# Semi-Supervised Rice Leaf Disease and Pest Classification Using IoT Field Images

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***Abstract*—Rice is a vital crop for global food security, but its productivity is frequently threatened by diseases and pests, necessitating rapid and accurate detection. This study presents a semi-supervised deep learning approach to automate the classification of ten categories of rice leaf conditions, including seven diseases, two pests, and a healthy class. Field images were acquired using a custom solar-powered ESP32-CAM- based Internet of Things (IoT) edge node. To leverage unlabeled data and minimize manual annotation costs, the dataset was structured with 744 expert-labeled images and 10,249 unlabeled images. An initial Convolutional Neural Network (CNN) model was trained using the 744 expert-labeled images to generate pseudo-labels for the 10,249 unlabeled images. The combined labeled and pseudo-labeled dataset was subsequently partitioned into 80% training, 15% testing, and 5% validation sets to train the final transfer learning-based CNN and Support Vector Machine (SVM) models. Under the evaluated configurations, the CNN achieved higher performance than the SVM baseline, with an accuracy of 82.9%, precision of 83.0%, recall of 82.9%, F1-score of 0.829, and Matthews Correlation Coefficient (MCC) of 0.798, whereas the evaluated SVM configuration achieved an accuracy of 23.7%. These findings demonstrate the efficacy of combining low-cost IoT edge acquisition with semi-supervised deep learning for scalable, real-time crop disease monitoring in precision agriculture.**

***Keywords*—Semi-Supervised Learning (SSL); CNN; rice leaf disease; pest classification; IoT-based agriculture; deep learning; dataset**

## I. Introduction

Rice is one of the main staple foods that significantly contributes to global food security, especially in Asian countries, including Indonesia. About 480 million tons of rice are produced each year, with China and India accounting for more than 50% of the total production [1], [2]. Rice is not only important for meeting the caloric needs of the people but also plays a role in supporting the economy and social stability, providing jobs for millions of farmers[3], [4]. Sometimes, rice plants get sick or are eaten by bugs, and this can make it hard to grow enough rice. Among these diseases and pests are Brown Spot (BS), Hispa (Pest), Bacterial Leaf Blight (BLB), Blast, Sheath Blight (SB), Dead Heart (Pest), Bacterial Panicle Blight (BPB), Tungro, and Bacterial Leaf Streak (BLS). Diseases and pests can lead to major losses and put the long-term success of rice farming at risk [5]–[9]. It is important to spot pest and disease problems early so you can act quickly and control them effectively, thereby minimizing losses and maintaining rice productivity amidst existing challenges [8], [10], [11]. Conventional methods for detecting diseases in rice generally require the expertise of trained specialists, are subjective, and cannot be widely or scalably applied. In the context of modern agriculture, this leads to delays in responding to disease outbreaks and results in significant losses for farmers [12], [13]. As a solution, the development of computer vision technology offers new opportunities to improve accuracy and efficiency in real-time disease detection, becoming an integral part of precision agriculture systems. The two main streams in this technology are: 1) the classic machine learning approach that uses handcrafted feature extraction, such as color, texture, and shape, accompanied by the use of classifiers like Support Vector Machine (SVM); and 2) the deep learning approach that allows models to learn features end-to-end without requiring manual intervention for feature extraction [14], [15]. Recent research shows that deep learning methods, especially convolutional neural networks (CNNs), can improve disease detection capabilities with high accuracy, reaching over 97% [16], [17]. This approach not only improves efficiency but also has the potential to save crops and enhance the sustainability of rice production by providing faster and more accurate detection of various diseases such as Leaf Blight, Brown Spot, and Blast [13], [18]. With the implementation of these techniques, it is expected that farmers will be better prepared to face disease threats, thereby maintaining food security more effectively[19], [20].

Against this practical context, the present study investigates a semi-supervised workflow that combines a limited expert-labeled set with a substantially larger pool of unlabeled field images for rice leaf disease and pest classification. The study integrates IoT-based field image acquisition using an ESP32-CAM node with CNN-based pseudo-label generation and compares the resulting CNN classifier with an SVM reference classifier across ten rice leaf condition classes. The objective is to evaluate a practical classification workflow for variable and imbalanced field imagery while reducing dependence on exhaustive expert annotation.

The remainder of this study is organized as follows. Section II reviews related work; Section III describes the materials and methods; Section IV presents the experimental results; Section V discusses the findings and deployment implications; and Section VI concludes the study and outlines future work.

