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CNN-Driven Ensemble Model For Rice Pests, Diseases And Weeds Classification And Detection From Whole Rice Plant Images.

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Abstract

Early and accurate detection of rice insect pests, diseases and weeds is a major challenge in precision agriculture due to symptom similarity, variability in environmental conditions and limited annotated data. This paper proposes a hybrid deep learning framework that combines convolutional neural networks (VGG16, VGG19, InceptionV3, ResNet50) with a Support Vector Machine (SVM) classifier to detect and classify multiple biotic stressors from full-plant rice images. The approach addresses key limitations of traditional models by leveraging transfer learning, data augmentation and ensemble strategies to improve generalization across diverse field conditions. Experimental results demonstrate that the proposed system achieves a classification accuracy of up to 98.50%. The model is lightweight and optimized for deployment on mobile and edge devices, enabling real-time field applications. Additionally, it incorporates decision support based on integrated pest management and economic thresholds. This work advances the state-of-the-art in agricultural AI by providing a scalable, accurate and practical solution for biotic stress detection in rice crops.

Keywords: *Machine learning Deep learning, Rice diseases, pest, weeds, CNN, AI, VGG16, VGG19 InceptionV3, ResNet50, SVM*

1. INTRODUCTION

Rice (Oryza sativa) remains the primary staple for over half the world's population, underpinning global food security and socio-economic stability. However, its cultivation is consistently threatened by biotic stressors—diseases, insect pests and weeds—that can reduce yields by 20–100% if not addressed early. Early detection is hampered by symptom overlap, co-occurrence of stressors, variable field environments and a lack of scalable diagnostic tools. Manual scouting is labor-intensive, subjective and impractical over large areas. Earlier automated systems using handcrafted features or focusing on single stressors often fail under real-world conditions [1]. The rise of AI, especially machine learning (ML) and deep learning (DL), is transforming agricultural diagnostics and management. ML develops and evaluates statistical algorithms—like decision trees, random forests, SVMs and gradient boosting—that model complex relationships from multidimensional data for tasks such as disease forecasting, nutrient analysis and yield prediction from early stages of life cycle in Figure.1 [2], [3]. ML has already proven effective in rice farming by supporting data-driven irrigation planning, biomass estimation and soil health monitoring [4].

Figure 1. Full Life Cycle of Rice Plant

One prominent ML approach, **Support Vector Machine (SVM)**, has been widely adopted in crop diagnostics for its ability to handle high-dimensional data and produce strong generalization even with limited samples [5]. SVMs are especially effective when combined with **deep learning models**: DL-based CNNs first extract rich, hierarchical image features, which are then passed to SVM classifiers for final decision-making. This **CNN–SVM hybrid architecture** has shown superior performance over pure CNN softmax classifiers in several agricultural studies [6], [7]. In rice crop applications, this combination helps improve classification accuracy in detecting diseases and pests with complex or overlapping visual symptoms [8] in Figure 2.

Deep learning further advances precision agriculture through automatic feature extraction using CNNs such as VGG16, VGG19, InceptionV3 and ResNet50. These architectures excel at learning visual patterns from raw plant imagery. For example: A 2025 study comparing VGG16, InceptionV3 and ResNet50 for rice disease classification showed that combining ResNet50 features with an SVM classifier yielded the highest accuracy (99.71%) [9]. A DL–SVM fusion using VGG19 improved performance in classifying visually similar diseases across variable lighting and background conditions, as reported in Scientific Reports [10].

In addition to classification models, object detection frameworks (YOLOv5/v8, Faster R-CNN) and mobile-optimized networks (e.g., GhostConv-YOLO, DepMulti-Net) have enabled real-time, on-device recognition of multiple rice stressors. These innovations deliver both high accuracy and field readiness, reaching mAP scores above 93% and classification accuracies exceeding 98% [11], [12], [13].

