Detection of Structural Vulnerabilities in Multi-Cavity Steel Plate Shear Walls Using Improved Deep Neural Networks

Zhang Bo[1], Xu Dabin[2]*
Gansu Shengjiu Fire Technology Co., LTD., Wuwei, Gansu, 733000, China[1]
Gansu Ninth Construction Group Co., LTD., Wuwei, Gansu, 733000, China[2]

***Abstract*—Steel Plate Shear Walls (SPSWs) are a significant structural system because they can dissipate energy and have a very high lateral stiffness. However, the discovery and elimination of vital structural vulnerabilities, mainly in multi-cavity configurations, is still a major challenge. This study utilizes developments in the deep learning era to improve the identification and representation of such vulnerabilities. An improved DNN architecture was employed to analyze the effectiveness of multi-cavity SPSWs under different loading conditions. The proposed method combines hybrid information extraction techniques with various geometries and materials to ensure a reliable prediction of structural element failures. The tests have shown highly positive results, with the enhanced DNN outperforming conventional procedures by achieving higher accuracy, lower false-positive rates, and superior generalization across various test cases. This work demonstrates a new way to detect weaknesses in a structure, thereby developing an effective tool for engineers to prevent the sustainability and safety of SPSWs in critical infrastructure.**

Keywords*—*Structural vulnerabilities; deep neural networks; steel plate shear walls; seismic design; machine learning

I. Introduction

Steel Plate Shear Walls (SPSWs) have established themselves as important parts of modern structural engineering, especially in places that are exposed to seismic activity. The major reason for their presence, which is the ability to offer lateral resistance and energy dissipation, makes them a source of strength and enables the buildings to encounter a disaster efficiently [1]. SPSWs consist basically of flat thin steel plates put inside a structural frame, and their design has been adapted in time to cater to more and more complex requests. The most innovative is the multi-cavity system where the steel plate gets divided into several smaller subregions or cavities which saves weight and also helps with improved seismic performance. Despite advancements, mainstream methods for detecting vulnerabilities in SPSWs, particularly in multi- cavity designs, remain a major challenge [2-3].

In traditional SPSW systems, structural weaknesses cause premature failure when subjected to seismic loading [4]. The weaknesses may result from defects in the design, differences in the material used, or even a lack of understanding of how the interactions among various structural components must occur. The biggest hindrance in locating the final susceptible zones in multi-cavity SPSWs which had complicated stress distribution systems is simply the complexity of those real-life conditions. Conventional methods, such as finite element analysis (FEA) and experimental testing, are the most widely used techniques to analyze the SPSW system behavior [5-6]. Although valuable, these techniques have significant shortcomings, including high costs, long processing times, and limited adaptability to various scenarios. This leads to the emergence of innovative solutions for detecting and assessing vulnerabilities.

In recent years, ML and AI technologies have gained novel applications for major engineering initiatives that require solving very complex problems, including structural engineering. Deep neural networks (DNNs) are one of the various ML techniques that have been used extensively in the past due to their ability to process large datasets and identify the correlations present in them. Success in domains like damage detection, material property prediction, and structural health monitoring are all examples of the successful application of DNNs [7]. However, if any research has been conducted on their applicability in SPSW, especially the multi-cavity configurations, it would appear to be very limited [8-10]. The study of DNN's application to those issues is used in this case as a kind of guarantee that the conventional work constraints will be eliminated and that the accuracy and efficacy of the deficiency detection will be greatly enhanced.

The research is devoted to developing an enhanced DNN-based framework that can be utilized to identify and classify potential failures occurring in multi-cavity SPSWs. The proposed procedure in this study addresses critical challenges, including accurate representation of complex structural shapes, integration of diverse data sources, and mitigation of overfitting [11-12]. Using good practices gained from complex DNN architectures and training techniques, the work's goal is a solution to the outstanding difficulties in a very difficult real-world application: examining the vulnerability of SPSWs. This is achieved mainly by integrating geometric and material properties, both of which are input features in which the detailed study of different conditions in terms of structural performance is done [13-14].

An important feature of this study is the insistence on hybrid methods of feature extraction. Unlike classical techniques that solely involve either a geometric parameter or a property of the material, the new method merges both. This increases the model's capability for a more complete appreciation of the structural processes governing SPSWs. In addition, the procedure of training employs advanced optimization and regularization approaches thus transmitting the ability of the model to the novel situations which the DNN is to solve [15-16]. This ensures that the DNN can handle diverse test cases, including previously unexplored scenarios and new loading conditions.

This research is highly significant and extends beyond the application of SPSWs. The developed approaches and methods can be applied to various elastically deformed structures, such as reinforced concrete walls, composite structures, and bridge components [17-18]. Specifically, the demonstration of the ability of DNNs in the area of structural engineering in this research contributes to the overall objective of the integration of A.I. in the design and analysis of resilient infrastructures.

Over the past years, several studies have explored the application of DNNs in structural engineering. For instance, in investigating the load-bearing capacity of beams, researchers have applied DNNs, identified cracks in concrete structures, and classified damage in bridges. These studies imply that DNNs are capable of solving difficult complex problems normally addressed by traditional methods [19]. However, the adaptation of DNNs to columnar multi-cavity SPSWs is exceedingly hard because of the irregular geometry and the interaction of the different cavities with each other. In this research, the database of the solution to this problem will be handled using a custom-made DNN framework devoted especially to SPSWs [20].