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## II. Background and Related Work

Semi-supervised learning (SSL) has recently emerged as an effective strategy for reducing the heavy annotation burden in agricultural computer vision, leveraging abundant unlabeled imagery alongside a small expert-labeled set. Reported applications span crop classification from satellite image time series [21], UAV-based maize seedling monitoring and counting [22], [23], multi-class weed detection and robotic weed management [24], [25], pixel-level and panoptic crop segmentation [26], [27], region-of-interest monitoring in vertical farms [28], and plant counting in aerial images under domain shift [29], with several pipelines approaching fully supervised accuracy while using only 5–30% of labeled data [21], [22], [23], [24], [25], [29], [30]. Within plant pathology specifically, SSL and self-training have improved disease and pest recognition: a lightweight self-training CNN achieved near-supervised accuracy for real-time jute leaf disease classification [31]; a semi-supervised one-stage detector raised mean average precision for maize leaf disease at low labeling ratios [32]; memory-based mutual learning produced robust pest detection from small labeled fractions [33]; and pseudo-labeling with consistency regularization (the Wheat Teacher detector) together with collaborative SSL enabled accurate wheat-head detection and wheat-lodging segmentation [34], [35].

A consistent finding across this literature is that the reliability of pseudo-labels governs SSL success; high-confidence pseudo-labels yield large gains, whereas unfiltered or erroneous labels propagate noise and can erode accuracy [32], [33], [36], [37]. Accordingly, several safeguards have been proposed: ambiguity-aware rejection of uncertain predictions [36], dynamic pseudo-label allocation with adaptive loss thresholds [34], iterative correction of noisy annotations [38], knowledge-distillation-based and one-shot pseudo-labeling demonstrated even for livestock video and animal identification [37], and depth-informed, almost-unsupervised pseudo-labeling for dense crop segmentation [39], [40]. Where the deployment domain differs from the training domain (different crops, growth stages, or imaging conditions), semi-supervised and semi-self-supervised domain adaptation, few-shot learning, and self-training improve cross-domain robustness [29], [30], [41], [42]. Collectively, these studies establish SSL with curated pseudo-labels rather than naive self-training as the practical route to scalable field analytics under limited supervision.

Despite this progress, two gaps motivate the present study. First, the very high accuracies, frequently exceeding 97%, reported for CNN-based rice-disease classification are predominantly obtained on curated, class-balanced secondary datasets captured under controlled conditions [43], [44]; images acquired in situ by low-cost IoT edge devices instead exhibit variable illumination, viewpoint, occlusion, and pronounced class imbalance, which substantially depress real-world performance consistent with the 82.9% accuracy obtained here on field-captured data. Second, most agricultural SSL studies target UAV or satellite imagery and crops other than rice, and few couple edge-based IoT image acquisition with a pseudo-label-driven semi-supervised workflow on a single, real field dataset. This study addresses both gaps by pairing a solar-powered ESP32-CAM acquisition node with a pseudo-labeling CNN that converts 10,249 unlabeled field images into usable training signal, and by benchmarking it against a handcrafted-feature SVM under realistic, imbalanced field conditions.

Research on plant disease classification using Support Vector Machine (SVM) has shown good accuracy, especially on limited and controlled datasets [12], [20]. SVM is often effective in classifying and detecting diseases because of its ability to separate data classes with an optimal decision boundary. However, a significant drawback of this approach is its dependence on the limited quantity and quality of training data, which does not always represent real-world conditions. On the other hand, the use of Convolutional Neural Networks (CNNs) in rice disease detection has shown superior performance, especially when using large datasets consisting of balanced labeled images from online repositories [45], [46]. Nevertheless, this approach tends to be less effective when applied to field datasets with more variable conditions. Previous studies generally focused only on balanced labeled data and did not consider challenges such as class imbalance and environmental variability caused by data acquisition through the Internet of Things (IoT). Current research clearly still lacks systematic comparisons between the two approaches, SVM and CNN, on real field datasets with unique characteristics, namely, limited labeled data (744) and abundant unlabeled data (10,249). This creates additional challenges for effective and efficient disease detection and highlights the need for further research to develop methodologies that can address these weaknesses in rice farming contexts [45], [46], [47]. This study makes a significant contribution to understanding and managing rice diseases by providing a comprehensive field dataset consisting of 744 labeled and 10,249 unlabeled data points, covering 10 classes of rice leaf conditions. The dataset was acquired through IoT technology, enabling more representative data collection aligned with dynamic field conditions [12], [46]. Furthermore, this research systematically compares traditional approaches (SVM with handcrafted feature extraction) and modern approaches (semi-supervised CNN) in limited data scenarios. This approach aims to enhance understanding of each method's strengths and weaknesses in a realistic context [13], [48]. Additionally, the study investigates the effectiveness of using unlabeled data by applying semi-supervised learning techniques, which aim to improve CNN model performance in rice disease detection. This method offers great potential to maximize available data and address the common issue of limited labeled data faced in previous research [49], [50]. Finally, the study provides recommendations for optimal architecture and strategies for field implementation based on IoT, intended to assist farmers in detecting and managing rice diseases efficiently and effectively. With support for integrating this technology, it is hoped that this research can contribute not only to increased agricultural yields but also to overall food security [14], [51], [52]

## III. Materials and Methods

In this study, rice disease and pest classification on leaves was conducted using deep learning approaches based on Convolutional Neural Networks (CNN). The dataset used consists of 10,249 unlabeled images and 744 images labeled by experts. These images were obtained directly from the field using IoT devices that enable real-time monitoring of rice leaf conditions in agricultural environments. The types of diseases and pests classified include Brown Spot (disease), Hispa (pest),

Bacterial Leaf Blight (disease), Blast (disease), Sheath Blight (disease), Dead Heart (pest), Bacterial Panicle Blight (disease), Bacterial Leaf Streak (disease), and Tungro (disease), with varying numbers of images. Representative examples of the ten classes are shown in Fig. 1.