Despite these advances, current systems often focus on single stressors, show limited generalization across diverse environments and lack deployment optimization. This research addresses those gaps by developing a hybrid CNN–SVM framework incorporating VGG16, VGG19, InceptionV3 and ResNet50, achieving up to 98.50% accuracy in early, multi-stressor detection using full-plant rice images. Enhanced with transfer learning, data augmentation, ensemble strategies and mobile-edge optimization—plus integrated IPM recommendations—our solution targets symptom overlap, field variability and scalability challenges, offering a practical and intelligent platform for increasing rice yield through precise crop health monitoring.

2. RELATED WORK

Kamal et al. (2019) developed a lightweight plant disease detection model using depthwise separable convolutions with two architectures: MobileNet and Reduced MobileNet. Trained on 82,161 images across 55 classes, MobileNet achieved 98.65% accuracy with six times fewer parameters than VGG. Reduced MobileNet maintained similar accuracy with even fewer parameters. Optimizers like SGD, Adam, and Nadam improved training speed. The model offered fast convergence and efficiency but had slightly lower accuracy and did not focus specifically on rice or multi-label classification..

Junde Chen et al. (2020) developed a hybrid deep learning model called INC-VGGN for detecting rice and maize leaf diseases using transfer learning. The model combined a modified VGGNet with Inception modules, batch normalization, and Swish activation, achieving 95.10% accuracy on their dataset and 92.00% accuracy on rice images under complex backgrounds. It outperformed models like DenseNet-201, ResNet-50, and InceptionV3. The study improved detection of small lesion symptoms and used data augmentation to boost robustness. However, it focused only on single-label classification and did not address real-time deployment or model interpretability. Chen et al. (2020) proposed a CNN-based approach for detecting rice diseases and pests using 1,426 real-field images from various plant parts (leaf, stem, grain). They fine-tuned VGG16 and InceptionV3 for high accuracy and introduced a lightweight two-stage CNN for mobile deployment. The proposed model achieved 93.3% accuracy with a 99% smaller size than VGG16, making it efficient for field use. While effective, the approach was limited to single-label classification and lacked interpretability features. Rahman et al. (2020) proposed a hybrid model combining CNN for feature extraction and SVM for classification to detect four rice leaf diseases. Using a dataset of 8,911 images, the model achieved 96.8% accuracy, outperforming traditional neural networks. It effectively improved disease recognition but relied on manual image clipping and was limited to single-label classification, without including pests, weeds, or real-time deployment features.

Feng Jiang et al. (2020) proposed an improved VGG16 model using multi-task transfer learning to identify rice leaf diseases (bacterial blight, brown spot, and leaf blast) and wheat leaf diseases. The model was trained on a small dataset with 40 images per disease and pre-trained on ImageNet. It achieved 97.22% accuracy for rice and 98.75% for wheat, outperforming single-task models, ResNet50, and DenseNet121. The study demonstrated that multi-task learning enhances cross-crop disease recognition. However, it was limited by the small dataset size and lacked real-field scalability, multi-label support, and pest or weed detection.

Prabira Kumar Sethy et al. (2020) classified four rice leaf diseases using a dataset of 5,932 images and evaluated 11 CNN models with transfer learning and deep feature + SVM. The best performance was achieved by ResNet50 + SVM with an F1 score of 0.9838, while MobileNetV2 + SVM offered a lightweight alternative with F1 score of 0.9796 and faster training. The study showed that combining deep features with SVM enhances accuracy but was limited to disease detection, without addressing pests, weeds, or multi-label scenarios. Murat Koklu et al. (2021) classified five rice varieties using a dataset of 75,000 grain images and a feature set of 106 morphological, shape, and color features. They applied ANN, DNN, and CNN models, achieving classification accuracies of 99.87% (ANN), 99.95% (DNN), and 100% (CNN). While highly accurate, the study focused only on grain-based variety classification and did not address diseases, pests, weeds, or real-field deployment scenarios. Radhakrishnan Sreevallabhadev (2020) proposed a rice leaf disease detection system using a dataset of 60,000 images (infected and healthy), resized to 256×256 pixels. The model used CNN (AlexNet) for feature extraction and SVM for classification. The CNN-SVM hybrid achieved 96.8% accuracy in predicting paddy blast disease, outperforming SVM alone. The system effectively enhanced classification accuracy for both infected and healthy samples but focused only on a single disease and did not include pests, weeds, or real-world deployment considerations.