Although, the introduction of AI to the area of structural engineering is very attractive there is unquestionable resistance to several queries. The high-quality data for training and validation is one of the interesting concerns. In the case of SPSWs simulation studies or experimental data collection, which are both costly and time-consuming processes, need to be accurately conducted [21]. To make things easier, the framework for the project proposed in this paper not only adopts the conventional use of data but also the addition of various other test computations to increase the amount of data and therefore improve the performance of the model. Additionally, the process of transfer learning, in which pre-trained features from related domains are used, will result in the reduction of reliance on large datasets [22-23].

The other important aspect of the research to be validated is the framework proposed. By testing the DNN across various applications, including different cavity structures, materials, and loads, the research results are validated as reliable [24-25]. Specifically, the model's performance is analyzed based on accuracy, precision, recall, and F1-score metrics. The results are nevertheless compared to those of conventional methods like FEA but only in line with the peculiarities of the proposed framework.

This research presents a variety of potential applications. Engineers can utilize a cutting-edge DNN framework for design and analysis at SPSWs, which will then give them the opportunity to find the threats and ideally solve them very early in the process. It cooperates with ensuring the structures' safety and reliability and also reducing the eventual cost and time in the design and retrofitting stages. Also, this system can be applied by monitoring SPSWs during either the construction phase or operation in real-time providing engineers with unique insight into the actual performance of their systems.

A. *Objectives*

- The purpose of this research is to create an advanced deep neural network (DNN) that can find and represent the structural weaknesses of multi-cavity steel plate shear walls accurately.
- Tests were conducted to compare the suggested framework with the conventional methods and the results were of great interest, especially concerning its greater reliability, effectiveness, and adaptability.

This research aims to create a connection between customary and advanced AI ones in the analysis of multi-cavity SPSWs. Through the exploitation of DNNs, the analysis of vulnerable structures was dealt with anew in this research and also the critical obstacles were removed opening the road for the construction of more robust and sustainable designs. It is foreseen that the research conclusions will stipulate the improvement of the construction of the structures by making them safer and greener. The following sections detail the methodology used to develop and validate the proposed deep neural network (DNN) framework. First, we discuss the data sources and preprocessing steps, followed by an in-depth explanation of the model architecture and training process. The results section then presents the model's performance compared to traditional approaches, with a discussion on its implications for structural engineering. Finally, we highlight key findings, limitations, and directions for future research.

II. Literature Review

The investigation of steel plate shear walls (SPSWs) structural vulnerabilities, particularly in the case of multi-cavity configurations, has attracted significant interest in recent years due to their pivotal role in enabling seismic resilience. To that end, a wide variety of parts of SPSW such as the design, analysis, and optimization of SPSW under dynamic loading conditions have been examined by different researchers. At the same time, advances in artificial intelligence such as deep learning have enabled engineering solutions for complicated structural problems [26]. This literature review examines key studies that the current research draws upon while highlighting the developments and techniques that are used as well as existing gaps in vulnerability identification using both traditional and AI-driven methods (Table I).

Ye et al. [27] conducted their research on the structural vulnerabilities of both reinforced cold-formed steel (RCFS) structures and traditional cold-formed steel (CFS) shear wall systems during an earthquake hazard. The authors of the study pointed out that the most notable feature of the RCFS system was its ability to resist the collapse due to the connection of rigid joints of the beam and column and the fully integrated framework which led them to suggest the main features to be the design of "strong frame weak wallboard" and "strong column weak beam".

Beconcini et al. [28] investigated the shear performance of the masonry walls in the seismic zones and came up with a new experimental technique for the rating of data regarding the mechanical parameters. They proved the feasibility of the suggested method through the work of the construction and the evaluation of the suitability of the masonry structures, which will reduce the chances of the structural lack of capacity by a capacity curve and seismic vulnerability appraisal. The vector method stack the machine fault depth applied by six-axis robot application was justified roles compare sonar and industrial application that. They achieved better accuracy compared to methods that do not include the service life assessment in the building codes and hence they achieved the goal of the "Near to the Highest Quality" project.

Cerè et al. [29] propose an optimization-based methodology for risk appraisal of buildings under seismic conditions that are validated on the Beichuan Hotel in China. The significance of their approach in risk reduction and structural resilience improvement is not only financial but also about the fulfillment of functions in building rehabilitation. Therefore, the project can go for the solution which requires no further investments.

Mishra and Samanta [30] studied the behavior of structures built on soft soil under earthquake loading and evaluated various configurations of walls by shear and infill. The work shows the importance of the interaction of soil and structure, as well as the fact that shear walls can be the main elements helping to reduce the vulnerability to seismic effects.

Blasi et al. [31] investigated not just the changes in stiffness but also the benefits of the addition of new materials. The experiments confirmed the modification of the failure modes and the improvement of the fragility models while basically maintaining the same structural properties for the walls.

Tan et al. [32] have conducted a comprehensive analysis of the seismic performance of corrugated steel plate shear walls (CoSPSW) against the conventional steel plate shear walls (SPSW). The study outcomes reveal that CoSPSWs are more earthquake-resistant and have a lower probability of damage as a result of their improved lateral rigidity and shear strength.