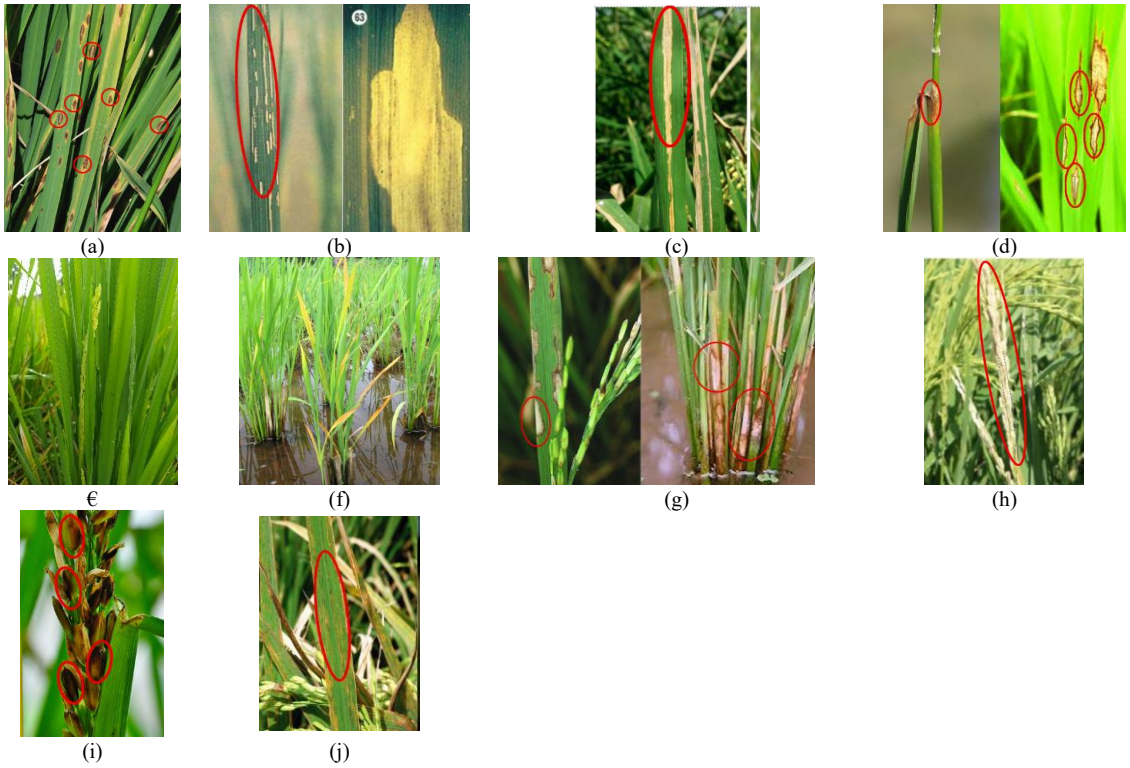


Fig. 1. Samples of the rice leaf diseases and pests dataset: (a) Brown Spot; (b) Hispa; (c) Bacterial Leaf Blight; (d) Blast; (e) Normal; (f) Tungro; (g) Sheath Blight; (h) Dead Heart; (i) Bacterial Panicle Blight; and (j) Bacterial Leaf Streak.

The collected data comprise images of rice leaves obtained from the field using IoT devices, totaling 10,249 unlabeled images and 744 labeled by experts. From this data, the dataset is divided into two groups: training data (learning dataset) and performance data (performance dataset). In the training dataset, the process is carried out gradually until a trained model is produced. The model is then tested to measure accuracy using performance data. If the accuracy meets the standard, the model is finalized. If not, other methods are applied until satisfactory performance is achieved. This methodology aims to continuously optimize the rice leaf disease and pest classification model by improving accuracy. The overall research workflow is summarized in Fig. 2.

This flowchart diagram illustrates the research methodology for classifying rice leaf diseases and pests using CNN and SVM. The process begins with data collection, preprocessing (normalization and augmentation), followed by data splitting. Two models are selected, CNN and SVM, and trained using the data. A semi-supervised approach is used for unlabeled data. After training, the models are evaluated based on accuracy, precision, recall, and F1 score, and then the best model is used to predict unlabeled rice leaf images. The final stage involves applying the model for real-time field prediction of diseases and pests.

