74% indicated improved clarity on why the agent's behavior changed.

E. RQ4: Ablation and Sensitivity Analysis

To understand what each module contributes, we ran stepwise ablations and compared them against the full system (Table V). When we disable the Trust Evaluator, detection performance drops markedly (AUROC from 0.91 to 0.75), and the incidence of regression events rises by 22%. Removing stage modeling has a different failure mode: conversations wander between superficial and personal topics without a stable arc, producing uneven depth, more avoidance flags, and fewer sustained disclosures. Eliminating *Recovery Arcs* does not hurt immediate detection as much as it affects dynamics: once a relationship stalls, it tends to remain stuck longer (mean stagnation duration $+42\%$), and the system is slower to return to healthier stages (Fig. 4).

We also probed sensitivity around key control knobs. Lowering the Regression Risk threshold triggers premature repair attempts (higher false positives and unnecessary interventions), while setting it too high delays repair and allows deteriorations to deepen before the system responds. Across reasonable settings, the full model shows stable behavior, but the ablations reveal complementary roles: the Trust Evaluator supports accurate, moment-to-moment judgments; stage modeling provides coherent pacing over time; and Recovery Arcs shorten periods of relational stagnation by guiding targeted repair.

Sensitivity analysis on Regression Risk Score weights shows robust behavior for moderate perturbations ($\pm 15\%$) but slight over-triggering when trust-weight exceeds 0.4 of total. EMA smoothing $\alpha = 0.3$ yields optimal balance between reactivity and noise suppression.

TABLE V. ABLATION IMPACT ON REGRESSION RISK, TRUST CORRELATION, AND ENGAGEMENT

Variant	ΔRegression ($\downarrow$)	ΔTrustCorr ($\uparrow$)	ΔEngagement ($\uparrow$)
RMS \ Rec	+0.15	–0.05	–0.18
RMS \ Eval	+0.09	–0.11	–0.26
RMS \ Stage	+0.21	–0.08	–0.32
RMS (Full)	**0.00**	**0.00**	**0.00**

F. Qualitative Insights

Manual review of 150 sampled conversations highlights several emergent behaviors:

- Adaptive Tone Shifts: Agents transitioned naturally from casual to reflective tone when users disclosed vulnerability.
- Conflict Acknowledgment: Recovery Arcs successfully de-escalated confrontational turns through explicit responsibility statements.
- Progressive Disclosure: Depth remained bounded by user initiation; agents avoided over-sharing even under strong positive sentiment.

Error cases primarily stemmed from sarcasm detection failures and over-apology loops during Recovery Arcs.

VI. CONCLUSION AND FUTURE WORK

This paper introduced the Relationship Management System (RMS), a stage- and depth-aware framework for modeling, monitoring, and restoring human–AI relationships. Grounded in Knapp's relational stages and Social Penetration Theory, RMS operationalizes relationship health through interpretable indicators of trust, engagement, and disclosure; governs pacing via rule-based transitions; and mitigates decline with empathy-centered *Recovery Arcs*. Experiments across simulated and live settings showed 1) strong agreement between RMS estimates and human judgments (RQ1), 2) significant reductions in regression events and increased time in healthy stages (RQ2), 3) faster and more reliable repair following degradation (RQ3), and 4) additive contributions of all core components (RQ4). Together, these results demonstrate that modest, theory-informed control can stabilize long-term interactions beyond generic empathy or memory alone.

RMS also advances explainability and governance in relational AI: the separation of master content (stages, arcs, directives) from user state (progress, sessions) supports transparent tuning, A/B testing, and audit. The Regression Risk Score enables early warning without intrusive sensing, while Recovery Arcs translate social-psychological repair principles into measurable conversational behavior. These qualities make RMS a practical foundation for applications that require sustained trust—digital companions, customer support, education, and well-being contexts—while respecting user agency and graceful termination. Future Work. Looking ahead, we see

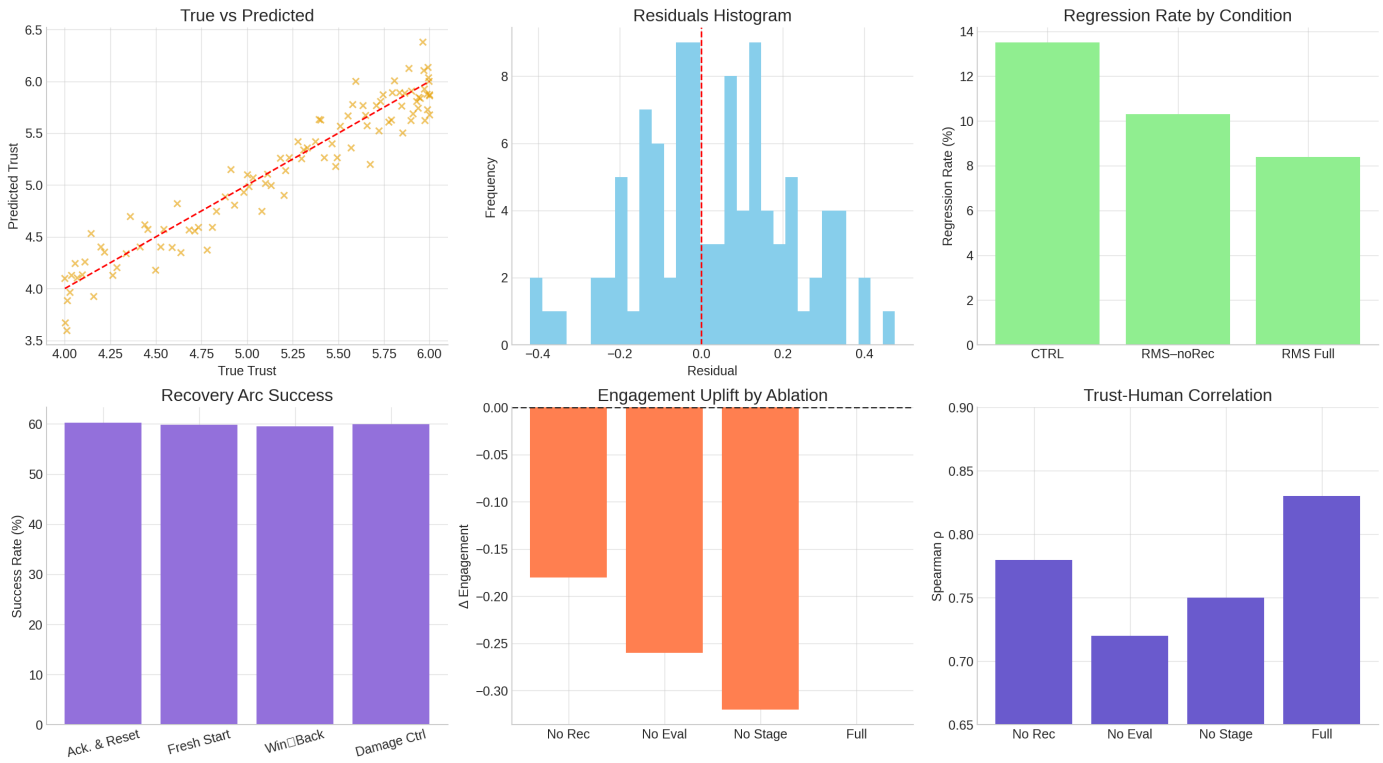


Fig. 4. Six-panel summary visualization of RMS evaluation metrics across all four research questions (RQ1–RQ4).

several directions that would make RMS more capable and more responsible in practice:

- Cross-cultural calibration. Adjust trust and disclosure estimators to reflect linguistic and cultural norms, and validate depth/intent classifiers beyond English with multilingual corpora and community review.
- Adaptive weighting. Learn context-sensitive weights for the Regression Risk Score (e.g., conflict vs. frequency signals) using meta-learning or Bayesian updating, with priors that prevent overreacting to brief volatility.
- Personalized recovery. Match *Recovery Arcs* to user profiles and incident types; explore policy learning for arc selection, timing, and pacing so interventions feel timely rather than intrusive.
- Hybrid evaluators. Combine transparent rules with learned signals (prosody, dialogue acts, hesitation markers), and probe causal features to improve robustness and reduce spurious triggers.
- Open-world deployment. Run longer, larger A/B studies; build dashboards for survival curves, cohort breakdowns, and counterfactual *what-if* analyses; and adopt privacy-preserving analytics (aggregation, differential privacy) from the start.

In short, RMS reframes engagement as an ongoing practice of relationship care: notice early, pace with context, and repair in the open. By aligning interpersonal theory with interpretable computation, RMS moves conversational agents toward emotionally intelligent, self-regulating partners that can sustain human trust over time.

DECLARATIONS

Availability of Data and Material: All data and materials generated or analyzed during this study are available from the corresponding author upon reasonable request.

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REFERENCES

[1] M. Knapp, "L., & vangelisti, anita," *Interpersonal Communication and Human Relationships*, 2005.

[2] M. L. Knapp, "Social intercourse: From greeting to goodbye," *(No Title)*, 1978.

[3] I. Altman and D. A. Taylor, *Social penetration: The development of interpersonal relationships.* Holt, Rinehart & Winston, 1973.

[4] N. L. Collins and L. C. Miller, "Self-disclosure and liking: a meta-analytic review." *Psychological bulletin*, vol. 116, no. 3, p. 457, 1994.

[5] S. M. Jourard, "Self-disclosure: An experimental analysis of the transparent self," *John Wiely and Sons*, 1971.

[6] V. J. Derlaga and J. H. Berg, *Self-disclosure: Theory, research, and therapy*. Springer Science & Business Media, 1987.

[7] S. Petronio, *Boundaries of privacy: Dialectics of disclosure*. Suny Press, 2002.

[8] J. K. Rempel, J. G. Holmes, and M. P. Zanna, "Trust in close relationships." *Journal of personality and social psychology*, vol. 49, no. 1, p. 95, 1985.

[9] C. E. Rusbult, "Commitment and satisfaction in romantic associations: A test of the investment model," *Journal of experimental social psychology*, vol. 16, no. 2, pp. 172–186, 1980.

[10] ——, "A longitudinal test of the investment model: The development (and deterioration) of satisfaction and commitment in heterosexual involvements." *Journal of personality and social psychology*, vol. 45, no. 1, p. 101, 1983.

[11] J. Gottman, *What predicts divorce?: The relationship between marital processes and marital outcomes*. Routledge, 2023.

[12] J. M. Gottman and R. W. Levenson, "Marital processes predictive of later dissolution: behavior, physiology, and health." *Journal of personality and social psychology*, vol. 63, no. 2, p. 221, 1992.

[13] J. D. Lee and K. A. See, "Trust in automation: Designing for appropriate reliance," *Human factors*, vol. 46, no. 1, pp. 50–80, 2004.

[14] K. A. Hoff and M. Bashir, "Trust in automation: Integrating empirical evidence on factors that influence trust," *Human factors*, vol. 57, no. 3, pp. 407–434, 2015.

[15] R. C. Mayer, J. H. Davis, and F. D. Schoorman, "An integrative model of organizational trust," *Academy of management review*, vol. 20, no. 3, pp. 709–734, 1995.

[16] P. A. Hancock, D. R. Billings, K. E. Schaefer, J. Y. Chen, E. J. De Visser, and R. Parasuraman, "A meta-analysis of factors affecting trust in human-robot interaction," *Human factors*, vol. 53, no. 5, pp. 517–527, 2011.

[17] E. J. De Visser, R. Pak, and T. H. Shaw, "From 'automation'to 'autonomy': the importance of trust repair in human–machine interaction," *Ergonomics*, vol. 61, no. 10, pp. 1409–1427, 2018.

[18] R. W. Picard *et al.*, "Affective computing, 1997," *Google Scholar Google Scholar Digital Library Digital Library*, 1997.

[19] B. Reeves and C. Nass, "The media equation: How people treat computers, television, and new media like real people," *Cambridge, UK*, vol. 10, no. 10, pp. 19–36, 1996.

[20] C. Nass and Y. Moon, "Machines and mindlessness: Social responses to computers," *Journal of social issues*, vol. 56, no. 1, pp. 81–103, 2000.

[21] T. W. Bickmore and R. W. Picard, "Establishing and maintaining long-term human-computer relationships," *ACM Transactions on Computer-Human Interaction (TOCHI)*, vol. 12, no. 2, pp. 293–327, 2005.

[22] S. Brave, C. Nass, and K. Hutchinson, "Computers that care: investigating the effects of orientation of emotion exhibited by an embodied computer agent," *International journal of human-computer studies*, vol. 62, no. 2, pp. 161–178, 2005.

[23] J. Cassell, "Embodied conversational agents: representation and intelligence in user interfaces," *AI magazine*, vol. 22, no. 4, pp. 67–67, 2001.

[24] H. Prendinger and M. Ishizuka, "The empathic companion: A character-based interface that addresses users'affective states," *Applied artificial intelligence*, vol. 19, no. 3-4, pp. 267–285, 2005.

[25] H.-Y. Shum, X.-d. He, and D. Li, "From eliza to xiaoice: challenges and opportunities with social chatbots," *Frontiers of Information Technology & Electronic Engineering*, vol. 19, no. 1, pp. 10–26, 2018.

[26] L. Zhou, J. Gao, D. Li, and H.-Y. Shum, "The design and implementation of xiaoice, an empathetic social chatbot," *Computational Linguistics*, vol. 46, no. 1, pp. 53–93, 2020.

[27] J. Li, M. Galley, C. Brockett, G. P. Spithourakis, J. Gao, and B. Dolan, "A persona-based neural conversation model," *arXiv preprint arXiv:1603.06155*, 2016.