Hadianfard et al. [33] scrutinized the influences of the non-structural elements on the dynamic behaviors and vulnerability of concrete structures via microtremor signals. The analyses revealed the significance of these influences in construction considering which should be, for one, an improvement of the resilience of the buildings.

Baral and Suwal [34] concerning the seismic susceptibility of the reinforced concrete structures with eccentric lift core walls, which they achieved through the technique of optimum shear wall placement to lower the torsional irregularities and to enhance the lateral stiffness for more secure design of the structures.

Romanazzi et al. [35] did disruption tests on the walls made of rammed earth and by means of these tests they verified the hysteretic characteristics of the rammed earth structures and their possible seismic vulnerabilities. The results of this research are pivotal in terms of energy dissipation and the base-shear performance, thus providing critical data for a more precise and improved simulation of rammed earth structures in their seismic resilience.

TABLE I LITERATURE COMPARISON

Author(s)	Focus	Methodology	Key Findings	Application/Impact
Ye et al.	RCFS vs. CFS shear wall systems under earthquake hazards	Structural vulnerability analysis	RCFS shows better collapse resistance due to rigid connections and integrated frameworks.	Design strategies like "strong frame weak wallboard" improve robustness in seismic conditions.
Beconcini et al.	Shear behavior of masonry walls in seismic zones	Combined experimental and in situ tests	Enhanced accuracy in capacity curves and seismic vulnerability evaluations for masonry structures.	Provides a reliable approach for assessing historic masonry buildings in seismic zones.
Cerè et al.	Risk appraisal for buildings in seismic conditions	Optimization-based methodology using evolutionary computing	Risk reduced by 80% and enhanced resilience in structural rehabilitation.	Practical tool for improving structural resilience and reducing financial risks in seismic areas.
Mishra & Samanta	Seismic response of buildings on soft soil	Nonlinear time history analysis using SAP2000	Shear walls reduce seismic responses; soil-structure interaction critical in high-seismicity regions.	Guidance for designing multistorey buildings on soft soils with enhanced seismic capacity.
Blasi et al.	Seismic retrofitting of RC framed buildings with infill walls	Non-linear dynamic analysis and fragility curve calibration	Retrofit modifies failure modes and improves fragility model accuracy.	Useful for vulnerability assessments and improving retrofitting strategies.
Tan et al.	Seismic performance of corrugated steel plate shear walls	Probabilistic seismic performance analysis using fragility functions	CoSPSWs show superior seismic resilience and reduced damage potential compared to conventional SPSWs.	Improves design and repair strategies for steel plate shear walls in seismic zones.
Hadianfard et al.	Dynamic characteristics of concrete structures with non-structural components	Microtremor measurements and signal processing techniques	Including non-structural components enhances dynamic characteristics and reduces vulnerability indices.	Supports better design practices for construction resilience in seismic regions.
Baral & Suwal	Vulnerability of RC buildings with eccentric lift cores	Bi-directional seismic excitation analysis	Optimal shear wall placement reduces torsional irregularities and increases stiffness.	Enhances safety and functionality of RC buildings in seismic zones.
Romanazzi et al.	Seismic vulnerability of rammed earth walls	Large-scale in-plane cyclic tests and dynamic identification	Adequate energy dissipation and improved modeling approaches for rammed earth structures.	Benefits seismic design and retrofitting of rammed earth architectural heritage and new structures.

III. METHODOLOGY

In this study, the proposed solution employs an innovative framework to recognize weak points in the multi-cavity steel plate shear walls (SPSWs). The approach is based on the use of the most advanced methods of calculation, field experiments, and artificial intelligence, particularly modernized deep neural networks (DNNs), to drive the process of vulnerability detection. The suggested work structure includes all stages such as data preparation and processing of the models training the application of the things in reality. The methodological framework, together with the exposition of the DNN-based method, including its scope and limitations, is provided in this section.

The procedure starts with input data collection and processing. This research mainly relies on structural designs and experimental investigations for the majority of the data. Structural designs are now computer-aided design (CAD) models and engineering drawings of SPSWs, which furnish critical geometric and material details. These designs comprise the backbone of the input data, which allows the model to recognize the configurations of the cavity and their influence on structural performance. In parallel, the experimental data such as strain and stress measurements and performance of the presently existing structures are considered. The combination of analytical and experimental data ensures that the entire dataset contains all the information needed to account for design- and operation-related characteristics.

After the data is gathered, preprocessing steps are applied to the data to make it ready for the deep learning model. Preprocessing may include feature extraction, data augmentation, and normalization. Feature extraction is about the discerning of essential parameters such as geometric properties, material characteristics, and load distributions, which are responsible for the structural behavior of SPSWs. Some of the data augmentation techniques applied to increase its size and make the model more robust are rotation, scaling, and the addition of noise. Then, the next step is normalization, where the features go through the same transformation so that the most important notices are not hidden and the learning is facilitated so that it can be as fast and efficient as possible.