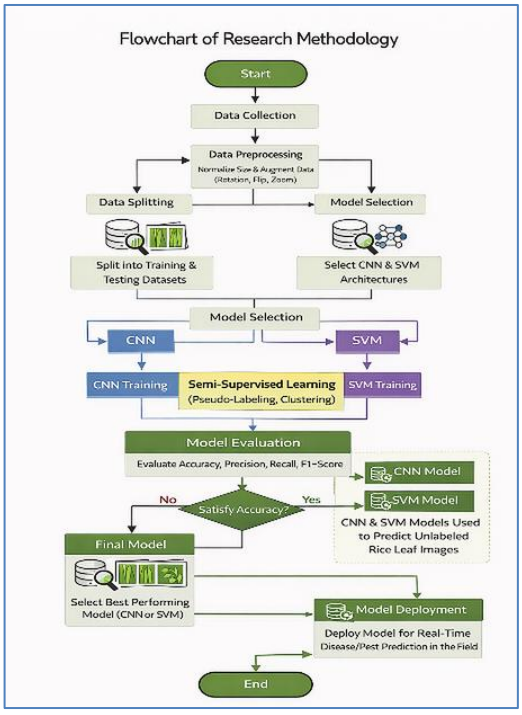


Fig. 2. Flowchart of research methodology.

### A. Data Acquisition and IoT Setup

The ESP32-CAM module attracts attention in agricultural IoT because it is inexpensive, has integrated Wi-Fi, and has enough resolution to monitor plant diseases [53]. Combined with ultrasonic sensors for distance measurement, servo motors for precise positioning, and GPS modules for geotagging, the ESP32-CAM-based system offers an affordable solution for automatic field image acquisition [54]. Table I summarizes the specifications of the IoT components used.

TABLE I. IOT NODE COMPONENT SPECIFICATIONS

| Components | Specifics | Function |
|---|---|---|
| ESP32-CAM | ESP32-S dual-core 240MHz, 4MB PSRAM, Wi-Fi | Main controller and camera |
| Camera OV2640 | 2MP, resolution 1600×1200 | Filming |
| Sensor HC-SR04 | Distance 2- 400 cm, accuracy ±3mm | Distance measurement |
| Servo MG90S (2) | Torque 2.2 kg·cm, 0-180° | Pan and tilt control |
| GPS NEO-6M | Accuracy 2.5m, update rate 5Hz | Geotagging |
| Buzzer 5V | 85dB, 10cm | Field operator alert |
| Solar Panel | 20W polycrystalline | Main resources |
| Battery | 12V 12Ah lead-acid | Power storage |
| Regulator LM2596 | Step-down 12V to 5V | Power regulation |
| Module TP4056 | Charging with protection | Battery management |

Fig. 3 illustrates the hardware assembly and pin connections of the IoT node. The ESP32-CAM is connected to the GPIO pins, and Fig. 4 shows the process of capturing images of rice leaves in the field.

Fig. 3. IoT device.

Fig. 4. Photographing in the rice field.

### B. Dataset and Ground Truth:

In this study, the dataset [55] used is divided into two main parts, namely Labeled Data and Unlabeled Pool. The Labeled Data consists of 744 images that were verified by three experts from the Faculty of Agriculture, Universitas Jenderal Soedirman (UNSOED), Purwokerto, Indonesia: Prof. Ir. Totok Agung Dwi Haryanto, M.P., Ph.D. (Plant Breeding); Woro Sri Suharti, S.P., M.P., Ph.D. (Plant Pathology); and Dr. Endang Mugiastuti, S.P., M.P. (Plant Pathology). Each image is classified into a category of disease or pest on rice leaves, with details available in Table II.

TABLE II. DISTRIBUTION OF RICE LEAF DISEASE CLASSES IN THE LABELED DATASET

| Disease Class | Number of Images | Class classification |
|---|---|---|
| Bacterial Leaf Blight | 85 | Diseases |
| Brown Spot | 120 | Diseases |
| Blast | 83 | Diseases |
| Sheath Blight | 59 | Diseases |
| Tungro | 50 | Diseases |
| Normal | 72 | Normal |
| Dead Heart | 56 | Pests and Diseases |
| Bacterial Panicle Blight | 53 | Diseases |
| Bacterial Leaf Streak | 50 | Diseases |
| Hispa | 116 | Pests and Diseases |
| Quantity | 744 | |

Meanwhile, the Unlabeled Pool contains 10,249 raw images taken directly from the field. These images do not yet have expert-assigned class labels and cover a variety of conditions, including different rice plant varieties, growth stages, lighting conditions, and viewing angles. In the semi-supervised workflow, this pool is processed by the initial teacher CNN to obtain predicted class labels. The prediction output is then converted into the class-label field and combined with the expert-labeled data before the final train/test/validation partition is created. Representative samples from the unlabeled image pool are shown in Fig. 5.