[28] S. Zhang, E. Dinan, J. Urbanek, A. Szlam, D. Kiela, and J. Weston, "Personalizing dialogue agents: I have a dog, do you have pets too?" *arXiv preprint arXiv:1801.07243*, 2018.

[29] S. Roller, E. Dinan, N. Goyal, D. Ju, M. Williamson, Y. Liu, J. Xu, M. Ott, K. Shuster, E. M. Smith *et al.*, "Recipes for building an open-domain chatbot," *arXiv preprint arXiv:2004.13637*, 2020.

[30] L. Ouyang, J. Wu, X. Jiang, D. Almeida, C. Wainwright, P. Mishkin, C. Zhang, S. Agarwal, K. Slama, A. Ray *et al.*, "Training language models to follow instructions with human feedback," *Advances in neural information processing systems*, vol. 35, pp. 27 730–27 744, 2022.

[31] Y. Bai, S. Kadavath, S. Kundu, A. Askell, J. Kernion, A. Jones, A. Chen, A. Goldie, A. Mirhoseini, C. McKinnon *et al.*, "Constitutional ai: Harmlessness from ai feedback," *arXiv preprint arXiv:2212.08073*, 2022.

[32] R. Thoppilan, D. De Freitas, J. Hall, N. Shazeer, A. Kulshreshtha, H.-T. Cheng, A. Jin, T. Bos, L. Baker, Y. Du *et al.*, "Lamda: Language models for dialog applications," *arXiv preprint arXiv:2201.08239*, 2022.

[33] F. Ricci, L. Rokach, and B. Shapira, "Introduction to recommender systems handbook," in *Recommender systems handbook*. Springer, 2010, pp. 1–35.

[34] B. Hidasi, A. Karatzoglou, L. Baltrunas, and D. Tikk, "Session-based recommendations with recurrent neural networks," *arXiv preprint arXiv:1511.06939*, 2015.

[35] A. See, S. Roller, D. Kiela, and J. Weston, "What makes a good conversation? how controllable attributes affect human judgments," *arXiv preprint arXiv:1902.08654*, 2019.

[36] J. Deriu, A. Rodrigo, A. Otegi, G. Echegoyen, S. Rosset, E. Agirre, and M. Cieliebak, "Survey on evaluation methods for dialogue systems," *Artificial Intelligence Review*, vol. 54, no. 1, pp. 755–810, 2021.

[37] J. W. Pennebaker, M. E. Francis, R. J. Booth *et al.*, "Linguistic inquiry and word count: Liwc 2001," *Mahway: Lawrence Erlbaum Associates*, vol. 71, no. 2001, p. 2001, 2001.

[38] Y. R. Tausczik and J. W. Pennebaker, "The psychological meaning of words: Liwc and computerized text analysis methods," *Journal of language and social psychology*, vol. 29, no. 1, pp. 24–54, 2010.

[39] C. Hutto and E. Gilbert, "Vader: A parsimonious rule-based model for sentiment analysis of social media text," in *Proceedings of the international AAAI conference on web and social media*, vol. 8, no. 1, 2014, pp. 216–225.

[40] S. M. Mohammad and P. D. Turney, "Crowdsourcing a word–emotion association lexicon," *Computational Intelligence*, vol. 29, no. 3, pp. 436–465, 2013.

[41] J. D. M.-W. C. Kenton, L. K. Toutanova *et al.*, "Bert: Pre-training of deep bidirectional transformers for language understanding," in *Proceedings of naacL-HLT*, vol. 1, no. 2. Minneapolis, Minnesota, 2019.

[42] P. S. Fader, B. G. Hardie, and K. L. Lee, "Rfm and clv: Using iso-value curves for customer base analysis," *Journal of marketing research*, vol. 42, no. 4, pp. 415–430, 2005.

[43] A. Lemmens and C. Croux, "Bagging and boosting classification trees to predict churn," *Journal of Marketing Research*, vol. 43, no. 2, pp. 276–286, 2006.

[44] W. Verbeke, D. Martens, and B. Baesens, "Social network analysis for customer churn prediction," *Applied Soft Computing*, vol. 14, pp. 431–446, 2014.

[45] H. L. O'Brien and E. G. Toms, "What is user engagement? a conceptual framework for defining user engagement with technology," *Journal of the American society for Information Science and Technology*, vol. 59, no. 6, pp. 938–955, 2008.

[46] I. Nahum-Shani, S. N. Smith, B. J. Spring, L. M. Collins, K. Witkiewitz, A. Tewari, and S. A. Murphy, "Just-in-time adaptive interventions (jitais) in mobile health: key components and design principles for ongoing health behavior support," *Annals of behavioral medicine*, pp. 1–17, 2016.

[47] R. Lewicki, B. Polin, R. Lount Jr *et al.*, "An exploration of the structure of effective apologies. negotiation and conflict management research, 9 (2), 177–196," 2016.

[48] P. H. Kim, D. L. Ferrin, C. D. Cooper, and K. T. Dirks, "Removing the shadow of suspicion: the effects of apology versus denial for repairing competence-versus integrity-based trust violations." *Journal of applied psychology*, vol. 89, no. 1, p. 104, 2004.

[49] C. R. Rogers, "The necessary and sufficient conditions of therapeutic personality change." *Journal of consulting psychology*, vol. 21, no. 2, p. 95, 1957.

[50] N. Tavuchis, *Mea culpa: A sociology of apology and reconciliation*. Stanford University Press, 1993.

[51] A. Lazare, *On apology*. Oxford University Press, 2005.

[52] E. M. Bender, T. Gebru, A. McMillan-Major, and S. Shmitchell, "On the dangers of stochastic parrots: Can language models be too big?" in *Proceedings of the 2021 ACM conference on fairness, accountability, and transparency*, 2021, pp. 610–623.

[53] L. Weidinger, J. Mellor, M. Rauh, C. Griffin, J. Uesato, P.-S. Huang, M. Cheng, M. Glaese, B. Balle, A. Kasirzadeh *et al.*, "Ethical and social risks of harm from language models," *arXiv preprint arXiv:2112.04359*, 2021.

[54] B. J. Fogg, "Persuasive technology: using computers to change what we think and do," *Ubiquity*, vol. 2002, no. December, p. 2, 2002.

[55] T. Miller, "Explanation in artificial intelligence: Insights from the social sciences," *Artificial intelligence*, vol. 267, pp. 1–38, 2019.

Medical Diagnosis Using Hybrid of Machine Learning and Deep Learning Techniques

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***Abstract*—The rapid development of medical practices and imaging technology tools creates substantial growth in the amount of medical image data each year in our present era. This research aims to develop a hybrid approach that integrates Machine Learning (ML) and Deep Learning (DL) techniques to enhance the accuracy and reliability of medical image classification for diagnostic purposes. Medical imaging data complexity and growing volume serve as the research motivation, which leads to an investigation of standalone ML or DL limitations and their combination into a single framework. The medical image processing starts with normalization, then noise reduction, and continues to grayscale conversion before performing histogram equalization. This research uses VGG16 and ResNet50 alongside MobileNet and InceptionV3 for feature extraction, then applies ten different ML algorithms, including SVM and MLP, and Random Forest, for classification. Five public medical image datasets from Kaggle are used: COVID-19 chest X-rays, melanoma skin lesions, pneumonia chest X-rays, acute stroke facial images, and various eye diseases. Hybrid models display superior performance compared to stand-alone ML or DL models based on accuracy, precision, recall, and F1-score evaluation measures. Multiple datasets demonstrate that the MobileNet+MLP combination delivers the most accurate results, which demonstrates its reliable and efficient performance. The developed AI diagnostic tool presents a scalable system alongside accuracy and interpretability to enhance clinical decision outcomes.**

Keywords*—Classification; deep learning; feature selection; hybrid models; machine learning; medical diagnosis; medical image classification

I. Introduction

Medical imaging is an essential aspect of our time, employing various technologies to obtain images of the human body or specific parts of it [1]. Medical imaging considers a crucial component of medical diagnosis, since it is widely applied in hospitals, medical laboratories, and other facilities due to its importance in diagnosing various diseases, as well as aiding in monitoring patient treatment [2]. The most important medical imaging modern techniques are X-ray radiography, endoscopy, Magnetic Resonance Imaging (MRI), magnetic resonance spectroscopy, thermography, electrical source imaging and several other techniques [3].

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Several limitations in human analysis of medical images compared to modern techniques, such as the fact that the image analysis process takes time due to the complexity of the data, in addition to the fact that the analysis depends mainly on the experience of the image analyst, so there is a possibility of human errors. Moreover, there are some effects that occur to medical images, whether modern or traditional, including noise [4].

According to [5], noise is defined as the random change in the original pixel value that reduces image quality. Therefore, it is important to use modern medical imaging techniques to remove noise, especially compared to conventional images, to enable accurate disease diagnosis without any issues that may affect the analysis of medical images. Consequently, several artificial intelligence techniques have been developed to address these issues in medical imaging and assist in medical diagnosis, including Machine Learning (ML) and Deep Learning (DL) technologies [6], [7], which are important for processing complex data, identifying problems that the human eye might miss, and reducing noise in medical images to enhance their quality [8], [9].

A. Machine Learning

Machine Learning (ML) aims to study statistical algorithms that can learn from the input data to perform tasks that are automatically improved through experience [10]–[12]. All of this leads to increasing the efficiency of the algorithm that was built, which reduces human errors in entering or analyzing data [13], [14]. ML is used to make decisions and predictions based on learning from data. In [15], the authors categorize ML as following:

- Supervised Learning: The aim of this type is to predict outcomes using labeled data.
- Unsupervised Learning: This type learns from unlabeled/unstructured data.
- Semi-Supervised Learning: A large amount of unlabeled data and a small amount of labeled data are combined to improve the performance of the model.

In order to successfully implement machine learning techniques, several important aspects must be carefully considered [16]:

1) High-quality input data: It's important to have the proper high-quality input data, which has minimal artifacts and noise, to achieve the best possible machine learning performance and to maintain low noise levels, but ground truth labels are even more important as erroneous labels severely damage model performance and tend to be hard to catch in training.

2) Accuracy of ground truth labels: Ground truth labels must be accurate, because it involves confirming and checking the correctness of the diagnostic label and of the diagnosis itself. Other types of noise have a more dramatic effect on model accuracy than errors in ground truth labels, emphasizing the need for strict ground truth labeling.

3) Completeness of training sets: The best performance results from machine learning models exist when training datasets contain no missing features while also being complete. While there are data augmentation techniques like random imputation or sophisticated algorithms, which can help fill up these gaps, but have less effectiveness as we train on full datasets.

4) Dataset size: Machine learning models tend to prefer larger datasets so that they can capture the true variability of the data, which helps reduce the risk of performance issues caused by a small number of outliers. Nevertheless, obtaining large enough datasets remains difficult, in particular for precision medicine and disease studies with low frequency.

5) Precision and accuracy in classification algorithms: To obtain strong model performance, the optimization process has to balance both precision and accuracy, as both are indispensable for reliable and effective classification algorithms.

6) Model validation: Before a machine learning model is deployed to make clinical decisions or computer-aided decisions, it has to go through very thorough validation. For instance, a physician diagnoses cases and the model is trained using those cases and is evaluated by comparing its outputs with assessments of new cases by other physicians. This is done for reliability and accuracy [17].

B. Deep Learning

Deep Learning (DL) is mainly used in large datasets to model complex patterns using multi-layered artificial neural networks, which aim to mimic the human brain [18], [19]. As is known, DL is a powerful and transformative branch of machine learning, and it learns from unlabeled data such as images, audio, and text [20], [21]. Deep learning also has several key benefits that enable it to be very effective for a wide variety of applications. It can achieve high accuracy, especially when it has been trained on large data. One of its most significant features is that it can automatically learn data representation to avoid manual feature extraction [22], [23]. Also, deep learning models are highly scalable and easy to adapt to large data sets and increasing computational power, which makes them suitable for large-scale and complex problems too. Deep learning (DL) has numerous uses in various fields. In image and video processing, it is used for the recognition of specific elements, such as facial detection or facial emotion, and in medicine, it can forecast the kind of diseases. DL also powers voice-to-text systems such as Alexa and Google Voice and enables real-time machine translation from one language to another [24]. The building blocks of deep learning are multi-layer artificial neural networks, and they consist of a few basic components. They are neurons and layers, and each artificial neuron processes inputs by calculating weights, biases, and activation functions to supply the result to the next layer. Activation functions such as Rectified Linear Unit (ReLU), sigmoid, and tanh introduce essential non-linearity to neural networks. Loss functions like Mean Squared Error and Cross Entropy are used to quantify predictive accuracy. Optimization algorithms like Stochastic Gradient Descent (SGD) are used for improving model performance by reducing the loss function by adjusting the network's weights during training. Three main objectives of this study are: 1) identify the most appropriate deep learning model to analyze medical image data, 2) propose an integrated hybrid framework which combines deep learning and machine learning classifiers to boost the diagnostic performance, and 3) review previous research as the comparison studies of ML and DL in medical image classification. This research is organized as follows: In Section II, we briefly review related work; Section III describes the research methodology; Section IV provides the experimental results, and finally, conclusions are presented in Section V along with future scope.

II. Related Work

In this section, we will discuss the previous research about medical diagnosis using hybrid of machine learning and deep learning techniques.