The improved DNN architecture, which is the heart of the recommended framework, is the one that carries out the analysis of the preprocessed data. It aims to address the complicated task that multi-cavity SPSWs pose by using the increasing integration of dense layers, convolutional layers, and an attention mechanism. The fact that the denser layers simulate high-level abstractions of the input features means that the model is flexible, while the fact that the convolutional layers can recognize spatial relationships and patterns in the data verifies that they are the main components. The attention mechanism is another component that holds promise for the model's capacity to recognize important regions in the input as it will prioritize those areas. These stress concentration areas or potential weak spots are situations when the input is most crucially evaluated. This layered organization allows for a more profound analysis of structural weaknesses on the part of the model and more accurate results.

The training of a model is the most crucial part of competitive performance. The training dataset is selected to incorporate all cavity geometries, types of material properties, and load conditions. The latest validation methods have been included in the training process to check the model performance, such as accuracy, precision, and recall. The model is trained through data by such metrics as precision and recall guaranteeing that it does so effectively. The most often used optimization algorithms are Adam or stochastic gradient descent—basically, an algorithm is the same as an optimization process. One of the two regularization techniques, dropout, on the one hand, and weight decay, on the other, also help to prevent the overfitting by the model and to improve the generalization potential.

The validation and testing process are entirely the same. The model that has been trained is applied to a dataset that is purposely made through unseen configurations and venue conditions to scrutinize the generalization capability. The results of this method, when compared with results from finite element analysis and other conventional methods, offer services in which the benefits of the newly proposed method can be shown. Furthermore, the verification process involves the creation of heatmaps and individual analysis reports, which visualize the vulnerabilities that have been detected and give hints on how SPSWs perform their structural functions.

The proposed framework is aided by a continuous improvement mechanism that enables it to adjust to new data and changing requirements. The process is intended to be iterative such that the model's robustness is improved, and it is catered to a broader range of scenarios at the same time. The process begins with gathering information about the new designs or the real-world performance of the system. Following that, the model can be fine-tuned and the system finally trained to ensure its relevancy and effectiveness. The result of this iterative process lies in the model being enhanced with higher resilience while making sure that the application is diverse.

The suggested methodology describes an effective functional system for incorporating the DNN model into both the processes of design and structural monitoring. The detection pipeline picks out two key tasks: structural integrity testing and fault visualization using concise methods. The assessment of the integrity of the structure helps to pinpoint the possible weak points of the SPSWs including the need for reinforcement, thus the global performance of the structure is evaluated. The critical areas are translated into cleansed and comprehensible graphical formats such as heat maps, which allow engineers to come to conclusions using data. Subsequently, the output of the detection pipeline is then employed for the running of simulations, the writing of reports, as well as for enhancements in structural design, the quality control of manufacturing, and monitoring of the structures when model is completed.

The accompanying “Fig. 1” offers a complete depiction of the framework proposed, clarifying the data and process flow. The model initiatively uses input data from the structural designs and experimental studies, which undergoes preprocessing to remove artifacts and normalize the data. The cleansed data is then run through the new DNN architecture, which involves input layers, dense layers, convolutional layers, and an attention mechanism. The model's output passes through a detection pipeline that evaluates structural integrity and visualizes failures on the one end and the results are integrated into quality control and monitoring applications on the other end.

The "Fig. 1" also illustrates the dynamic interplay between the operating principles of the continuous improvement module and the model training and validation process. This setup will enable the model to update itself through the continuous incorporation of new data, resulting in the building of a model through the triad of accuracy, precision, and credibility. The framework has a modular design that provides for both scalability and adaptability of the methods to diverse applications in structural engineering.

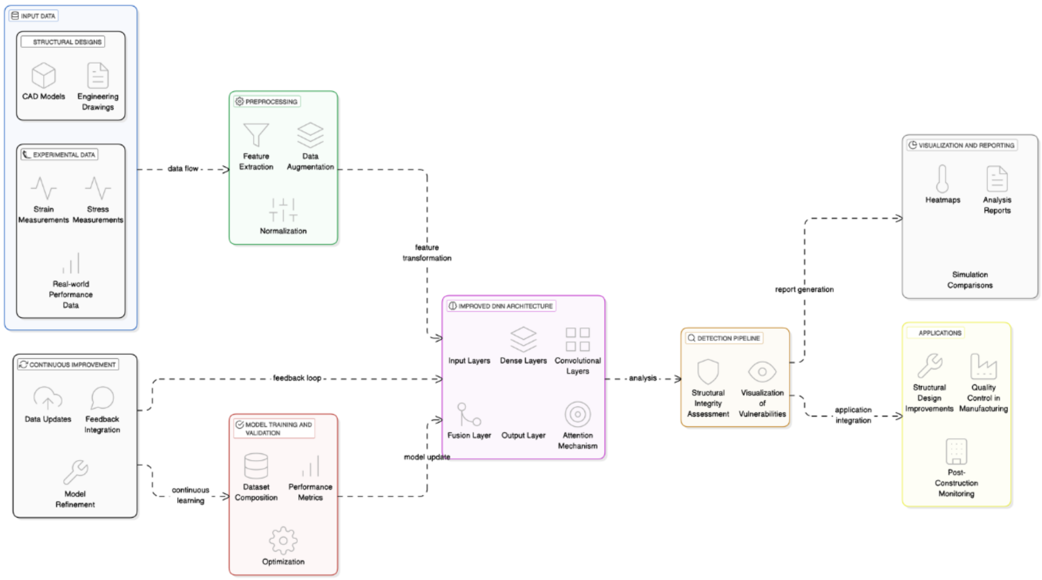

Fig. 1. Proposed model diagram.