Fig. 5. Unlabeled data.

### C. Pre-Processing Data

In the data preprocessing stage, all images in the dataset are resized to suit the needs of each model. Images for the Convolutional Neural Network (CNN) model are resized to 224x224 pixels, while images for feature extraction with Support Vector Machine (SVM) are reduced to 227x227 pixels.

### D. Convolutional Neural Network

Semi-supervised CNN is a machine learning approach that combines labeled and unlabeled data to train object detection and classification models in images. The model is trained with a small amount of labeled data to learn initial representations, then optimized with unlabeled data through the creation of pseudo-labels. The main challenge is errors in pseudo-labels, which can reduce accuracy if not handled properly [56].

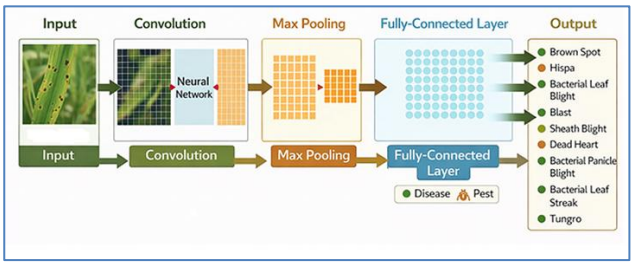


Fig. 6. CNN workflow.

Fig. 6 illustrates the process of classifying rice leaf diseases and pests using a CNN, starting from an input image measuring 224x224 pixels. The image is processed through convolution to extract features such as texture and shape, then through max pooling to reduce dimensions while preserving key features. The features are then classified as Brown Spot, Hispa, and others via a fully connected layer, enabling the system to automatically detect rice plant diseases and pests, thereby assisting agricultural management. CNN utilizes the convolution process to divide the image into small parts, extract numerical features through encoding, and use down-sampling (max pooling) to reduce the array size, which speeds up training and decreases layer complexity. At the end of the convolutional network, there is an evaluation section used to measure the system's performance. The model is optimized using the categorical cross-entropy loss, while its classification performance is assessed using Accuracy, Precision, Recall, F1-score, and the Matthews Correlation Coefficient (MCC), as defined in Equations (1)–(6). Here, TP, TN, FP, and FN denote the true positives, true negatives, false positives, and false negatives, respectively; N is the number of observations and K is the number of classes.

$$\text{Accuracy} = \frac{\sum_{k=1}^{K} \text{TP}_k}{N} \tag{1}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

$$\text{F}_1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

$$\text{MCC} = \frac{\text{TP} \times \text{TN} - \text{FP} \times \text{FN}}{\sqrt{(\text{TP} + \text{FP})(\text{TP} + \text{FN})(\text{TN} + \text{FP})(\text{TN} + \text{FN})}} \tag{5}$$

$$L = -\frac{1}{N} \sum_{i=1}^{N} \sum_{k=1}^{K} y_{i,k} \log(\hat{y}_{i,k}) \tag{6}$$

The initial preprocessing stage of rice leaf data involves configuring and collecting data to train a CNN model. Out of 10,993 IoT images, 744 are validated and labeled by plant experts across 10 categories, while 10,249 images form the unlabeled pool used for semi-supervised learning. After training on the 744 expert-labeled images, the initial CNN is applied to the 10,249 unlabeled images in the Predictions Data widget. The predicted class output is passed through the Edit Domain ("Edit Label") widget to standardize it as the target class variable, producing the pseudo-labeled pool used in the subsequent combined-data stage. For comparison, the study also employs Support Vector Machine (SVM) as a conventional reference classifier using handcrafted features and the fixed configuration listed in Table V, including a sigmoid kernel. Evaluation is performed using confusion matrices and metrics including accuracy, precision, recall, F1-score, and MCC.

To preserve separation in the final evaluation stage, the expert-labeled and pseudo-labeled data are concatenated before the final-model split. The first stratified Data Sampler, using a fixed seed, allocates 80% of the combined pool to training. From the remaining 20%, a second stratified sampler allocates 75% to testing, corresponding to 15% of the complete pool, while the remaining 5% is reserved for validation. Consequently, the final CNN and SVM are trained only on the 80% training partition, while the 15% test and 5% validation partitions remain non-overlapping hold-out subsets.

### E. Support Vector Machine

Support Vector Machine (SVM) is a machine learning algorithm used in classification and regression analysis. This algorithm belongs to the category of supervised learning, which means it requires labeled data for training. SVM is well-known for its ability to find the optimal hyperplane that separates classes in the feature space with the maximum margin between data points from two different classes. The basis of SVM is the search for a hyperplane that separates two classes of data. This hyperplane can be viewed as a line (in two dimensions), or a plane (in three dimensions), and the model aims to maximize the margin, which is the distance between the closest data points of each class. The data points closest to the hyperplane are called support vectors, which are crucial points because they determine the position of the hyperplane [56], [57].