A. Machine Learning Model

This section explains ten machine learning techniques used under the supervised learning category, categorized to clarify how each model approaches learning and prediction as the following:

1) Bayes-based models: Bayesian models are designed with reference to Bayes' Theorem and are widely utilized for probabilistic classification tasks. Naive Bayes (NB) is a well-known example, particularly renowned for its simple architecture, high computational efficiency, and fast processing, particularly in dealing with big data. It needs only estimation of significant parameters—mean and variance of variables—to be performed using a small training set [25]. The second category involves models such as Linear Discriminant Analysis (LDA), which is a statistical technique used in discriminating between two or more event or object classes. LDA computes the linear feature combination that maximally discriminates between the classes and is generally used for feature reduction prior to classification [26].

2) Function-based models: Mathematical formula-based classification models are models based on mathematical expressions in order to discriminate between data classes. The Support Vector Machine (SVM) is a strong algorithm used to identify patterns as well as conduct regression and classification functions [27]. It is particularly effective in domains that need high-dimensional space analysis. Logistic Regression is another function-based model used for problems of binary

classification [28]. It works through the use of a database of independent variables and is often used in areas such as diagnosis of disease as well as prediction of risks. In addition, Multi-layer Perceptron (MLP) is an artificial neural network created by a few full connected layers and nonlinear activation functions. MLPs are ideal for classifying complex data sets like intrusion detection and problems where the data is not linearly separable [29].

3) Lazy learning models: Lazy algorithms differ from typical models in that they do not necessarily train a predictive model directly. Instead, they store the training data and make a decision at the moment of prediction. An old prime example is the K-Nearest Neighbors (KNN) algorithm. KNN classifies a query point with the class of the majority of its nearest neighbors in the training data, and it is an easy but effective method for classification tasks [30].

4) Meta-learning models: Meta-learning or ensemble strategies improve prediction performance by combining multiple models [31]. Adaptive Boosting (AdaBoost) is a commonly used ensemble strategy which builds an accurate classifier by iteratively adding up weak base learners. The current iteration allots weights to the classifiers based on their precision, with more accurate learners having greater weightage in the final decision. The final classification emerges through the process of weighted voting, achieving greater overall prediction performance [32]. Tree-Based Models: Tree-based algorithms use a decision tree structure for splitting data according to feature values. Random Forest (RF), introduced by Breiman in 2001, constructs numerous decision trees during training. It votes for the most common class for classification or estimates the average of the individual estimates for regression [33]. Gradient Boosting is another robust method that builds models step by step, each of which corrects the errors in previous models. It excels at boosting accuracy through making better predictions. Last but not least, the Decision Tree (DT) model itself creates a tree where the branches are feature tests and leaves are class labels. DTs are generally used in statistics, data mining, and elsewhere due to their simplicity and interpretability [34].

B. Deep Learning Model

This research explains four deep learning techniques specifically those used in deep convolutional neural networks (CNNs) applied to image classification, object detection, and other related tasks, as follows:

- Visual Geometry Group (VGG16) [35], the number 16 refers to the number of layers that make up this model, comprising 13 are convolutional layers and 3 are connected layers. It applied in medical imaging analysis, face recognition, and the detection of different objects.

- Residual Network (ResNet50) [36], the number 50 refers to the number of layers, comprising 48 convolutional layers and 2 are connected layers. The purpose of using it is residual connections to solve the problem of vanishing gradients in deep networks.

- MobileNet [37], designed specifically for mobile and embedded devices, mobileNet was designed to reduce computational cost and number of parameters by using depthwise separable convolutions.

- InceptionV3 [38], the number three refers to the third version of the model, which released in 2016. It is one of the powerful models in deep learning because of its ability to recognize and classify different images and used in all modern CNN networks.

In [39], the authors explore the application of Machine Learning (ML) models to improve the accuracy of breast cancer detection. They used the Wisconsin Diagnostic Breast Cancer (WDBC) dataset, then applied data normalization techniques and handled missing values to ensure data quality. The hybrid feature selection method, combining Correlation based Feature Selection (CFS) and Recursive Feature Elimination (RFE), was chosen to reduce the dataset to 11 key attributes. Different machine learning models, including Random Forest, Gradient Boosting, SVM, ANN, and MLP, were evaluated using 5-fold cross-validation. The Multilayer Perceptron (MLP) achieved the highest accuracy of 99.12. The study focuses of the importance of advanced machine learning algorithms for accurate breast cancer diagnosis in real-world applications. In [40], the authors focused on diagnosing diabetes using machine learning and its various techniques to select the best classifier for predicting the disease. The authors evaluated four feature selection techniques (e.g., Correlation Attribute Evaluator) and 12 classifiers across two datasets using metrics like accuracy, precision, recall, and F1-measure. They concluded that the Correlation Attribute Evaluator was optimal for feature selection, and MultiClassClassifier performed best in diagnosis tasks. This work demonstrates the effectiveness of machine learning in medical diagnostics [41]. Machine learning techniques are used to predict the outcomes of COVID-19 diagnosis and treatment. Different techniques such as decision trees, random forests, and support vector machines used to analyze the symptoms and medical history of patients. They trained the models to give severity predictions of the disease (mild, moderate, severe) and to recommend appropriate treatment for that severity prediction. The results showed that machine-learning models can be used to predict the amount of disease and therefore decreased the workload of healthcare providers and efficiency in the treatment.

In [42], the authors developed a deep learning-based model to diagnose five types of lung and colon tissues (two benign and three malignant), by using deep learning techniques and image processing such as (convolutional neural networks (CNNs)) on histopathological images. Their results showed on their proposed model high classification accuracy of (96.33%) in the early detection of cancer. In [43], the authors address the limitations of traditional machine learning models in medical diagnostics, which often rely on associative patterns between symptoms and diseases. The purpose of this study is to improve diagnostic accuracy by integrating causal reasoning into machine learning models, leading to greater alignment with clinical diagnostic processes. The authors applied the proposed model to clinical vignettes and compared its performance with standard associative algorithms and human doctors. The results showed that their causal model outperformed associative models with an accuracy comparable to the top (25%) of doctors. In [44], the authors proposed a deep learning model for brain tumor classification using both a standard Convolutional Neural Network (CNN) and the ResNet50 model. In

TABLE I. SUMMARIZING THE RECENT REFERENCES: REFERENCE, YEAR, TITLE, METHODS, ADVANTAGES, AND LIMITATIONS

Reference	Year	Title	Methods	Advantages	Limitations
Salma et al. [39]	2025	Leveraging Machine Learning for Effective Breast Cancer Diagnosis	Machine Learning (ML) models including classification algorithms	High diagnostic accuracy for breast cancer; improved efficiency in early detection	Limited to breast cancer data; generalizability to other datasets not evaluated
Alzyoud et al. [40]	2024	Diagnosing Diabetes Mellitus Using Machine Learning Techniques	ML classification techniques (e.g., SVM, Decision Tree)	Efficient identification of diabetic patients; applicable to real-world datasets	Accuracy depends on data quality; lacks deep learning integration
Rudra Kumar et al. [41]	2022	Diagnosis and Medicine Prediction for COVID-19 Using Machine Learning Approach	ML algorithms for diagnosis and treatment prediction	Supports both diagnosis and treatment planning; fast processing	Limited to COVID-19; based on initial pandemic data with possible bias
Masud et al. [42]	2021	A Machine Learning Approach to Diagnosing Lung and Colon Cancer Using a Deep Learning-Based Classification Framework	Deep learning (CNN-based classification)	High performance in cancer type classification; robust feature extraction	Computationally intensive; requires large labeled datasets
Richens et al. [43]	2020	Improving the Accuracy of Medical Diagnosis with Causal Machine Learning	Causal ML techniques to improve prediction accuracy	Enhances interpretability and accuracy; reduces bias in predictions	Complex model structure; harder to implement in standard ML workflows
Ali et al. [44]	2025	Learning Architecture for Brain Tumor Classification Based on Deep Convolutional Neural Network: Classic and ResNet50	CNN and ResNet50 architectures	High classification accuracy; effective for medical imaging	Deep models require high computation and large data for training

their work, deep CNNs were shown to accurately distinguish among the different tumor types through the extraction of high-level features from medical imaging data. Comparison of the baseline CNN and ResNet50 revealed that state-of-the-art deep architectures like ResNet50 achieved superior accuracy, underlining the strength of higher-order deep learning models in medical diagnosis and image-based classification.

The comparison table (Table I) highlights a line of recent research studies based on machine learning (ML) and deep learning techniques in medical diagnosis. Various methods were employed throughout the research studies, from popular ML algorithms Support Vector Machines and Decision Trees to more advanced deep learning models such as Convolutional Neural Networks (CNNs) and ResNet50.

These approaches have demonstrated superb performance in the diagnosis of the disease: breast cancer, diabetes, COVID-19, lung and colon cancer, and brain tumors. Notable strengths that they reported are improved accuracy in diagnosis, operational efficiency for early detection, and the capability to process large and multidimensional medical datasets. However, each of the studies came with certain limitations. For instance, models that involve deep learning require a lot of computational power and vast amounts of labeled data, while typical ML approaches may struggle with generalizability or lack the ability to process complex patterns in data. Notably, adding causal machine learning to a single experiment gave better interpretability, but at the cost of more complex models. Overall, the table underscores the growing effectiveness of ML in medicine as well as the necessity for balancing accuracy, interpretability, and computational efficiency.

III. PROPOSED METHODOLOGY

This section presents the research methodology, including the framework, datasets, evaluation metrics, and a summary of the findings. Section III(A) provides a detailed description of the five selected datasets. Section III(B) presents the methodology.

A. Description of the Dataset

In this study, five publicly available medical image datasets from Kaggle were utilized to ensure comprehensive evaluation across a wide range of clinical scenarios. These datasets include chest X-ray images for COVID-19 and pneumonia detection, dermoscopic images for melanoma skin lesion classification, facial images for acute stroke diagnosis, and a multi-class collection of ocular images for eye disease identification. This diversity provides a robust test bed for assessing the generalizability and effectiveness of hybrid deep learning and machine learning approaches in automated medical diagnosis. Each dataset covers multiple conditions or disease classes with varying sample sizes, enabling a thorough assessment of model performance across different diagnostic challenges. The key characteristics and class distributions of these datasets are summarized in Table II.

B. Methodology

The main idea of this research is to build a hybrid model that combines ML and DL algorithms to determine the best combination suitable for medical diagnosis tasks; Fig. 1 illustrates the general methodology of the current research. The following subsections provide a detailed explanation of the main steps considered in the methodology of this research.

1) Data collection: At this stage, different datasets have been searched to suit the purpose of this research, images containing different diseases have been collected.

Five datasets have been downloaded from the Kaggle website: COVID-19 images, melanoma skin cancer images, chest X-ray images, various eye diseases, and facial images of acute stroke and non-acute stroke. More information regarding the collected datasets is provided later in this section.

2) Image pre-processing: At this stage, the collected images are pre-processed to ensure they are suitable for machine learning or deep learning models. Initial pre-processing steps in image analysis begin with rescaling the image pixel values from 0 to 255 to be OpenCV compatible, as it is a widely used computer vision library. Normalizing the input data using this standard allows for uniform and reliable utilization of OpenCV

functions throughout the processing chain. The second significant step is applying denoising using GaussianBlur, an extremely common technique for reducing noise by smoothing pixel intensity values through averaging neighboring pixels in the context of a Gaussian function. It suppresses random noise, exaggerates prominent image features, and ultimately improves the accuracy and resilience of image analysis models.

Convert the image to grayscale Converting an image to grayscale simplifies the data which removes the unnecessary color information and only leaves the image with the intensity values. It merges the three-color channels (Red, Green, and Blue) into one where a pixel is a value of light intensity. Grayscale format reduces computational complexity and puts the focus on the structural information. Histogram application: Histogram application enhances image contrast, making features more distinguishable and improving visual clarity. Histogram equalization merely reshapes pixel intensity values from 0–255 to distribute them across the full range of 0–255 in order to highlight small details that are a point or two overshadowed by greater attention to detail. This also allows edges and textures which are necessary for tasks such as the edge detection and image segmentation. Fig. 2 show the image pre-processing pipeline starts by rescaling pixel values to the range of 0 to 255. GaussianBlur is then used to smooth pixel intensities and reduce noise, enhancing key features. After that, the pictures are converted to grayscale, which reduces computational complexity by combining color channels into a single intensity channel. Last but not least, histogram equalization is used to enhance image contrast by redistributing pixel intensities, emphasizing textures, edges, and minute details that are essential for precise image analysis. The images are ready for efficient machine learning or deep learning model training thanks to this series of actions. Many studies have highlighted the importance of image pre-processing for boosting the performance of machine learning-based medical diagnosis. As an example, [45] shows that application of Contrast Limited Adaptive Histogram Equalization (CLAHE) improved classification performance of histopathology images in terms of F1-score, which was 98% with pre-processing and 93% without it. Similarly, [46] proposed to use convolutional denoising autoencoders for effective denoising of medical images, thereby, maintaining essential clinical information even in noisy case. Furthermore, the combination of Gaussian smoothing and clustering techniques applied before CNN training, according to [47], enhanced the detection accuracy of tumors. These findings validate the image pre-processing techniques in this study, which include grayscale conversion along with histogram equalization and Gaussian denoising for improving model robustness and feature detection through noise reduction.