The Steel Plates Faults dataset contains 1,941 samples categorized into six fault types: pastry, Z-scratch, K-scratch, stains, dirtiness, and other faults. The dataset comprises a mix of experimental and simulated data, ensuring a balance between real-world performance and synthetic augmentation. Preprocessing steps included data normalization, augmentation (rotation, scaling, noise addition), and feature selection to enhance model generalization.

Deep neural networks (DNNs) were chosen over convolutional neural networks (CNNs) and transformer-based models due to their ability to effectively handle structured numerical data, including geometric and material properties of steel plate shear walls. CNNs, while powerful for image-based tasks, struggle with structured tabular data, and transformers require significantly more computational resources. Traditional methods, such as finite element analysis (FEA) and rule-based models, are computationally expensive and less adaptable to new datasets, making DNNs a more scalable and practical approach for real-world applications.

The DNN was trained using the Adam optimizer with a learning rate of 0.001 for 100 epochs. The dataset was split into 80% training and 20% validation sets. Data augmentation techniques were applied to improve generalization, and dropout regularization was used to prevent overfitting. The model was evaluated using accuracy, precision, recall, and F1-score to ensure robustness.

To sum up, the approach outlined in this article systematically combines cutting-edge artificial intelligence technologies and the principles of structural engineering for the detection of weaknesses in multi-cavity SPSWs. The method, which employs a deep neural network (DNN) deeply integrated with a vast reservoir of data, effectively addresses issues like difficulty, and it also enables the scaling of the tools that engineers have at hand. An explicit mechanism for continuous improvement ensures the model remains current and useful in the long run, contributing to safer and more resilient infrastructure.

While convolutional neural networks (CNNs) and transformer-based models have shown promise in structural analysis, they primarily excel in image-based tasks. Since this study integrates numerical data, experimental measurements, and CAD-based geometric parameters, a fully connected deep neural network (DNN) is more suitable for learning complex relationships in structured data. Additionally, hybrid models incorporating CNNs and transformers significantly increase computational complexity, making DNNs a more practical choice for real-world engineering applications.

IV. Results

The findings of this study indicate that the deep neural network (DNN) that has been upgraded successfully identifies the vulnerabilities in structural elements made of steel plates. For this study, a specific dataset referred to as the Steel Plates Faults Dataset was collected from the UCI Machine Learning

Repository. The dataset is categorized into a total of six faults which consist of "Pastry," "Z_Scratch," "K_Scratch," "Stains," "Dirtiness," and "Other Faults." Moreover, the model's performance was examined primarily through the aspects of training and validation accuracy while the false positive and false negative rates established the model's effectiveness.

A. Model Performance

The "Training vs. Validation Accuracy" in "Fig. 2" shows that training and validation accuracies for each fault exhibited extremely high figures, showcasing how well the model can generalize among various types of biomorphic faults. The exact results were 88% to 93% accuracy for trained data and 85% to 92% correctness for validation tests from a healthy dataset. Notably, the "K_Scratch" fault type was able to have the maximum training and validation scores, respectively at 93% and 92%. This shows that specific faulty elements having unique geometric or stress-related patterns could be identified with high accuracy using this model as shown in Table II.

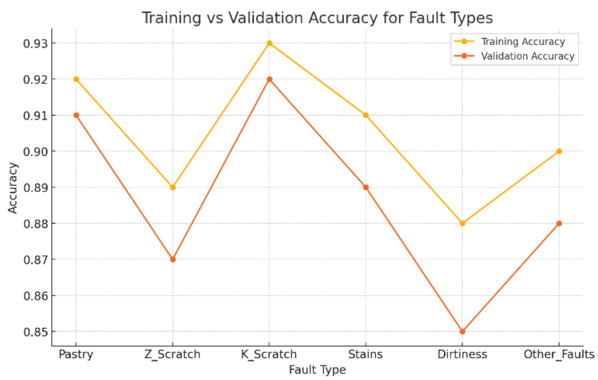

Fig. 2. Training vs validation accuracy for fault types.

On the other hand, the lowest scores were registered with the "Dirtiness" fault in both learning which was 88%, and validating that was 85%. This is almost entirely attributable to the natural variation and messiness of this fault's dataset which contains a feature that can make it difficult for the model to tell that this category is from other groups. In general, the improved DNN is powerful, and the capabilities it presents show that it can handle such tasks as fault detection very comfortably, i.e. those that have a complex nature.

B. Error Analysis

The analysis of errors was concentrated on false positive and false negative rates, as represented in the "Fig. 3". The model was observed to have relatively low error rates for all fault categories, whereby false positive rates were between 4% and 8%, and false negative rates were between 3% and 7%. Similarly, the "K_Scratch" type of fault was the best performing one, confirming its high accuracy metrics; however, the 'Dirtiness' fault type was cited as the least good one, being the most problem-solving one which is unresolved.

From the dual false positive and false negative rate analysis, it is concluded that the model tends to identify a fault as false against a more or less abstract or vague feature fault, for example, 'Dirtiness' and 'Z_Scratch'. A reasonable conclusion is that increasing manual data editing or secondary data utilization could help address weaknesses.