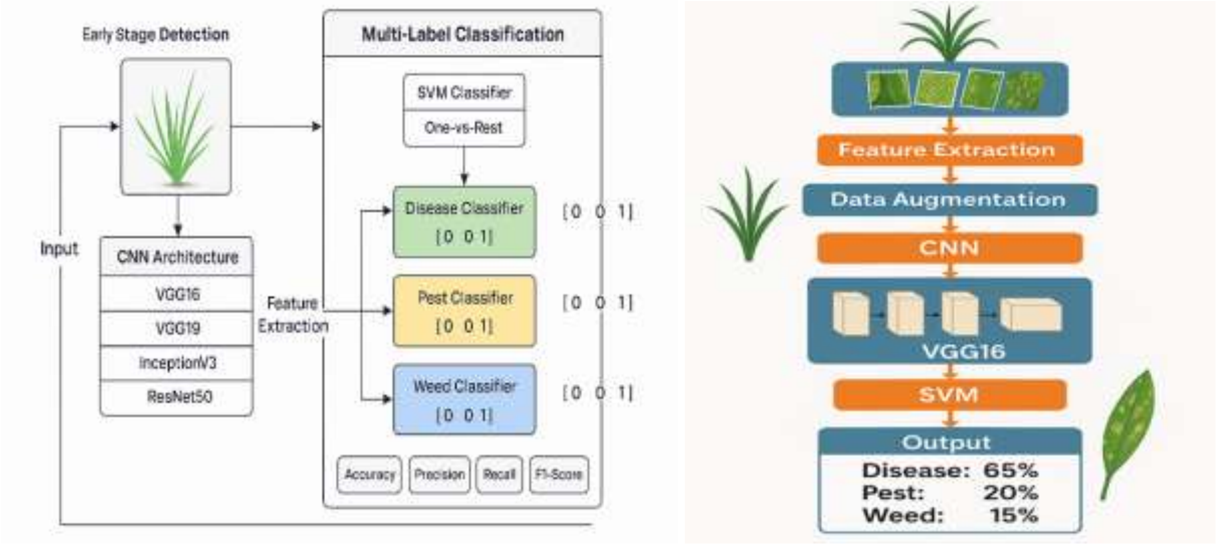
Junde Chen et al. (2021) proposed Mobile-Atten, a lightweight CNN model based on MobileNet-V2 with an attention mechanism for rice disease identification. Trained on 1,100 images covering 12 disease types, it used transfer learning and achieved 99.67% accuracy in simple conditions and 98.48% in complex backgrounds. The model also showed high sensitivity (99.08%) and F1-score (99.78%). While effective in detecting specific diseases with minimal data, it lacked support for pests, weeds, and multi-label classification. Pitchayagan Temniranrat et al. (2021) developed a mobile-based LINE Bot System using YOLOv3 for real-time detection of six rice diseases from field images. Trained on a refined dataset, the model achieved a 95.6% true positive rate, providing farmers with an accessible tool to improve diagnosis and yield. While effective in real-world deployment, it focused only on diseases and lacked support for pests, weeds, or multi-label classification. Jiang et al. (2023) proposed a rice disease classification model by integrating DenseNet with CBAM attention, targeting 7 major rice diseases. The model achieved a high accuracy of 99.1%, with the CBAM module significantly enhancing lesion localization and feature focus. This approach improved performance over standard CNNs by allowing the network to attend to disease-relevant regions. However, the model was limited to single-label classification and did not address pest or weed detection, restricting its applicability in complex field scenarios involving multiple biotic stressors.