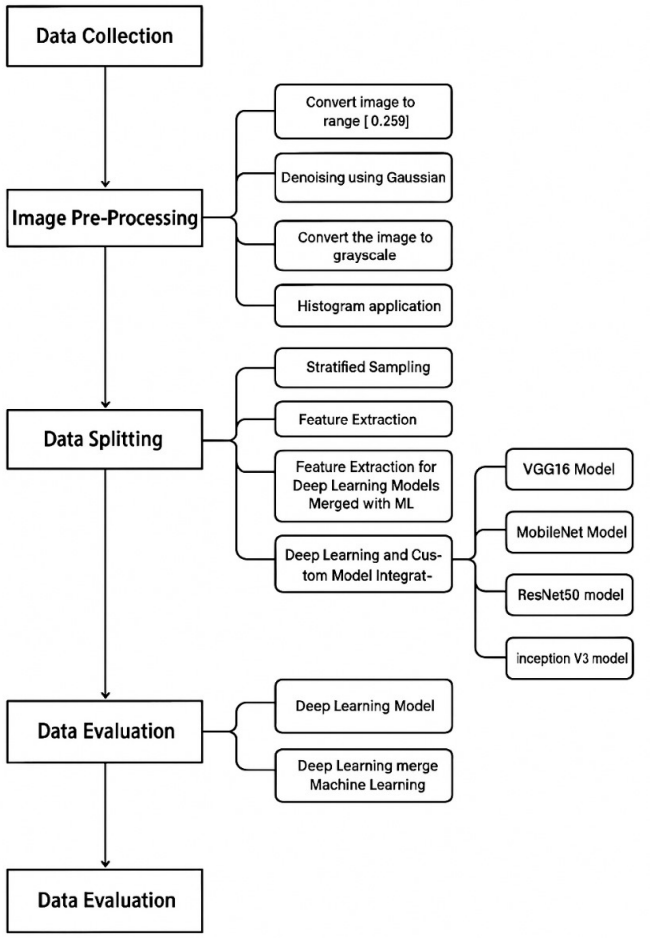


Fig. 1. Research methodology.

TABLE II. CHARACTERISTICS OF THE DATASETS

Dataset	Condition (Class)	Frequency
COVID CXR Image	COVID-19	536
COVID CXR Image	Viral pneumonia	619
COVID CXR Image	Normal cases	668
COVID CXR Image	**Total**	**1823**
Melanoma Skin Cancer	Benign	5000
Melanoma Skin Cancer	Malignant	4605
Melanoma Skin Cancer	**Total**	**9605**
Chest X-Ray	NORMAL	1341
Chest X-Ray	PNEUMONIA	3875
Chest X-Ray	**Total**	**5216**
Face Images of Acute Stroke and Non-Acute Stroke	noStroke_data	2511
Face Images of Acute Stroke and Non-Acute Stroke	stroke_data	1259
Face Images of Acute Stroke and Non-Acute Stroke	**Total**	**3770**
Different Eye Disease	ACRIMA	560
Different Eye Disease	Glaucoma	212
Different Eye Disease	ODIR-5K	7000
Different Eye Disease	ORIGA	517
Different Eye Disease	Cataract	70
Different Eye Disease	retina_disease	70
Different Eye Disease	**Total**	**8429**

3) Data splitting: Once the images are pre-processed, the data is prepared for model training and evaluation. The primary activities of this method start with stratified sampling, ensuring that there is a well-distributed balance of classes between the training, validation, and test datasets, hence enabling representative data splits. Shuffling is then used to avoid bias by the data sample order, enabling randomness in the dataset. Feature extraction plays a vital role in that it utilizes deep

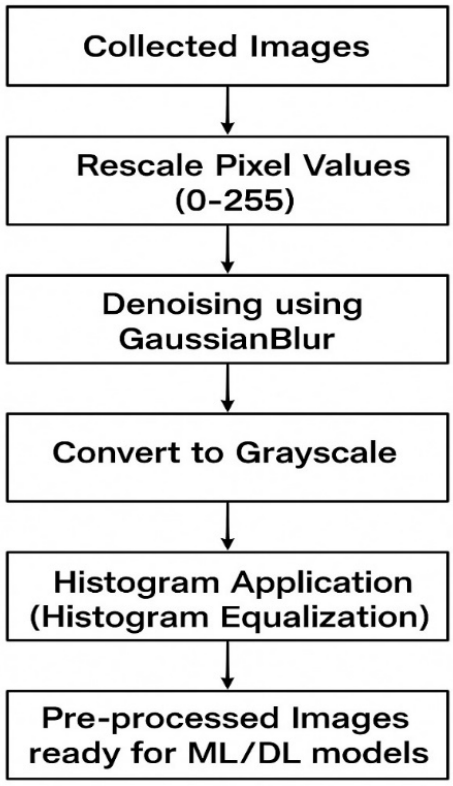


Fig. 2. Images preprocessing flowchart.

models to extract useful image features, which are blended with machine learning to increase prediction precision. Several deep learning architectures are blended and adjusted to provide optimal performance: VGG16 is blended with ten different machine algorithms to optimize predictive capacity; MobileNet is customized to provide light-weight and efficient image processing; ResNet50, a residual very deep network, is utilized to provide effective image classification and prediction; and Inception V3 is utilized due to its advanced structure to provide high-performance predictions in complex tasks.Many researchers endorse the efficacy of hybrid and ensemble methods in medical AI applications, combining deep learning capabilities with conventional machine learning classifiers has shown good promise in enhancing the precision of medical image classification. A comparative study showed that hybrid models where pre-trained convolutional neural networks like MobileNet, VGG16, and Inception V3 are used as feature extraction and then machine learning algorithms are used for classification, attained very high accuracy [48]. Furthermore, ensembling techniques that integrate predictions from different classifiers showed the ability to increase the robustness and reliability of models in clinical environments, as shown by an evaluation of a revised medical image classification process [49]. Fig. 3 shows the data splitting diagram.

4) Data training: Data training involves running deep learning models with preprocessed data for improved predictions. This section explains details about the specific models, their configurations and how deep learning is merged with a machine learning algorithm. Fig. 4 shows the data training process.

- Deep Learning Model. We train on the preprocessed images in this phase to extract our feature using different deep learning models for prediction. The models used in this research include: *VGG16*, *MobileNet*, *ResNet50*, and *Inception V3* models.

- Deep Learning merge with Machine Learning. Features from the deep learning models are merged with various machine learning algorithms in order to better increase the predictive power of the deep learning models.

  This hybrid approach involves the following steps:
  - Feature Extraction: Using the deep learning models (such as VGG16, MobileNet, ResNet50 and Inception V3) are used to automatically extract relevant features from the images. Features that typically include textures, edges, and patterns which are essential for disease classification can be included in these features.

  - Using Machine Learning Algorithms: When features are extracted, we input them into various machine learning algorithms for classification and prediction. Ten machine learning algorithms are used including: (Naive Bayes (NB), Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), Logistic Regression (LG), Multi-layer Perceptron (MLP), K-Nearest Neighbors Algorithm (KNN), Adaptive Boosting (AdaBoost), Random Forest (RF), Gradient Boosting, Decision Tree (DT)). The deep learning models tries to create predictions while these algorithms optimization for the predictions in order to increase accuracy and performance of the overall system.

  - Hybrid Model: This method combines the abilities of deep learning to extract features with the flexibility and efficiency of machine learning for prediction to improve the overall predictive ability of classification, especially in classifying images with high accuracy.

5) Evaluation phase: The hybrid model performance is evaluated in terms of accuracy and efficiency using evaluation metrics in classifying medical images accurately and efficiently. In [42], the authors presented a hybrid model that is a combination of a deep CNN and SVM classifier to improve brain tumor classification. They used common metrics, were Accuracy, Precision, Recall, F1-score, and Dice Similarity Coefficient (DSC) for the assessment of the model. The model achieved an accuracy of (98.3%) and DSC of (97.8%) on the Brain Dataset-1. Their finding showed the efficiency of combining deep learning for feature extraction with machine learning for classification in medical imaging tasks. In this research, four evaluation measures have been used as the following:

C. Evaluation Metrics

Accuracy: Calculates the proportion of correctly classified instances (both positive and negative) out of all instances; it

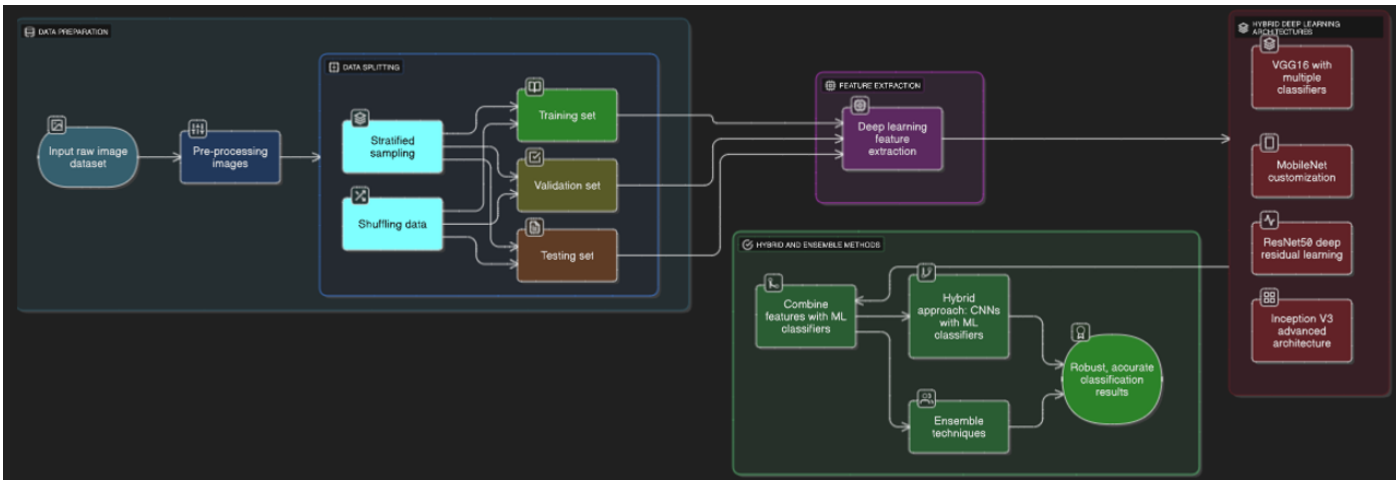


Fig. 3. Data splitting process.

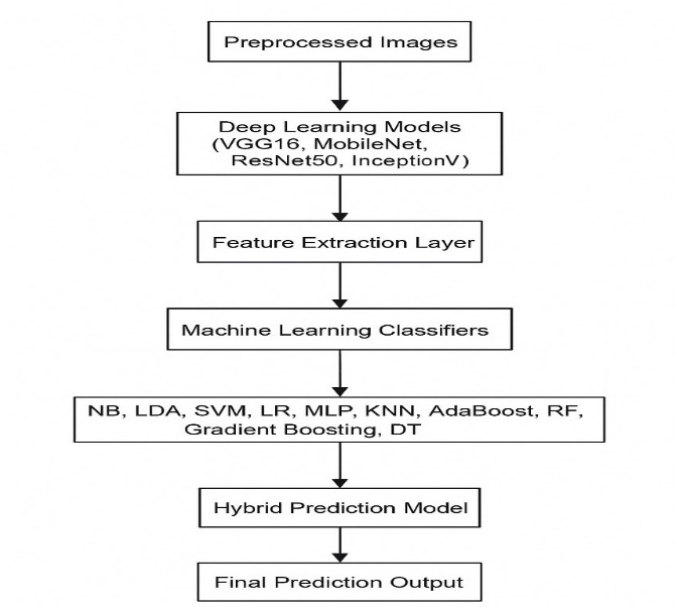


Fig. 4. Data training process diagram.

measures the model's overall correctness.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}. \tag{1}$$

Precision: Measures how many of the predicted positives are actually positive.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}. \tag{2}$$

Recall: Measures the model's ability to capture all actual positive cases.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}. \tag{3}$$

F1-score: The harmonic mean of Precision and Recall.

$$\text{F1} = \frac{2\,\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}. \tag{4}$$

IV. Experimental Results

This section presents the evaluation results of the experiments on developing an efficient medical image classification model. The model is a hybrid that combines machine learning and deep learning algorithms. This model aims to enhance the predictive performance by taking advantage of the strengths of both techniques.

- Identifying the Most Appropriate DL Model That Suits Medical Data. In this phase, which is considered the most important step of this research, the predictive performance of the four deep learning models (*VGG16*, *ResNet50*, *MobileNet*, and *InceptionV3*) is evaluated across five different datasets related to medical image classification, considering four evaluation metrics (Accuracy, Precision, Recall, and F1-Score), as shown in Table III.

The most significant key insights that could be concluded from Table III are listed next with respect to the five considered datasets.

- COVID-19 Dataset. Out of the models it was compared with, *MobileNet* performed the most accurately at 0.97, outperforming *VGG16* and *InceptionV3* with accuracies of 0.96 each. *ResNet50* performed the worst at 0.74. Additionally, Precision, Recall, and F1-score indicate that *MobileNet*, *VGG16*, and *InceptionV3* performed comparably, while *ResNet50* lagged on this task.

- Melanoma Skin Cancer Dataset. *MobileNet* was best with 0.93 accuracy, slightly above *VGG16* and *InceptionV3* (0.92 each). *ResNet50* was worst (0.78). Precision, Recall, and F1-score were high for *MobileNet*, *VGG16*, and *InceptionV3*, highlighting their suitability for melanoma identification.