## IV. RESULT

The data preparation process is implemented to ensure consistency across the entire dataset. A total of 10,993 rice leaf images are used, consisting of 744 labeled images validated by experts and 10,249 unlabeled field images taken through IoT devices (Fig. 8). The labeled dataset includes 10 different classes, including 7 disease categories (bacterial leaf blight, bacterial leaf streak, bacterial panicle blight, blast, brown spot, sheath blight, and tungro), 2 pest categories (dead heart and hispa), and 1 healthy class (normal). The 744 expert-labeled images are first used to train the initial CNN model, which subsequently generates predictions for the 10,249 unlabeled field images. After label assignment, the resulting data are combined with the expert-labeled dataset for final model development. The combined dataset is then partitioned using stratified sampling into 80% training, 15% testing, and 5% validation subsets. The reported performance metrics therefore correspond to this predefined stratified hold-out evaluation.

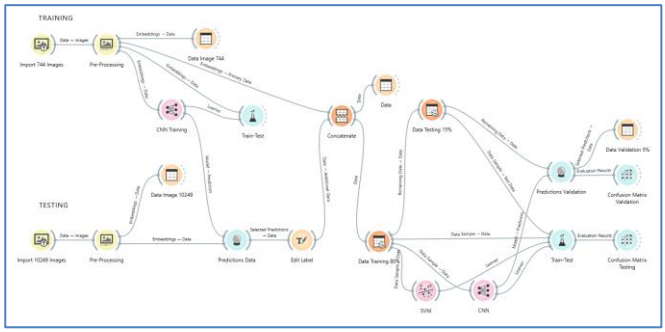


Fig. 7. Result of model development using graphical data mining application.

Based on the workflow in Fig. 6, the classification procedure consists of an initial teacher-model and pseudo-labeling stage followed by final model development and evaluation. In the first stage, the 744 expert-validated images are processed through pre-processing and feature extraction to train the initial CNN, which is then used to predict labels for the 10,249 unlabeled field images. The prediction output is standardized as the class variable through the Edit Label step and then concatenated with the expert-labeled data. Only after this label-assignment stage is the combined dataset divided into 80% training data, 15% testing data, and 5% validation data. The final CNN and SVM models are evaluated using confusion matrices and performance measures including accuracy, precision, recall, F1-score, and MCC (Fig. 7).

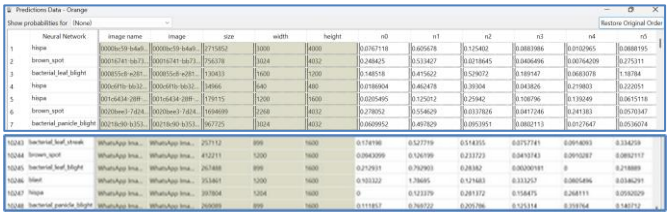

Fig. 8. Image labeling process of 10,993 images.

### A. Convolutional Neural Network

CNN Training serves as an initial model that functions as a 'teacher' before the final model is created. Starting with the expert-labeled rice leaf images, the CNN learns visual patterns from the disease and pest classes and is then used in the Predictions Data widget to assign pseudo-labels to the unlabeled image pool. The predicted class output is standardized through the Edit Label widget and combined with the expert-labeled data through the Concatenate widget. The combined pool is then divided into 80% training, 15% testing, and 5% validation using the sequential stratified samplers. The 5% validation partition contains 549 images and is used for the confusion-matrix analysis in Fig. 9, whereas the 15% test partition is used for the summary performance metrics reported in Table IV. CNN Training therefore functions as the teacher stage for expanding the available training signal before the final CNN and SVM evaluation.

Details of the training configuration for the CNN model from the Graphical Data Mining Application are shown in Table III.

TABLE III. DETAILS OF THE TRAINING LAYERS FOR THE CNN

| No | Parameters | Value |
|---|---|---|
| 1 | Neuron in Hidden Layer | 200,100 |
| 2 | Activation | ReLu |
| 3 | Solver/Optimizer | Adam |
| 4 | Regulation optimizer | 0,001 |
| 5 | Iteration | 500 |

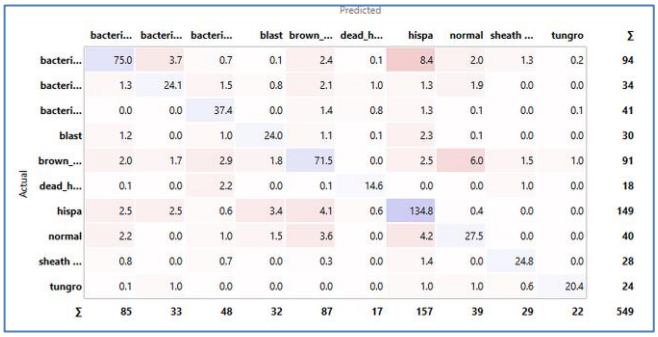


Fig. 9. CNN validation confusion matrix 5%.