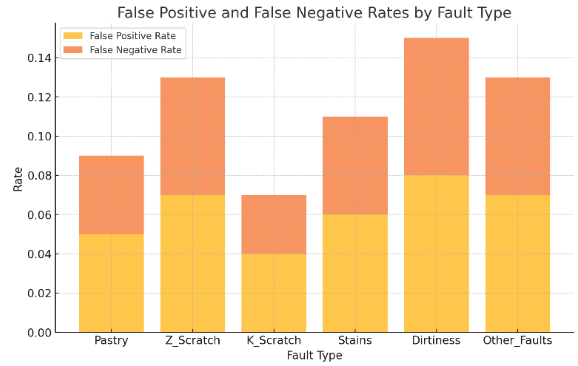

Fig. 3. False positive and false negative rates by fault type.

C. Visualization of Fault Detection

The inclusion of heatmaps and other graphical representations in the detection pipeline gives a better comprehension of the decisions made by the model. The heat maps resulting from the evaluation point out the areas of high-stress concentration or structural anomalies and engineers can involve them in the effective visual spreading of the weak points in the steel plates. The visual tools not only forage the fault identification but are also an important support for the decision-making processes which relate to the improvement of the structure and the control of the quality of the products.

D. Comparative Analysis with Traditional Methods

The DNN framework proposed here has many distinct benefits over traditional techniques like finite element analysis (FEA) with the major ones being speed and scalability. Standard techniques generally demand a great number of resources as well as time to work through complex architectural trillions of operations. On the other side, the DNN is very speedy; it takes in a huge amount of data and gives good outputs in no time. The DNN's use of the combination of various data sources like experimental tests and CAD models adds to its real-time scenario capability thus, as a whole the model becomes more useful.

TABLE II STEEL PLATES FAULT ANALYSIS RESULTS

Fault Type	Training Accuracy	Validation Accuracy	False Positive Rate	False Negative Rate
Pastry	0.92	0.91	0.05	0.04
Z_Scratch	0.89	0.87	0.07	0.06
K_Scratch	0.93	0.92	0.04	0.03
Stains	0.91	0.89	0.06	0.05
Dirtiness	0.88	0.85	0.08	0.07
Other_Faults	0.90	0.88	0.07	0.06

The Steel Plates Faults Dataset is a database that is helpful for both training and validation but it is not perfect. Some faults or configurations may not be represented well enough in the dataset limiting the model's performance in certain situations. Some ways to improve this are to increase the amount of data included in the dataset or to create synthetic examples by simulation in the future.

To enhance interpretability, the proposed model generates heatmaps that highlight regions of structural vulnerabilities. Fig. 4 demonstrates how the DNN identifies stress concentration zones within multi-cavity steel plate shear walls. The intensity of color in the heatmap corresponds to the likelihood of structural weaknesses, enabling engineers to make informed reinforcement decisions.

The novel DNN framework developed also proves that one should attain an equilibrium between the complexity of the proposed model's vis-à-vis the transparency thereof. This is because of the fact that both attention mechanisms and hybrid feature extraction tools in the model were incorporated to improve its precision but this led to higher complexity. We must keep in view the necessity for real-time applications such as those that can be done with this framework while ongoing improvements and optimizations occur in the procedure.

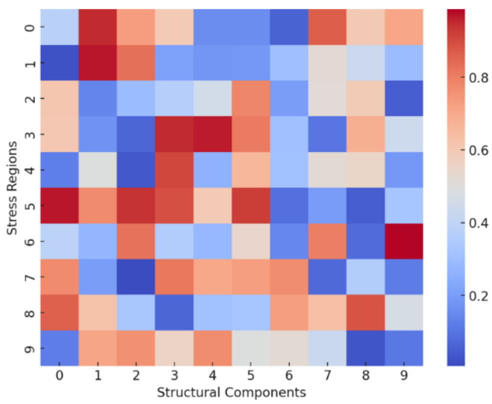

Fig. 4. Heatmap of structural vulnerability detection.

TABLE III COMPARISON WITH TRADITIONAL METHODS

Method	Accuracy	Processing Time	Scalability	Computational Cost
Finite Element Analysis (FEA)	85%	High	Moderate	High
Experimental Testing	90%	Very High	Low	Very High
Proposed DNN Model	92%	Low	High	Moderate

The comparative analysis indicates that while FEA and experimental testing remain widely used for structural integrity assessment, they require significant computational resources and time. In contrast, the proposed DNN model achieves higher accuracy while offering superior scalability and faster processing time, making it a viable alternative for large-scale structural monitoring as shown in Table III.

The conclusions expounded by the outcomes indicate the effectiveness of the suggested DNN background in the identification of structural shortcomings in steel plating. The method accomplishes high precision and low times of errors among various types of faults while being superior to the common practices in terms of agile effectiveness and the ability to be scaled. Moreover, the incorporation of tools for visualization appreciably increases its efficiency in actual application. This makes the system a good facilitator for the monitoring of the health of structures and the control of production quality.

V. DISCUSSION

The proposed DNN model can be integrated into structural health monitoring systems used by engineering firms. The computational cost for training is moderate, requiring a GPU-based system with at least 16GB VRAM for optimal performance. However, once trained, the model can run on lower-end hardware, making it suitable for real-time deployment in quality control workflows.