- Chest X-Ray Images. *MobileNet* achieved the maximum accuracy (0.99), followed by *VGG16* (0.98) and

TABLE III. PERFORMANCE COMPARISON OF DEEP LEARNING MODELS ON VARIOUS MEDICAL DATASETS

Dataset	Deep Learning Model	Acc	Prec	Rec	F1
COVID-19 Dataset	VGG16	0.96	0.97	0.97	0.97
COVID-19 Dataset	ResNet50	0.74	0.73	0.74	0.74
COVID-19 Dataset	MobileNet	0.97	0.97	0.97	0.97
COVID-19 Dataset	InceptionV3	0.96	0.97	0.97	0.97
Melanoma Skin Cancer Dataset	VGG16	0.92	0.92	0.92	0.92
Melanoma Skin Cancer Dataset	ResNet50	0.78	0.78	0.78	0.78
Melanoma Skin Cancer Dataset	MobileNet	0.93	0.93	0.93	0.93
Melanoma Skin Cancer Dataset	InceptionV3	0.92	0.92	0.92	0.91
Chest X-Ray Images	VGG16	0.98	0.97	0.97	0.97
Chest X-Ray Images	ResNet50	0.91	0.88	0.90	0.89
Chest X-Ray Images	MobileNet	0.99	0.98	0.99	0.98
Chest X-Ray Images	InceptionV3	0.97	0.97	0.97	0.97
Face Images of Acute Stroke and Non-Acute Stroke	VGG16	0.99	0.99	0.99	0.99
Face Images of Acute Stroke and Non-Acute Stroke	ResNet50	0.76	0.74	0.70	0.71
Face Images of Acute Stroke and Non-Acute Stroke	MobileNet	0.99	0.99	0.99	0.99
Face Images of Acute Stroke and Non-Acute Stroke	InceptionV3	0.98	0.98	0.98	0.98
Dataset for Different Eye Disease	VGG16	0.96	0.78	0.76	0.74
Dataset for Different Eye Disease	ResNet50	0.90	0.44	0.44	0.44
Dataset for Different Eye Disease	MobileNet	0.94	0.76	0.72	0.73
Dataset for Different Eye Disease	InceptionV3	0.96	0.95	0.96	0.95

InceptionV3 (0.97). *ResNet50* scored 0.91. Across metrics, *MobileNet* is the optimal choice for this dataset.

- Face Images of Acute Stroke and Non-Acute Stroke. Both *VGG16* and *MobileNet* obtained the highest accuracy (0.99), with *InceptionV3* at 0.98. *ResNet50* was much lower (0.76). Precision/Recall/F1 confirm that *VGG16*, *MobileNet*, and *InceptionV3* are very effective for stroke classification.

- Dataset for Different Eye Disease. *InceptionV3* and *VGG16* reached the highest accuracy (0.96), *MobileNet* achieved 0.94, whereas *ResNet50* underperformed (0.90) with poor Precision/Recall/F1 (around 0.44). Overall performance was strong, with *InceptionV3* most reliable across metrics.

Main findings (Objective 1):

- *MobileNet* showed consistently high performance across all datasets, often achieving the highest Accuracy.

- *ResNet50* had the worst performance across Accuracy, Precision, Recall, and F1-score.

- *VGG16* and *InceptionV3* performed similarly well, with *InceptionV3* slightly more consistent.

- *MobileNet* and *InceptionV3* appear to be the most reliable for medical image classification, while *ResNet50* is not recommended.

TABLE IV. PERFORMANCE COMPARISON OF ML CLASSIFIERS WITH VGG16 FOR COVID-19 DATASET

Model	Accuracy	Precision	Recall	F1-Score
VGG16+SVM	0.89	0.90	0.89	0.89
VGG16+Random Forest	0.95	0.95	0.95	0.95
VGG16+Gradient Boosting	0.94	0.94	0.94	0.94
VGG16+AdaBoost	0.87	0.88	0.87	0.87
VGG16+KNN	0.94	0.94	0.94	0.94
VGG16+Logistic Regression	0.94	0.94	0.94	0.94
VGG16+Decision Tree	0.83	0.83	0.83	0.83
VGG16+Naïve Bayes	0.82	0.84	0.82	0.82
VGG16+LDA	**0.95**	**0.96**	**0.95**	**0.96**
VGG16+MLP	0.94	0.94	0.94	0.94

TABLE V. PERFORMANCE COMPARISON OF ML CLASSIFIERS WITH RESNET50 FOR COVID-19 DATASET

Model	Accuracy	Precision	Recall	F1-Score
ResNet50+SVM	0.44	0.25	0.40	0.30
ResNet50+Random Forest	0.89	0.89	0.89	0.89
ResNet50+Gradient Boosting	**0.93**	**0.93**	**0.93**	**0.93**
ResNet50+AdaBoost	0.85	0.85	0.85	0.85
ResNet50+KNN	0.87	0.88	0.87	0.87
ResNet50+Logistic Regression	0.85	0.85	0.85	0.85
ResNet50+Decision Tree	0.79	0.79	0.80	0.79
ResNet50+Naïve Bayes	0.78	0.78	0.78	0.78
ResNet50+LDA	0.91	0.91	0.91	0.91
ResNet50+MLP	0.78	0.81	0.78	0.76

A. Combine Deep Learning Models with Machine Learning Techniques

This section presents the evaluation results of combining deep learning models and machine learning techniques with respect to the five considered datasets.

1) Evaluation results with respect to the COVID-19 dataset: This part evaluates several ML classifiers combined with the four DL models for the COVID-19 dataset.

a) VGG16 performance: In Table IV, *VGG16* with LDA (Linear Discriminant Analysis) achieved the best results, demonstrating strong performance and making it an optimal choice for COVID-19 classification. However, *VGG16* with Naïve Bayes and with Decision Tree performed worst, implying these classifiers may be less appropriate for this dataset.

ResNet50 Performance. Table V shows that Gradient Boosting achieved the highest performance across all metrics (**Accuracy=0.93**, **Precision=0.93**, **Recall=0.93**, **F1=0.93**), highlighting its strength for COVID-19 classification and its ability to learn the underlying patterns in the dataset. In contrast, the SVM variant recorded the weakest results and exhibited an imbalanced precision–recall trade-off.

MobileNet Performance.

Table VI shows that MobileNet + MLP achieved the best results across all metrics (**Accuracy=0.97**, **Precision=0.97**, **Recall=0.97**, **F1=0.97**), making it the most effective combination. In contrast, MobileNet + Decision Tree recorded

TABLE VI. PERFORMANCE COMPARISON OF ML CLASSIFIERS WITH MOBILENET FOR COVID-19 DATASET

Model	Accuracy	Precision	Recall	F1-Score
MobileNet+SVM	0.96	0.96	0.96	0.96
MobileNet+Random Forest	0.95	0.95	0.95	0.95
MobileNet+Gradient Boosting	0.95	0.95	0.95	0.95
MobileNet+AdaBoost	0.92	0.92	0.92	0.92
MobileNet+KNN	0.94	0.94	0.94	0.94
MobileNet+Logistic Regression	0.96	0.96	0.96	0.96
MobileNet+Decision Tree	0.85	0.86	0.86	0.86
MobileNet+Naïve Bayes	0.93	0.93	0.93	0.93
MobileNet+LDA	0.92	0.92	0.92	0.92
MobileNet+MLP	**0.97**	**0.97**	**0.97**	**0.97**

TABLE VII. PERFORMANCE COMPARISON OF ML CLASSIFIERS WITH INCEPTIONV3 FOR COVID-19 DATASET

Model	Accuracy	Precision	Recall	F1-Score
InceptionV3+SVM	0.93	0.94	0.94	0.94
InceptionV3+Random Forest	0.91	0.91	0.92	0.91
InceptionV3+Gradient Boosting	0.92	0.93	0.93	0.92
InceptionV3+AdaBoost	0.87	0.88	0.88	0.88
InceptionV3+KNN	0.87	0.89	0.88	0.88
InceptionV3+Logistic Regression	0.92	0.92	0.92	0.92
InceptionV3+Decision Tree	0.79	0.81	0.79	0.79
InceptionV3+Naïve Bayes	0.85	0.85	0.85	0.85
InceptionV3+LDA	0.73	0.74	0.73	0.74
InceptionV3+MLP	0.92	0.92	0.92	0.92

the weakest performance (**Accuracy**=0.85, **Precision**=0.86, **Recall**=0.86, **F1**=0.86).

InceptionV3 Performance.

Table VII shows that *InceptionV3 + SVM* achieved the strongest, well-balanced results across all metrics (**Accuracy**=0.93, **Precision**=0.94, **Recall**=0.94, **F1**=0.94). In contrast, *InceptionV3 + LDA* exhibited the weakest performance (**Accuracy**=0.73, **Precision**=0.74, **Recall**=0.73, **F1**=0.74).

Based on the previous performance metrics, the most suitable machine learning (ML) classifier for the COVID-19 medical data depends on the chosen deep learning (DL) feature extractor. The best combinations by *Accuracy* are:

- If *MobileNet* is used, *MLP* is the best choice (Accuracy: **0.97**).
- If *VGG16* is used, *LDA* is the best choice (Accuracy: **0.95**).
- If *ResNet50* is used, *Gradient Boosting* is the best (Accuracy: **0.93**).
- If *InceptionV3* is used, *SVM* is the best (Accuracy: **0.93**).

For the COVID-19 dataset, **MobileNet + MLP** is the strongest overall. Final model selection should also consider interpretability, computational cost, and dataset-specific requirements, as summarized in Fig. 5.

TABLE VIII. PERFORMANCE COMPARISON OF ML CLASSIFIERS WITH VGG16 FOR MELANOMA SKIN CANCER DATASET

Model	Accuracy	Precision	Recall	F1-score
VGG16+SVM	0.84	0.85	0.84	0.84
VGG16+Random Forest	0.89	0.89	0.89	0.89
VGG16+Gradient Boosting	0.90	0.90	0.90	0.90
VGG16+AdaBoost	0.89	0.89	0.89	0.89
VGG16+KNN	0.88	0.89	0.88	0.88
VGG16+Logistic Regression	0.89	0.89	0.89	0.89
VGG16+Decision Tree	0.85	0.85	0.85	0.85
VGG16+Naïve Bayes	0.70	0.76	0.70	0.68
VGG16+LDA	0.90	0.90	0.90	0.90
VGG16+MLP	0.92	0.92	0.92	0.91

TABLE IX. PERFORMANCE COMPARISON OF ML CLASSIFIERS WITH RESNET50 FOR MELANOMA SKIN CANCER DATASET

Model	Accuracy	Precision	Recall	F1-Score
ResNet50+SVM	0.62	0.75	0.62	0.56
ResNet50+Random Forest	0.89	0.89	0.89	0.89
ResNet50+Gradient Boosting	0.90	0.90	0.90	0.90
ResNet50+AdaBoost	0.88	0.88	0.88	0.88
ResNet50+KNN	0.87	0.87	0.87	0.87
ResNet50+Logistic Regression	0.89	0.89	0.89	0.89
ResNet50+Decision Tree	0.82	0.82	0.82	0.82
ResNet50+Naïve Bayes	0.63	0.73	0.63	0.60
ResNet50+LDA	0.90	0.90	0.90	0.90
ResNet50+MLP	0.85	0.85	0.85	0.85

2) Evaluation results with respect to the melanoma skin cancer dataset:

a) VGG16 performance: Table VIII shows that the best performing model among all models was *VGG16* with *MLP*, achieving the highest values across all metrics. In contrast, *VGG16* with Naïve Bayes performed the worst, making it the least effective classifier in this comparison.

ResNet50 Performance.

Table IX shows that *ResNet50 + Gradient Boosting* and *ResNet50 + LDA* achieved the highest scores across all metrics (**Accuracy=0.90**, **Precision=0.90**, **Recall=0.90**, **F1=0.90**), indicating strong generalization and a balanced precision–recall trade-off. In contrast, *ResNet50 + SVM* produced the weakest performance among the compared classifiers.

MobileNet Performance. Table X shows that *MobileNet + SVM* achieved the highest scores across all metrics (Accuracy, Precision, Recall, and F1), making it the top-performing configuration for this dataset. In contrast, *MobileNet + Naive Bayes* yielded the weakest results, recording the lowest values on all evaluated metrics.

b) InceptionV3 performance: Table XI illustrates that the *InceptionV3* with *SVM* model achieved the highest Accuracy, Precision, Recall, and F1-score. Meanwhile, the *InceptionV3* combined with the *Decision Tree* model showed the weakest performance across all metrics.