The confusion matrix shown in this analysis illustrates the detailed performance of the Convolutional Neural Network (CNN) model in classifying ten categories of rice leaf conditions, including seven types of diseases, two types of pests, and one healthy class. In the matrix, the actual labels are shown by rows and the model predictions by columns, while the main diagonal represents correctly assigned class membership. The matrix is calculated on the 5% validation partition of the combined dataset, comprising 549 images. This validation partition is distinct from the test partition used for the summary performance metrics reported in Table IV.

The CNN confusion matrix indicates comparatively strong class-level recall for Hispa (90.5%) and Bacterial Leaf Streak (91.2%), followed by Sheath Blight (88.6%) and Dead Heart (81.1%). In contrast, Tungro showed the lowest recall at 52.2%, with a notable tendency to be confused with Sheath Blight. Bacterial Panicle Blight and Brown Spot achieved class-level recall of 65.1% and 73.7%, respectively. The matrix also indicates overprediction of Hispa and underprediction of

Tungro. Overall, most classes showed comparatively strong recall, while some classes, particularly Tungro, remained more challenging. These class-wise confusion patterns indicate that visually similar symptoms continue to be an important source of classification error and motivate further improvements through additional representative samples and data augmentation.

TABLE IV. RESULTS OF THE DEVELOPED MODEL CNN

| No | Result | Value on Data Testing (%) |
|---|---|---|
| 1 | Accuracy | 82,9 |
| 2 | Precision | 83 |
| 3 | Recall | 82,9 |
| 4 | F1-Score | 0,829 |
| 5 | MCC | 0.798 |

Table IV summarizes the performance of the Convolutional Neural Network (CNN) model for classifying 10 categories of rice leaf conditions (7 diseases, 2 pests, and 1 healthy class) on the final combined-data test partition defined by the 80% training, 15% testing, and 5% validation split. The separate 5% validation partition, comprising 549 images, is used for the confusion-matrix analysis in Fig. 9. The reported metrics include accuracy, precision, recall, F1-score, MCC, and AUC. The CNN achieved an AUC of 0.985, indicating strong discriminative capability across the evaluated classes.

### B. Support Vector Machine

Pre-processing methods for the SVM and CNN models follow the same scheme as the workflow diagram that shows the data splitting details. The data is grouped into ten folders according to the rice disease class names, including Bacterial Leaf Blight and Blast. Images are converted into a format readable by the model after being resized using the pre-processing widget in Orange, and visual features are extracted through an Image Embedding method based on Inception v3. For initial CNN training, 744 labeled images are used, generating predictions for 10,249 unlabeled images through pseudo-labeling. All labeled data are then combined into approximately 11,000 images. For final model development, the combined dataset is partitioned into training (80%), testing (15%), and validation (5%) subsets used by both the CNN and SVM evaluation workflows in Orange Data Mining. The SVM shows lower performance than the CNN under the evaluated configuration, as reflected by CA, F1, Precision, Recall, and MCC, with higher prediction errors especially in visually similar classes such as Blast and Brown Spot. The performance of both models can be viewed through the Confusion Matrix. Details of the SVM configuration from the Graphical Data Mining Application in Fig. 10 are shown in Table V.

TABLE V. SVM MODEL CONFIGURATION

| No | Parameters | Value |
|---|---|---|
| 1 | SVM Cost | 1,0 |
| 2 | Regression loss epsilon | 0,10 |
| 3 | Kernel | Sigmoid |
| 4 | SVM optimizer tolerance | 0,0010 |
| 5 | SVM Iteration Limit | 100 |

Fig. 10. SVM validation confusion matrix 5%.

The SVM confusion matrix shows limited class-wise performance across the 10 rice leaf categories. Hispa achieved the highest class-level recall at 42.8%, while several other classes showed substantially lower recall, and Bacterial Leaf Blight and Blast were rarely classified correctly. These patterns are consistent with the overall SVM results in Table VI and indicate that the evaluated SVM configuration had difficulty separating visually similar disease and pest classes.

TABLE VI. RESULTS OF THE DEVELOPMENT MODEL SVM

| No | Result | Value on Data Testing (%) |
|---|---|---|
| 1 | Accuracy | 23,7 |
| 2 | Precision | 27,6 |
| 3 | Recall | 23,7 |
| 4 | F1-Score | 25,5 |
| 5 | MCC | 15,1 |

This study compares CNN and SVM for rice leaf image classification. The SVM is trained and evaluated using the same final combined-data split described above, with 80% allocated to training, 15% to testing, and 5% to validation. On the test partition, the SVM achieved an AUC of 0.761 and an accuracy of 23.7%. The F1-Score of 0.255 indicates prediction imbalance, and the MCC of 0.151 reflects limited agreement between predicted and actual classes under the evaluated configuration.