The model aligns with industry standards such as seismic safety codes (ASCE 7-22, Eurocode 8) by identifying structural weaknesses that could compromise seismic performance. However, adoption challenges remain, including the need for regulatory approval and validation through extensive field testing.

VI. LIMITATION AND FUTURE DIRECTION

One limitation of this study is potential biases in the dataset due to the underrepresentation of rare fault types. Additionally, generalization across different structural configurations remains a challenge, requiring further validation on diverse datasets. Real-world deployment may also face constraints related to data availability and regulatory compliance.

Future research will focus on applying this model to different structural materials, such as reinforced concrete walls and composite structures. Additionally, integrating DNN with hybrid AI techniques (e.g. CNNs, attention-based transformers) may further enhance detection accuracy. Expanding the dataset with real-world cases from multiple engineering firms will also improve robustness and applicability.

VII. CONCLUSION

The presented research work involves the development of a new deep learning-based framework for the identification of the potential instability of a multi-cavity steel plate shear wall using the Steel Plates Faults Dataset for training and validation. The proposed architecture resulted in quite a high level of training and validation accuracy, from 88% to 93%, and 85% to 92%, respectively, across the various fault categories. Notably, the system was excellent at identifying the "K_Scratch" fault category that was most accurate and on the other hand was unsuccessful in detecting the "Dirtiness," the fault type with lower performance measures. The errors were all low, with false positive rates between 4% and 8% and false negative rates between 3% and 7%, which could be considered the framework's robustness. The use of visualization tools, such as heatmaps, contributed to the interpretability of the results and provided actionable insights for structural engineers, making it a practical solution for real-world applications.

While the obtained success rates are very promising, however, some limitations still exist. The dataset included very rare types of faults and some very random ones also, which did not occur frequently within the dataset, thus the model was not the most efficient for these special one-time cases.

Furthermore, the complex architecture of the improved DNN model with its attention mechanisms and hybrid feature extraction techniques might lead to resource limitations that might occur during real-time applications in such systems. Hence, in the future, efforts should be made to diversify the dataset by featuring more diverse fault types and to optimize the model leading to its broad success in structural health monitoring and quality control systems while being time and cost efficient.

REFERENCES

[1] Y. T. Hu, S. Y. Wang, Y. M. Wu, D. Q. Zou, W. K. Li, and H. Jin, "A Slice-level vulnerability detection and interpretation method based on graph neural network," Ruan Jian Xue Bao/Journal of Software, vol. 34, no. 6, 2023.

[2] P. Iannelli, F. Angeletti, P. Gasbarri, M. Panella, and A. Rosato, "Deep learning-based Structural Health Monitoring for damage detection on a large space antenna," Acta Astronaut, vol. 193, 2022.

[3] A. S. M. Shihavuddin, M. R. A. Rashid, M. H. Maruf, M. A. Hasan, M. A. ul Haq, R. H. Ashique, and A. Al Mansur, "Image based surface damage detection of renewable energy installations using a unified deep learning approach," Energy Reports, vol. 7, 2021.

[4] Z. Wang and Y. Cha, "Unsupervised machine and deep learning methods for structural damage detection: A comparative study," Engineering Reports, 2022.

[5] X. W. Ye, T. Jin, and C. B. Yun, "A review on deep learning-based structural health monitoring of civil infrastructures," Smart Structures and Systems, vol. 24, no. 5. 2019.

[6] J. Zhang, J. Zhang, S. Teng, G. Chen, and Z. Teng, "Structural Damage Detection Based on Vibration Signal Fusion and Deep Learning," Journal of Vibration Engineering and Technologies, vol. 10, no. 4, 2022.

[7] Y. Fan, C. Wan, C. Fu, L. Han, and H. Xu, "VDoTR: Vulnerability detection based on tensor representation of comprehensive code graphs," Comput Secur, vol. 130, 2023.

[8] Y. He, H. Chen, D. Liu, and L. Zhang, "A framework of structural damage detection for civil structures using fast fourier transform and deep convolutional neural networks," Applied Sciences (Switzerland), vol. 11, no. 19, 2021.

[9] Z. Wang and Y. J. Cha, "Unsupervised deep learning approach using a deep auto-encoder with a one-class support vector machine to detect damage," Struct Health Monit, vol. 20, no. 1, 2021.

[10] X. Han, Z. Zhao, L. Chen, X. Hu, Y. Tian, C. Zhai, L. Wang, and X. Huang, "Structural damage-causing concrete cracking detection based on a deep-learning method," Constr Build Mater, vol. 337, 2022.

[11] Y. zhou Lin, Z. hua Nie, and H. wei Ma, "Dynamics-based cross-domain structural damage detection through deep transfer learning," Computer-Aided Civil and Infrastructure Engineering, vol. 37, no. 1, 2022.

[12] F. Yessoufou and J. Zhu, "Deep autoencoder model for direct monitoring of bridges subjected to a moving vehicle load under varying temperature conditions," Structures, vol. 52, 2023.

[13] Z. Lingxin, S. Junkai, and Z. Baijie, "A review of the research and application of deep learning-based computer vision in structural damage detection," Earthquake Engineering and Engineering Vibration, vol. 21, no. 1, 2022.