Based on the above performance metrics, the most suitable ML classifier for the *Melanoma Skin Cancer* data depends on the chosen DL feature extractor. The best combinations by *Accuracy* are:

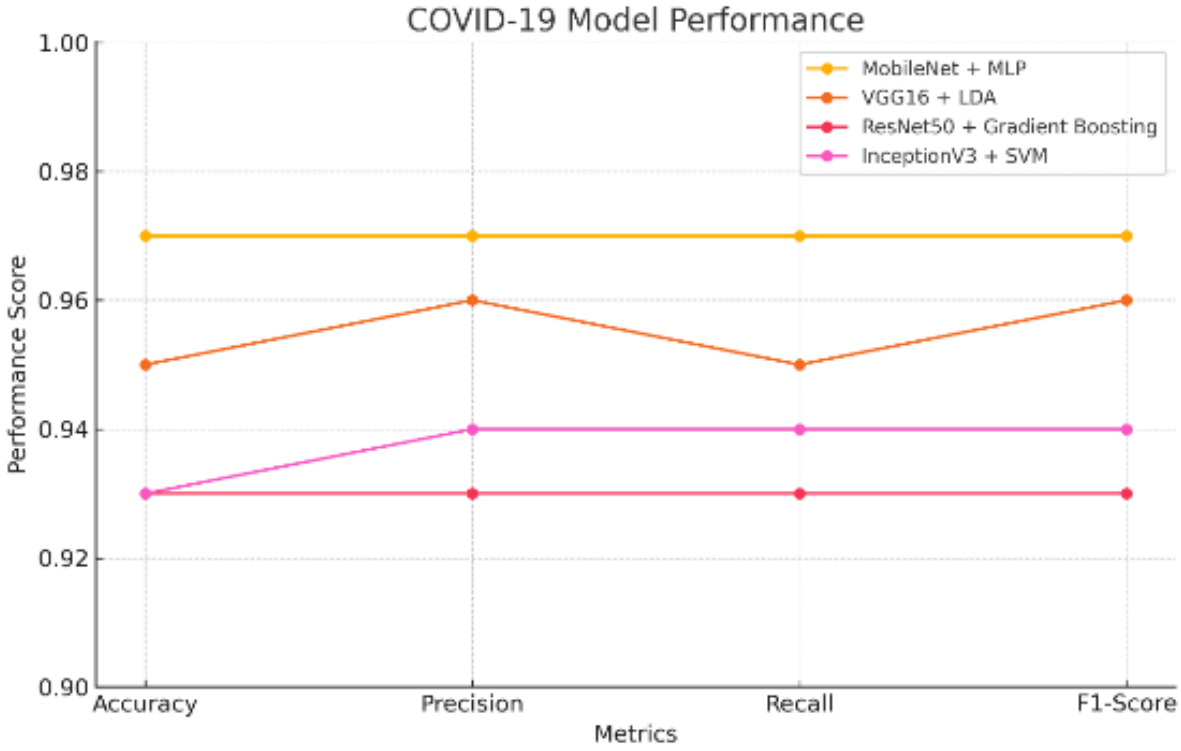


Fig. 5. COVID-19 model performance.

TABLE X. PERFORMANCE COMPARISON OF ML CLASSIFIERS WITH MOBILENET FOR MELANOMA SKIN CANCER DATASET

Model	Accuracy	Precision	Recall	F1-Score
MobileNet+SVM	0.92	0.92	0.92	0.92
MobileNet+Random Forest	0.90	0.90	0.90	0.90
MobileNet+Gradient Boosting	0.91	0.91	0.91	0.90
MobileNet+AdaBoost	0.86	0.86	0.86	0.86
MobileNet+KNN	0.90	0.90	0.90	0.90
MobileNet+Logistic Regression	0.89	0.89	0.89	0.89
MobileNet+Decision Tree	0.82	0.83	0.82	0.82
MobileNet+Naïve Bayes	0.80	0.80	0.80	0.80
MobileNet+LDA	0.90	0.90	0.90	0.90
MobileNet+MLP	0.91	0.91	0.91	0.91

TABLE XI. PERFORMANCE COMPARISON OF ML CLASSIFIERS WITH INCEPTIONV3 FOR MELANOMA SKIN CANCER DATASET

Model	Accuracy	Precision	Recall	F1-Score
InceptionV3+SVM	0.91	0.91	0.91	0.91
InceptionV3+Random Forest	0.87	0.87	0.87	0.87
InceptionV3+Gradient Boosting	0.90	0.90	0.90	0.90
InceptionV3+AdaBoost	0.87	0.87	0.87	0.87
InceptionV3+KNN	0.86	0.87	0.86	0.85
InceptionV3+Logistic Regression	0.89	0.89	0.89	0.89
InceptionV3+Decision Tree	0.78	0.78	0.78	0.78
InceptionV3+Naïve Bayes	0.80	0.80	0.80	0.80
InceptionV3+LDA	0.89	0.89	0.89	0.89
InceptionV3+MLP	0.90	0.90	0.90	0.90

- If *MobileNet* is used, *SVM* is best (Accuracy: **0.92**).
- If *VGG16* is used, *MLP* is best (Accuracy: **0.92**).
- If *InceptionV3* is used, *SVM* is best (Accuracy: **0.91**).
- If *ResNet50* is used, *Gradient Boosting/LDA* are best (Accuracy: **0.90**).

Overall, **MobileNet+SVM** is the strongest model for melanoma; **VGG16+MLP** is also a strong alternative, especially if computational efficiency matters (see Fig. 6 and Table XII).

ResNet50 Performance. Table XIII shows that *ResNet50 + MLP* achieved the highest scores across all metrics (**Accuracy**=0.96, **Precision**=0.95, **Recall**=0.95, **F1**=0.95). In contrast, *ResNet50 + Random Forest* exhibited the weakest performance among the compared models.

c) MobileNet performance: Table XIV shows that, across all evaluation metrics, the *MobileNet+MLP* model outperforms the rest (Accuracy 0.98, Precision 0.97, Recall 0.97, and F1-score 0.97). In contrast, *MobileNet+Decision Tree* has the lowest performance (Accuracy 0.90, Precision 0.87, Recall 0.88, F1-score 0.88), indicating notable limitations and making it the least reliable among the tested models.

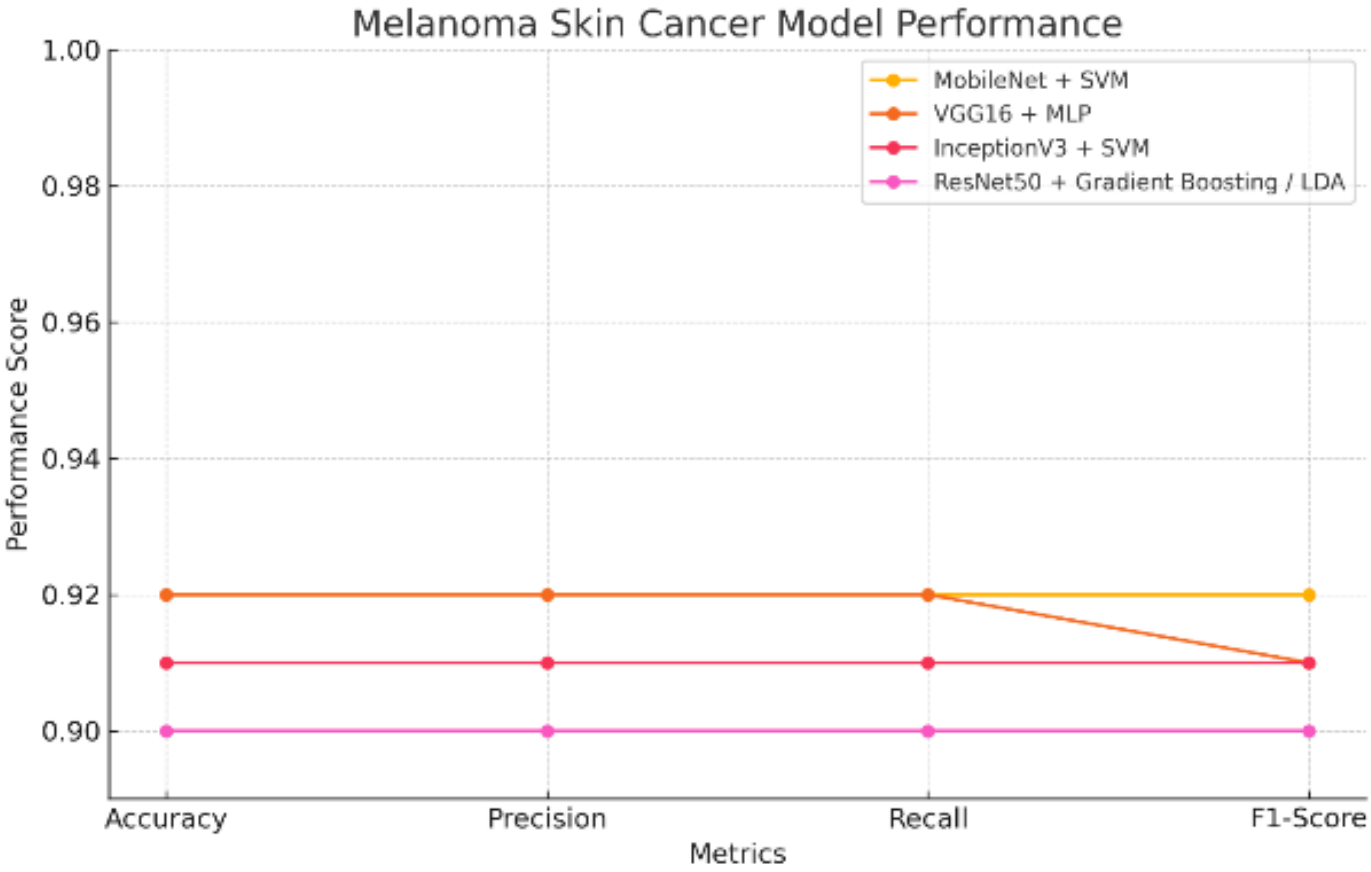


Fig. 6. Melanoma model performance.

TABLE XII. PERFORMANCE COMPARISON OF ML CLASSIFIERS WITH VGG16 FOR CHEST X-RAY IMAGES DATASET

Model	Accuracy	Precision	Recall	F1-Score
VGG16+SVM	0.93	0.91	0.91	0.91
VGG16+Random Forest	0.96	0.95	0.94	0.94
VGG16+Gradient Boosting	0.95	0.94	0.94	0.94
VGG16+AdaBoost	0.95	0.94	0.94	0.94
VGG16+KNN	0.95	0.93	0.93	0.94
VGG16+Logistic Regression	0.95	0.94	0.94	0.94
VGG16+Decision Tree	0.90	0.86	0.87	0.87
VGG16+Naïve Bayes	0.93	0.90	0.90	0.87
VGG16+LDA	0.97	0.96	0.95	0.96
VGG16+MLP	0.97	0.96	0.96	0.96

TABLE XIII. PERFORMANCE COMPARISON OF ML CLASSIFIERS WITH RESNET50 FOR CHEST X-RAY IMAGES DATASET

Model	Accuracy	Precision	Recall	F1-Score
ResNet50+SVM	0.91	0.88	0.90	0.89
ResNet50+Random Forest	0.74	0.37	0.50	0.43
ResNet50+Gradient Boosting	0.92	0.91	0.88	0.90
ResNet50+AdaBoost	0.94	0.93	0.92	0.92
ResNet50+KNN	0.94	0.96	0.93	0.93
ResNet50+Logistic Regression	0.90	0.86	0.89	0.88
ResNet50+Decision Tree	0.92	0.93	0.92	0.93
ResNet50+Naïve Bayes	0.89	0.86	0.86	0.86
ResNet50+LDA	0.83	0.78	0.90	0.88
ResNet50+MLP	0.96	0.95	0.95	0.95

d) InceptionV3 performance: The performance of models using the *InceptionV3* feature extractor with different ML classifiers is presented in Table XV. The best results were obtained with *InceptionV3+Logistic Regression* and *InceptionV3+MLP*, each achieving 0.96 for Accuracy, Precision, Recall, and F1-score. The weakest model was *InceptionV3+Decision Tree.*

- If *MobileNet* is used, *MLP* is best (Accuracy: **0.98**).
- If *VGG16* is used, *MLP* is best (Accuracy: **0.97**); *LDA* is a strong alternative.
- If *InceptionV3* is used, *MLP/Logistic Regression* are best (Accuracy: **0.96**).
- If *ResNet50* is used, *MLP* is best (Accuracy: **0.96**).

Overall, **MobileNet+MLP** achieves the highest Accuracy for Chest X-Ray Images, while **VGG16+MLP/LDA** is also a strong choice (see Fig. 7 and Table XVI).

e) ResNet50 performance: Table XVII shows that *ResNet50+KNN* achieved the best performance with the highest Accuracy (0.91), Precision (0.90), Recall (0.89), and F1-

TABLE XIV. PERFORMANCE COMPARISON OF ML CLASSIFIERS WITH MOBILENET FOR CHEST X-RAY IMAGES DATASET

Model	Accuracy	Precision	Recall	F1-Score
MobileNet+SVM	0.97	0.96	0.96	0.96
MobileNet+Random Forest	0.95	0.94	0.93	0.93
MobileNet+Gradient Boosting	0.96	0.95	0.94	0.94
MobileNet+AdaBoost	0.92	0.90	0.87	0.90
MobileNet+KNN	0.96	0.94	0.95	0.95
MobileNet+Logistic Regression	0.97	0.96	0.96	0.96
MobileNet+Decision Tree	0.90	0.87	0.88	0.88
MobileNet+Naïve Bayes	0.92	0.89	0.88	0.85
MobileNet+LDA	0.97	0.96	0.96	0.96
MobileNet+MLP	**0.98**	**0.97**	**0.97**	**0.97**

TABLE XV. PERFORMANCE COMPARISON OF ML CLASSIFIERS WITH INCEPTIONV3 FOR CHEST X-RAY IMAGES DATASET

Model	Accuracy	Precision	Recall	F1-Score
InceptionV3+SVM	0.95	0.95	0.95	0.95
InceptionV3+Random Forest	0.92	0.92	0.92	0.92
InceptionV3+Gradient Boosting	0.95	0.95	0.95	0.95
InceptionV3+AdaBoost	0.93	0.93	0.93	0.93
InceptionV3+KNN	0.91	0.92	0.91	0.91
InceptionV3+Logistic Regression	0.96	0.96	0.96	0.96
InceptionV3+Decision Tree	0.96	0.86	0.86	0.85
InceptionV3+Naïve Bayes	0.89	0.89	0.87	0.88
InceptionV3+LDA	0.94	0.94	0.94	0.94

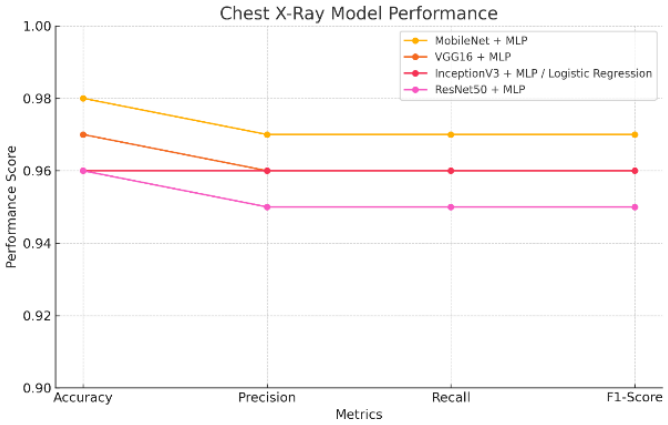


Fig. 7. Chest X-ray model performance.

score (0.89). Conversely, *ResNet50+SVM* recorded the lowest metrics (Accuracy 0.67, Precision 0.33, Recall 0.50, F1-score 0.40).

f) MobileNet performance: Table XVIII shows that the most effective models are *MobileNet+SVM*, *MobileNet+KNN*, *MobileNet+LDA*, and *MobileNet+MLP*, each achieving perfect scores (Accuracy, Precision, Recall, and F1-score of 1.00). In contrast, *MobileNet+Naïve Bayes* recorded the weakest performance (Accuracy 0.81, Precision 0.80, Recall 0.83, F1-score 0.80), making it the least effective classifier in this comparison.

g) InceptionV3 performance: Table XIX presents the results for models using the *InceptionV3* feature extractor.