## V. DISCUSSION

### A. Performance Comparison of CNN and SVM Classifiers

This study compares the CNN and SVM implementations evaluated for classifying rice leaf diseases and pests. The CNN achieved an AUC of 0.985, classification accuracy (CA) of 82.9%, F1-score of 0.829, precision of 83.0%, recall of 82.9%, and an MCC of 0.798. Under the specified SVM configuration, the corresponding testing accuracy was 23.7% with an MCC of 0.151. The SVM confusion matrix shows frequent misclassification, particularly for disease classes with overlapping visual symptoms such as Blast and Brown Spot. Accordingly, the comparison in this study is interpreted as the performance of the two implemented configurations on the same field-acquired dataset, rather than as an exhaustive assessment of all possible SVM parameterizations.

### B. Annotation and Computational Trade-Offs

While the CNN model offers high accuracy, it requires a substantial labeled dataset to initialize training. In this study, the

training of the initial "teacher" CNN utilized 744 expert-labeled images to generate pseudo-labels for the 10,249 unlabeled images. In terms of workflow constraints, expert manual annotation of the entire 10,993-image dataset represents a significant bottleneck in terms of time and cost. The SVM model presents a simpler alternative that does not require GPU acceleration for inference. However, traditional SVMs face scaling limitations as the size of the training feature space grows, leading to high training complexity, even though their final testing (inference) time remains negligible. Under the configurations evaluated in this study, the semi-supervised CNN provided the stronger classification performance. Future work may broaden the benchmark by examining alternative SVM parameterizations together with other classifiers such as Random Forest, K-Nearest Neighbors (KNN), and additional deep learning architectures.

### C. Impact of Semi-Supervised Learning on Class Imbalance

A key finding in this study is the interaction between Semi-Supervised Learning (SSL) and the class imbalance inherent in the labeled dataset (Table II). The majority class (Brown Spot) contains 120 images, whereas minority classes (Tungro and Bacterial Leaf Streak) contain only 50 images each. In self-training workflows, this imbalance presents a risk of confirmation bias because the pseudo-label assignments are generated by a model initialized from the same imbalanced expert-labeled distribution. As a result, class preferences learned during the teacher stage can be propagated into the pseudo-labeled pool and subsequently influence the combined-data training stage.

This behavior provides a plausible explanation for the lower class-level recall of Tungro (52.2%) and its recurring confusion with Sheath Blight, which shares visually similar yellowing symptoms. Conversely, Hispa tended to be overpredicted. These patterns are consistent with the general risk that pseudo-labeling can reinforce initial class preferences when visually overlapping classes are present. Future implementations could therefore consider class-aware pseudo-label selection and human-in-the-loop review of uncertain cases before final model retraining.

### D. Proposed Field Deployment Architecture and Real-Time Farmer Notification Pipeline

To illustrate how the classification framework could be extended into a practical precision agriculture service, a real-time data integration and notification architecture is proposed. In this architecture, the ESP32-CAM IoT edge node deployed in the field would perform image acquisition and geotagging via the NEO-6M GPS module, and the captured images could be transmitted to a cloud-based server through a local Wi-Fi gateway or cellular network such as 4G/5G. The computational task of running the trained transfer learning CNN model could then be handled by the cloud server. When a disease or pest is detected, the classification result, GPS coordinates, and timestamp could be stored in a Firebase Realtime Database.

In the proposed farmer-facing layer, database updates could trigger an automated webhook to send a push notification or instant message through services such as the WhatsApp Business API. The notification could link to a lightweight mobile dashboard displaying:

- The classified disease or pest type.
- A confidence score and the captured leaf image.
- The exact geographic location of the affected crop to facilitate targeted pesticide application or physical intervention.

Such a cloud-to-mobile pipeline would allow farmers to access the classification results without requiring specialized technical knowledge or high-performance local computing devices, and could support rapid, localized responses to pest and disease outbreaks.

## VI. Conclusion

This study investigated rice leaf disease and pest classification using a semi-supervised Convolutional Neural Network (CNN) workflow and a Support Vector Machine (SVM) reference classifier. The CNN used 744 expert-labeled images to generate labels for 10,249 unlabeled field images, after which the combined dataset was used for final model development. Under the configurations evaluated in this study, the CNN achieved 82.9% accuracy compared with 23.7% for the SVM baseline, while also providing a practical mechanism for exploiting the large unlabeled image pool. These results support the use of the semi-supervised CNN workflow for the field-image classification setting examined here. Future work may extend the comparison to additional classifier configurations and architectures, apply data-augmentation strategies, and explore lighter CNN models and more advanced semi-supervised techniques for resource-limited deployment. Future studies may complement this hold-out evaluation with repeated or cross-validation-based assessment across additional field datasets.

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