[14] D. E. Choe, H. C. Kim, and M. H. Kim, "Sequence-based modeling of deep learning with LSTM and GRU networks for structural damage detection of floating offshore wind turbine blades," Renew Energy, vol. 174, 2021.

[15] S. Sony, K. Dunphy, A. Sadhu, and M. Capretz, "A systematic review of convolutional neural network-based structural condition assessment techniques," Engineering Structures, vol. 226. 2021.

[16] K. Dunphy, M. N. Fekri, K. Grolinger, and A. Sadhu, "Data Augmentation for Deep-Learning-Based Multiclass Structural Damage Detection Using Limited Information," Sensors, vol. 22, no. 16, 2022.

[17] Z. Chen, C. Wang, J. Wu, C. Deng, and Y. Wang, "Deep convolutional transfer learning-based structural damage detection with domain adaptation," Applied Intelligence, vol. 53, no. 5, 2023.

[18] C. Feng, H. Zhang, S. Wang, Y. Li, H. Wang, and F. Yan, "Structural Damage Detection using Deep Convolutional Neural Network and Transfer Learning," KSCE Journal of Civil Engineering, vol. 23, no. 10, 2019.

[19] A. Asghari, G. Ghodrati Amiri, E. Darvishan, and A. Asghari, "A Novel Approach for Structural Damage Detection Using Multi-Headed Stacked Deep Ensemble Learning," Journal of Vibration Engineering and Technologies, vol. 12, no. 3, 2024.

[20] Y. Lee, H. Kim, S. Min, and H. Yoon, "Structural damage detection using deep learning and FE model updating techniques," Sci Rep, vol. 13, no. 1, 2023.

[21] F. Nex, D. Duarte, F. G. Tonolo, and N. Kerle, "Structural building damage detection with deep learning: Assessment of a state-of-the-art CNN in operational conditions," Remote Sens (Basel), vol. 11, no. 23, 2019.

[22] Y. Z. Lin, Z. H. Nie, and H. W. Ma, "Structural Damage Detection with Automatic Feature-Extraction through Deep Learning," Computer-Aided Civil and Infrastructure Engineering, vol. 32, no. 12, 2017.

[23] M. Mishra, P. B. Lourenço, and G. V. Ramana, "Structural health monitoring of civil engineering structures by using the internet of things: A review," Journal of Building Engineering, vol. 48. 2022.

[24] Y. Bai, B. Zha, H. Sezen, and A. Yilmaz, "Engineering deep learning methods on automatic detection of damage in infrastructure due to extreme events," Struct Health Monit, vol. 22, no. 1, 2023.

[25] O. Avci, O. Abdeljaber, S. Kiranyaz, M. Hussein, M. Gabbouj, and D. J. Inman, "A review of vibration-based damage detection in civil structures: From traditional methods to Machine Learning and Deep Learning applications," Mechanical Systems and Signal Processing, vol. 147. 2021.

[26] M. Azimi, A. D. Eslamlou, and G. Pekcan, "Data-driven structural health monitoring and damage detection through deep learning: State-ofthe- art review," Sensors (Switzerland), vol. 20, no. 10, 2020.

[27] J. Ye, L. Jiang, and X. Wang, "Seismic failure mechanism of reinforced cold-formed steel shear wall system based on structural vulnerability analysis," Applied Sciences (Switzerland), vol. 7, no. 2, 2017.

[28] M. L. Beconcini, P. Croce, P. Formichi, F. Landi, and B. Puccini, "Experimental evaluation of shear behavior of stone masonry wall," Materials, vol. 14, no. 9, 2021.

[29] G. Cerè, Y. Rezgui, W. Zhao, and I. Petri, "Shear walls optimization in a reinforced concrete framed building for seismic risk reduction," Journal of Building Engineering, vol. 54, 2022.

[30] S. Mishra and A. Samanta, "Seismic response of multi-storied building with shear wall considering soil-structure interaction in Patna, India," Structures, vol. 56, 2023.

[31] G. Blasi, D. Perrone, and M. A. Aiello, "Fragility curves for reinforced concrete frames with retrofitted masonry infills," Journal of Building Engineering, vol. 75, 2023.

[32] Z. Tan, Q. Zhao, Y. Zhao, and C. Yu, "Probabilistic Seismic Assessment of CoSPSW Structures Using Fragility Functions," Metals (Basel), vol. 12, no. 6, 2022.

[33] M. A. Hadianfard, M. Jahangiri, and S. Shojaei, "The effects of non-structural components on the dynamic characteristics and vulnerability of concrete structures using ambient vibration tests and Nakamura's criterion," Soil Dynamics and Earthquake Engineering, vol. 162, 2022.

[34] B. Baral and R. Suwal, "Seismic Performance of RC Buildings with Different Positions of Lift Core Wall and Added Shear Walls," Journal of Advanced College of Engineering and Management, vol. 8, no. 1, 2023.

[35] A. Romanazzi, D. V. Oliveira, R. A. Silva, A. Barontini, and N. Mendes, "Performance of rammed earth subjected to in-plane cyclic displacement," Materials and Structures/Materiaux et Constructions, vol. 55, no. 2, 2022.