TABLE XVI. PERFORMANCE COMPARISON OF ML CLASSIFIERS WITH VGG16 FOR FACE IMAGES DATASET

Model	Accuracy	Precision	Recall	F1-Score
VGG16+SVM	0.91	0.90	0.89	0.89
VGG16+Random Forest	0.98	0.98	0.97	0.98
VGG16+Gradient Boosting	0.98	0.98	0.98	0.98
VGG16+AdaBoost	0.96	0.96	0.95	0.95
VGG16+KNN	1.00	1.00	1.00	1.00
VGG16+Logistic Regression	0.97	0.97	0.97	0.97
VGG16+Decision Tree	0.90	0.89	0.89	0.89
VGG16+Naïve Bayes	0.84	0.83	0.87	0.83
VGG16+LDA	0.99	0.99	0.99	0.99
VGG16+MLP	1.00	1.00	1.00	1.00

TABLE XVII. PERFORMANCE COMPARISON OF ML CLASSIFIERS WITH RESNET50 FOR FACE IMAGES DATASET

Model	Accuracy	Precision	Recall	F1-Score
ResNet50+SVM	0.67	0.33	0.50	0.40
ResNet50+Random Forest	0.88	0.89	0.84	0.86
ResNet50+Gradient Boosting	0.88	0.86	0.85	0.86
ResNet50+AdaBoost	0.84	0.82	0.82	0.82
ResNet50+KNN	0.91	0.90	0.89	0.89
ResNet50+Logistic Regression	0.81	0.79	0.77	0.78
ResNet50+Decision Tree	0.78	0.75	0.75	0.75
ResNet50+Naïve Bayes	0.59	0.70	0.68	0.65
ResNet50+LDA	0.84	0.82	0.83	0.82
ResNet50+MLP	0.83	0.81	0.79	0.80

TABLE XVIII. PERFORMANCE COMPARISON OF ML CLASSIFIERS WITH MOBILENET FOR FACE IMAGES DATASET

Model	Accuracy	Precision	Recall	F1-Score
MobileNet+SVM	1.00	1.00	1.00	1.00
MobileNet+Random Forest	0.98	0.97	0.97	0.98
MobileNet+Gradient Boosting	0.99	0.99	0.99	0.99
MobileNet+AdaBoost	0.99	0.99	0.99	0.99
MobileNet+KNN	1.00	1.00	1.00	1.00
MobileNet+Logistic Regression	0.99	0.99	1.00	0.99
MobileNet+Decision Tree	0.88	0.86	0.80	0.87
MobileNet+Naïve Bayes	0.81	0.80	0.83	0.80
MobileNet+LDA	1.00	1.00	1.00	1.00
MobileNet+MLP	1.00	1.00	1.00	1.00

The best-performing classifiers were *SVM*, *KNN*, *Logistic Regression*, and *MLP*. In contrast, *InceptionV3+Naïve Bayes* recorded the weakest performance (Accuracy 0.75, Precision 0.79, Recall 0.75, F1-score 0.75).

Based on the previous performance metrics for the *Face Images of Acute Stroke and Non-Acute Stroke* dataset, the best ML classifier depends on the DL feature extractor:

- If *MobileNet* is used, *SVM*, *KNN*, *LDA*, or *MLP* achieved perfect scores (Accuracy: **1.00**).
- If *VGG16* is used, *KNN* or *MLP* are best (Accuracy: **1.00**).
- If *InceptionV3* is used, *SVM*, *KNN*, *Logistic Regression*, or *MLP* are best (Accuracy: **0.99**).

TABLE XIX. PERFORMANCE COMPARISON OF ML CLASSIFIERS WITH INCEPTIONV3 FOR FACE IMAGES DATASET

Model	Accuracy	Precision	Recall	F1-Score
InceptionV3+SVM	0.99	0.99	0.99	0.99
InceptionV3+Random Forest	0.94	0.94	0.94	0.94
InceptionV3+Gradient Boosting	0.95	0.96	0.95	0.95
InceptionV3+AdaBoost	0.93	0.93	0.93	0.93
InceptionV3+KNN	0.99	0.99	0.99	0.99
InceptionV3+Logistic Regression	0.99	0.99	0.99	0.99
InceptionV3+Decision Tree	0.83	0.84	0.84	0.84
InceptionV3+Naïve Bayes	0.75	0.79	0.75	0.75
InceptionV3+LDA	0.95	0.95	0.95	0.95
InceptionV3+MLP	0.99	0.99	0.99	0.99

TABLE XX. PERFORMANCE COMPARISON OF ML CLASSIFIERS WITH VGG16 FOR DIFFERENT EYE DISEASE DATASET

Model	Accuracy	Precision	Recall	F1-Score
VGG16+SVM	0.93	0.45	0.49	0.47
VGG16+Random Forest	0.92	0.67	0.62	0.62
VGG16+Gradient Boosting	0.92	0.67	0.61	0.63
VGG16+AdaBoost	0.81	0.30	0.29	0.29
VGG16+KNN	0.95	0.77	0.74	0.73
VGG16+Logistic Regression	0.94	0.80	0.58	0.59
VGG16+Decision Tree	0.88	0.58	0.61	0.59
VGG16+Naïve Bayes	0.62	0.54	0.67	0.54
VGG16+LDA	0.94	0.65	0.72	0.69
VGG16+MLP	0.95	0.75	0.73	0.72

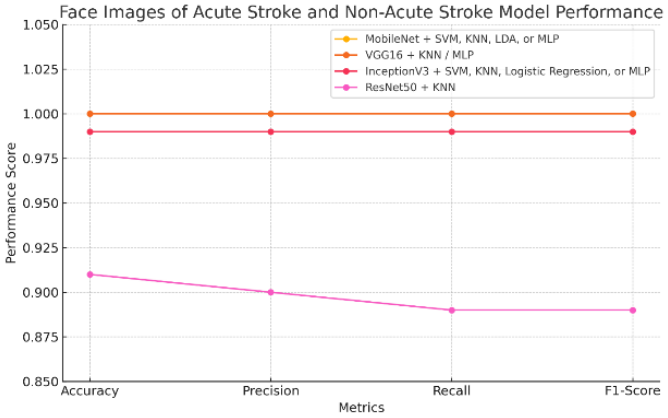


Fig. 8. Acute stroke model performance.

TABLE XXI. PERFORMANCE COMPARISON OF ML CLASSIFIERS WITH RESNET50 FOR DIFFERENT EYE DISEASE DATASET

Model	Accuracy	Precision	Recall	F1-Score
ResNet50+SVM	0.74	0.12	0.17	0.14
ResNet50+Random Forest	0.92	0.68	0.61	0.62
ResNet50+Gradient Boosting	0.90	0.54	0.53	0.53
ResNet50+AdaBoost	0.94	0.30	0.33	0.31
ResNet50+KNN	**0.93**	0.65	0.65	0.63
ResNet50+Logistic Regression	0.91	0.43	0.46	0.45
ResNet50+Decision Tree	0.88	0.39	0.32	0.34
ResNet50+Naïve Bayes	**0.38**	0.29	0.58	0.37
ResNet50+LDA	**0.93**	0.69	0.73	0.71
ResNet50+MLP	0.92	0.60	0.59	0.56

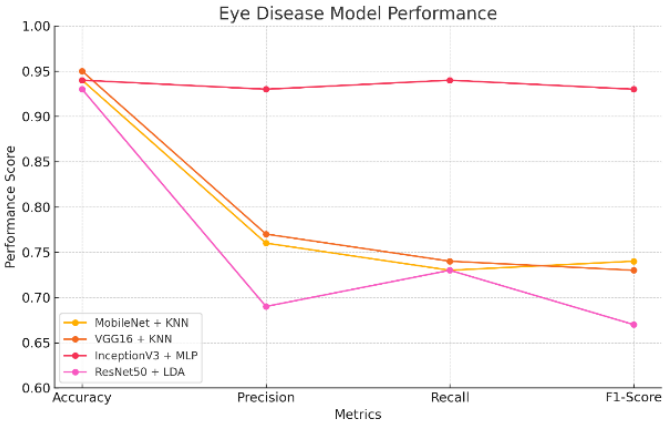


Fig. 9. Eye disease model performance.

TABLE XXII. PERFORMANCE COMPARISON OF ML CLASSIFIERS WITH INCEPTIONV3 FOR DIFFERENT EYE DISEASE DATASET

Model	Accuracy	Precision	Recall	F1-Score
InceptionV3+SVM	0.94	0.90	0.94	0.92
InceptionV3+Random Forest	0.91	0.88	0.91	0.89
InceptionV3+Gradient Boosting	0.91	0.89	0.90	0.90
InceptionV3+AdaBoost	0.85	0.85	0.78	0.79
InceptionV3+KNN	0.93	0.92	0.93	0.92
InceptionV3+Logistic Regression	0.93	0.93	0.93	0.93
InceptionV3+Decision Tree	0.79	0.86	0.76	0.83
InceptionV3+Naïve Bayes	0.70	0.73	0.75	0.74
InceptionV3+LDA	0.93	0.93	0.94	0.93
InceptionV3+MLP	0.94	0.93	0.94	0.93

- If *ResNet50* is used, *KNN* is best (Accuracy: **0.91**).

If computational efficiency and balanced performance are priorities, **MobileNet**-based models (especially with SVM, KNN, LDA, or MLP) are preferable due to MobileNet's lightweight nature. If interpretability and robustness are crucial, **VGG16** with **KNN** or **MLP** is an excellent choice (see Fig. 8 and Table XX).

h) ResNet50 performance: Table XXI shows that *ResNet50+KNN* and *ResNet50+LDA* achieved the highest Accuracy (0.93), with *ResNet50+LDA* delivering consistently strong results across all metrics. For the Precision metric, *ResNet50+Random Forest* obtained the best result (0.68). In contrast, *ResNet50+Naïve Bayes* was the weakest model, with the lowest Accuracy (0.38) and overall poor performance compared to the others.

i) InceptionV3 performance: Table XXII shows that *InceptionV3+SVM* and *InceptionV3+MLP* achieved the highest Accuracy (**0.94**). The highest Precision was obtained by *Logistic Regression*, *Naïve Bayes*, *LDA*, and *MLP*. The Recall was highest for *SVM* and *MLP*. Regarding F1-score, *Logistic Regression*, *LDA*, and *MLP* achieved the best results (**0.93**). In contrast, *InceptionV3+Naïve Bayes* was the weakest model overall, with the lowest Accuracy (**0.70**).

j) Summary: Different eye diseases dataset: Based on the previous performance metrics, the most suitable ML classifier depends on the chosen DL feature extractor. The best combinations by *Accuracy* are:

- If *VGG16* is used, *KNN* is best (Accuracy: **0.95**).
- If *InceptionV3* is used, *MLP* is best (Accuracy: **0.94**).
- If *MobileNet* is used, *SVM*/*KNN* are best (Accuracy: **0.94**).
- If *ResNet50* is used, *LDA* is best (Accuracy: **0.93**).

Overall, **VGG16+KNN** and **InceptionV3+MLP** are strong choices, while **MobileNet+SVM/KNN** provides competitive performance with efficient inference (see Fig. 9).

k) Different eye diseases dataset: For the *Different Eye Diseases* dataset, **VGG16+KNN** is the most appropriate model based on its highest Accuracy and balanced performance across evaluation metrics. However, **InceptionV3+MLP** is also a strong contender. The choice between them depends on application requirements such as computational efficiency and real-time processing needs (see Fig. 9).

B. Discussion

The primary aim of this study was to create and assess a hybrid model architecture that combines deep learning (DL) feature extraction with machine learning (ML) classification techniques for medical image analysis. Across the five datasets, performance varied with the particular pairing of DL feature extractor and ML classifier. Key findings are summarized below:

- COVID-19 Dataset: *MobileNet+MLP* achieved the highest Accuracy (0.97).
- Melanoma Skin Cancer Dataset: *MobileNet+SVM* and *VGG16+MLP* both reached top accuracies (0.92), showing that different hybrid configurations can yield competitive results depending on computational or interpretability needs.
- Chest X-Ray Dataset: *MobileNet+MLP* again achieved the highest accuracy (0.98).
- Face Images of Acute Stroke Dataset: *MobileNet* with several ML classifiers (SVM, KNN, LDA, MLP) achieved perfect accuracy (1.00), indicating strong discriminative power of facial feature embeddings for neurological conditions.
- Different Eye Diseases Dataset: The top performer was *VGG16+KNN* (Accuracy: 0.95), while *InceptionV3+MLP* also delivered competitive results (Accuracy: 0.94).

Overall, *MobileNet* consistently appears as the most adaptable and high-performing DL feature extractor across datasets, especially when paired with *MLP* or *SVM*, depending on the classification challenge. These results confirm the potential of hybrid DL–ML models in medical image classification.

Model selection should not rely on accuracy alone; additional factors include:

- Computational efficiency: e.g., *MobileNet* is favorable for time-sensitive applications due to high speed and low resource use.
- Interpretability: e.g., *LDA* or *Logistic Regression* offer clearer clinical insight.
- Dataset specifications: image resolution, noise levels, and class imbalance must be considered.

The evaluation demonstrates that combining DL and ML can yield hybrid models that improve classification while providing flexible solutions for varied medical domains.

V. Conclusion and Future Work

This research introduced a hybrid architecture that couples Deep Learning (DL) feature extraction with Machine Learning (ML) classification for medical image analysis across multiple datasets. Four pre-trained CNNs (VGG16, ResNet50, MobileNet, InceptionV3) served as deep feature extractors; their features were fed to ten traditional ML classifiers, forming a comprehensive hybrid framework. We evaluated the framework on five datasets: COVID-19 chest X-rays, melanoma skin cancer, general chest X-rays, acute stroke facial images, and a multi-class eye disease dataset.

Results show that performance depends on both the DL extractor and ML classifier. In most cases, *MobileNet* proved the most consistent and effective extractor, especially with *MLP* or *SVM*. This pairing achieved the highest accuracies in several datasets, such as COVID-19 (*MobileNet+MLP*, 0.97), chest X-rays (*MobileNet+MLP*, 0.99), and stroke images (*MobileNet+MLP/KNN/LDA*, 1.00). By contrast, *ResNet50* showed relatively lower performance on stroke and eye-disease classification, whereas *VGG16* and *InceptionV3* achieved strong results elsewhere and are good alternatives when interpretability, computational complexity, or domain-specific constraints are important.

The study further demonstrates that well-optimized hybrid DL–ML pipelines can outperform standalone ML or DL approaches, offering better generalization across neurological, dermatological, and respiratory imaging tasks.

Future work will expand to broader medical conditions and explore stronger denoising methods to enhance image quality. Another promising direction is multi-modal integration—combining images with clinical data—to improve accuracy and provide a more holistic diagnostic aid.

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REFERENCES

[1] S. Zhang and D. Metaxas, "On the challenges and perspectives of foundation models for medical image analysis," *Medical Image Analysis*, vol. 91, p. 102996, 2024.

[2] P. Rajpurkar and M. P. Lungren, "The current and future state of AI interpretation of medical images," *New England Journal of Medicine*, vol. 388, no. 21, pp. 1981–1990, 2023.

[3] S. Hussain *et al.*, "Modern diagnostic imaging technique applications and risk factors in the medical field: A review," *BioMed Research International*, vol. 2022, no. 1, p. 5164970, 2022.

[4] R. Najjar, "Redefining radiology: A review of artificial intelligence integration in medical imaging," *Diagnostics*, vol. 13, no. 17, p. 2760, 2023.

[5] S. V. M. Sagheer and S. N. George, "A review on medical image denoising algorithms," *Biomedical Signal Processing and Control*, vol. 61, p. 102036, 2020.

[6] O. Tarawneh, Q. Saber, A. Almaghthawi, H. A. Owida, A. Issa, N. Alshdaifat, G. Jaradat, S. Abuowaida, and M. Arabiat, "The effect of pre-processing on a convolutional neural network model for dorsal hand vein recognition." *International Journal of Advanced Computer Science & Applications*, vol. 15, no. 3, 2024.

[7] H. M. Turki, E. Al Daoud, G. Samara, R. Alazaidah, M. H. Qasem, M. Aljaidi, S. Abuowaida, and N. Alshdaifat, "Arabic fake news detection using hybrid contextual features." *International Journal of Electrical & Computer Engineering (2088-8708)*, vol. 15, no. 1, 2025.

[8] M. Radak, H. Y. Lafta, and H. Fallahi, "Machine learning and deep learning techniques for breast cancer diagnosis and classification: A comprehensive review of medical imaging studies," *Journal of Cancer Research and Clinical Oncology*, vol. 149, no. 12, pp. 10 473–10 491, 2023.

[9] A. Ehsan, Z. Iqbal, S. Abuowaida, M. Aljaidi, H. U. Zia, N. Alshdaifat, and N. K. Alshammry, "Enhanced anomaly detection in ethereum: Unveiling and classifying threats with machine learning," *IEEE Access*, 2024.

[10] N. A. Mahoto, A. Shaikh, A. Sulaiman, M. S. Al Reshan, A. Rajab, and K. Rajab, "A machine learning based data modeling for medical diagnosis," *Biomedical Signal Processing and Control*, vol. 81, p. 104481, 2023.

[11] M. Kamran and A. A.-A. Almaghthawi, "Case-based reasoning diagnostic system for antenatal research database." *International Journal of Online & Biomedical Engineering*, vol. 18, no. 7, 2022.

[12] A. Almaghthawi, F. Bourennani, and I. R. Khan, "Differential evolution-based approach for tone-mapping of high dynamic range images," *International Journal of Advanced Computer Science and Applications*, vol. 11, no. 7, 2020.

[13] B. Charbuty and A. Abdulazeez, "Classification based on decision tree algorithm for machine learning," *Journal of Applied Science and Technology Trends*, vol. 2, no. 01, pp. 20–28, 2021.

[14] S. Abuowaida, H. A. Owida, D. M. Alsekait, N. Alshdaifat, D. S. AbdElminaam, and M. Alshinwan, "Ultrasegnet: A hybrid deep learning framework for enhanced breast cancer segmentation and classification on ultrasound images." *Computers, Materials & Continua*, vol. 83, no. 2, 2025.

[15] V. Nasteski, "An overview of the supervised machine learning methods," *Horizons. B*, vol. 4, pp. 51–62, 2017.

[16] S. J. MacEachern and N. D. Forkert, "Machine learning for precision medicine," *Genome*, vol. 64, no. 4, pp. 416–425, 2021.

[17] I. Kononenko, "Machine learning for medical diagnosis: History, state of the art and perspective," *Artificial Intelligence in Medicine*, vol. 23, no. 1, pp. 89–109, 2001.

[18] H. A. Owida, I. A. El-Fattah, S. Abuowaida, N. Alshdaifat, H. A. Mashagba, A. B. Abd Aziz, A. Alzoubi, S. Larguech, and S. S. Al-Bawri, "A deep learning-based dual-branch framework for automated skin lesion segmentation and classification via dermoscopic images," *Scientific Reports*, vol. 15, no. 1, p. 37823, 2025.

[19] H. A. Owida, B. A.-h. Moh'd, and M. Al Takrouri, "Designing an integrated low-cost electrospinning device for nanofibrous scaffold fabrication," *HardwareX*, vol. 11, p. e00250, 2022.

[20] A. Halbouni, T. S. Gunawan, M. H. Habaebi, M. Halbouni, M. Kartiwi, and R. Ahmad, "Machine learning and deep learning approaches for cybersecurity: A review," *IEEE Access*, vol. 10, pp. 19 572–19 585, 2022.

[21] H. Abu Owida, "Recent biomimetic approaches for articular cartilage tissue engineering and their clinical applications: narrative review of the literature," *Advances in Orthopedics*, vol. 2022, no. 1, p. 8670174, 2022.

[22] A. Y. Alhusenat, H. A. Owida, H. A. Rababah, J. I. Al-Nabulsi, and S. Abuowaida, "A secured multi-stages authentication protocol for iot devices." *Mathematical Modelling of Engineering Problems*, vol. 10, no. 4, 2023.

[23] R. Alazaidah, H. A. Owida, N. Alshdaifat, A. Issa, S. Abuowaida, and N. Yousef, "A comprehensive analysis of eye diseases and medical data classification," *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, vol. 22, no. 6, pp. 1422–1430, 2024.

[24] H. Abu Owida, B. A.-H. Moh'd, N. Turab, J. Al-Nabulsi, and S. Abuowaida, "The evolution and reliability of machine learning techniques for oncology," *International Journal of Online and Biomedical Engineering (iJOE)*, vol. 19, no. 08, pp. 110–129, Jun. 2023. [Online]. Available: https://online-journals.org/index.php/i-joe/article/view/39433

[25] H. Chen, S. Hu, R. Hua, and X. Zhao, "Improved naive bayes classification algorithm for traffic risk management," *EURASIP Journal on Advances in Signal Processing*, vol. 2021, no. 1, p. 30, 2021.

[26] A. Bhardwaj, A. Gupta, P. Jain, A. Rani, and J. Yadav, "Classification of human emotions from EEG signals using SVM and LDA classifiers," in *2015 2nd International Conference on Signal Processing and Integrated Networks (SPIN)*. IEEE, 2015, pp. 180–185.

[27] S. R. Sain, *The Nature of Statistical Learning Theory*. Taylor & Francis, 1996.

[28] D. Bertsimas and A. King, "Logistic regression: From art to science," *Statistical Science*, pp. 367–384, 2017.

[29] A. M. Mubarek and E. Adalı, "Multilayer perceptron neural network technique for fraud detection," in *2017 International Conference on Computer Science and Engineering (UBMK)*. IEEE, 2017, pp. 383–387.

[30] V. Bijalwan, V. Kumar, P. Kumari, and J. Pascual, "KNN based machine learning approach for text and document mining," *International Journal of Database Theory and Application*, vol. 7, no. 1, pp. 61–70, 2014.

[31] S. Munawwar and P. V. Gopi Krishna Rao, "An efficient deep learning based multi-level feature extraction network for multi-modal medical image fusion," *International Arab Journal of Information Technology (IAJIT)*, vol. 22, no. 3, 2025.

[32] B. Kégl, "Introduction to adaboost," Technical report, 2009.

[33] B. Tatiparti and V. Dharmar, "GNN-DQL-based chronic kidney disease classification using GFR in the internet of medical things environment," *International Arab Journal of Information Technology (IAJIT)*, vol. 22, no. 3, 2025.

[34] G. Biau, "Analysis of a random forests model," *Journal of Machine Learning Research*, vol. 13, pp. 1063–1095, 2012.

[35] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv preprint arXiv:1409.1556*, 2014.

[36] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 770–778.

[37] A. G. Howard *et al.*, "Mobilenets: Efficient convolutional neural networks for mobile vision applications," *arXiv preprint arXiv:1704.04861*, 2017.

[38] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the inception architecture for computer vision," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 2818–2826.

[39] R. A. Salma, H. Kafajeh, R. Alazaidah, M. Assasfeh, A. Alsheriadeh, and N. Alshdaifat, "Leveraging machine learning for effective breast cancer diagnosis," *WSEAS Transactions on Computer Research*, vol. 13, pp. 34–46, 2025.

[40] M. Alzyoud *et al.*, "Diagnosing diabetes mellitus using machine learning techniques," *International Journal of Data & Network Science*, vol. 8, no. 1, 2024.

[41] M. Rudra Kumar, R. Pathak, and V. K. Gunjan, "Diagnosis and medicine prediction for COVID-19 using machine learning approach," in *Computational Intelligence in Machine Learning: Select Proceedings of ICCIML 2021*. Springer, 2022, pp. 123–133.

[42] M. Masud, N. Sikder, A.-A. Nahid, A. K. Bairagi, and M. A. AlZain, "A machine learning approach to diagnosing lung and colon cancer using a deep learning-based classification framework," *Sensors*, vol. 21, no. 3, p. 748, 2021.

[43] J. G. Richens, C. M. Lee, and S. Johri, "Improving the accuracy of medical diagnosis with causal machine learning," *Nature Communications*, vol. 11, no. 1, p. 3923, 2020.

[44] R. R. Ali *et al.*, "Learning architecture for brain tumor classification based on deep convolutional neural network: Classic and resnet50," *Diagnostics*, vol. 15, no. 5, p. 624, 2025.

[45] N. Şengöz, T. Yiğit, Ö. Özmen, and A. H. Isık, "Importance of preprocessing in histopathology image classification using deep convolutional neural network," *Advances in Artificial Intelligence Research*, vol. 2, no. 1, pp. 1–6, 2022.

[46] L. Gondara, "Medical image denoising using convolutional denoising autoencoders," in *2016 IEEE 16th International Conference on Data Mining Workshops (ICDMW)*. IEEE, 2016, pp. 241–246.

[47] H. A. Vu, "Integrating preprocessing methods and convolutional neural networks for effective tumor detection in medical imaging," *arXiv preprint arXiv:2402.16221*, 2024.

[48] S. Cui, Y. L. Su, K. Duan, and Y. Liu, "Maize leaf disease classification using CBAM and lightweight autoencoder network," *Journal of Ambient Intelligence and Humanized Computing*, vol. 14, no. 6, pp. 7297–7307, 2023.

[49] D. Müller, I. Soto-Rey, and F. Kramer, "An analysis on ensemble learning optimized medical image classification with deep convolutional neural networks," *IEEE Access*, vol. 10, pp. 66 467–66 480, 2022.