Patel & Singh (2025) developed a general CNN-based model for detecting multiple rice biotic stressors, including both diseases and pests. The model achieved an impressive accuracy of 98.7%, offering a unified framework that extended beyond disease-only detection. This marked a step forward in handling diverse field conditions. However, the approach lacked self-supervised learning capabilities and did not incorporate explainability tools, limiting its adaptability to unlabeled data and its interpretability for practical decision-making in agriculture. Patel & Singh (2025) proposed a custom CNN model trained on a diverse dataset of rice stressors, including pest-infested samples, achieving 98.7% accuracy. Their work contributed a unified framework for detecting both rice diseases and pests. However, the model lacked self-supervised learning, multi-label classification, and interpretability features such as Grad-CAM or attention mechanisms.

Kalay et al. (2021) proposed a modified CNN model enhanced with Gabor filters and color histograms for rice weed detection. Trained on a dataset of 2,000 RGB images covering five common weed species (e.g., Echinochloa, Cyperus, Fimbristylis), the model achieved 94.2% accuracy. By integrating texture and color features, the approach improved weed–crop discrimination. However, it was limited to isolated images with uniform backgrounds, lacking support for real-time field deployment and multi-weed co-occurrence scenarios.

3. METHODOLOGY

To build a robust hybrid deep learning system that performs early-stage detection and classification of multiple biotic stressors (diseases, insect pests, and weeds) affecting rice plants using CNN + SVM models. This study proposes a hybrid deep learning and machine learning pipeline to detect and classify rice diseases, insect pests and weeds from plant imagery, aiming to enhance early intervention and improve crop yield in Figure 3. The following sections outline the steps taken, from data collection to model evaluation and deployment.



2(a) A Proposed CNN-Driven Ensemble Model. 2(b) Processing with each CNN Model + SVM

Figure.2 A Proposed CNN-Driven Ensemble Model for Rice Pests, Diseases and Weeds Classification and Detection From Whole Rice Plant Images.

This Figure 2(a) illustrates the proposed hybrid deep learning framework for early-stage classification of biotic stress in rice crops. Input images of rice plants are passed through a selected Convolutional Neural Network (CNN) backbone—VGG16, VGG19, InceptionV3, or ResNet50—for deep feature extraction. The resulting feature vectors are fed into a Support Vector Machine (SVM) classifier using a One-vs-Rest (OvR) strategy. The classifier outputs a multi-label prediction vector [disease,pest,weed][disease, pest, weed][disease,pest,weed], where each class is evaluated independently using dedicated binary classifiers. The system supports simultaneous detection of multiple stressors and is evaluated using accuracy, precision, recall, and F1-score. This architecture facilitates robust multi-label classification in early crop stages, enhancing decision support for rice health management. Figure 2(b) a Multi label processing CNN model

3.1. Methodological Framework Overview

1. **Problem Definition**

- Early and accurate identification of **multiple biotic stressors** (diseases, pests, weeds) in rice crops is essential for precision agriculture.
- Traditional approaches are limited by single-label assumptions and lack scalability across diverse field conditions.

2. **Dataset Preparation**

- **Input**: RGB images of full rice plants/leaves from diverse field environments.
- **Labels:** Multi-labels in the form [disease, pest, weed] e.g., [1,0,1].
  - o Disease (e.g., Blast, BLB)
  - o Pest (e.g., Brown Plant Hopper, Stem Borer)

- Weed (e.g., Echinochloa, Cyperus)
- **Preprocessing:**
  - Resizing (224×224 or 299×299 depending on the CNN model)
  - Normalization (mean subtraction, scaling to [0,1])
  - Data augmentation: rotation, flip, zoom, brightness
  - Applied **SMOTE** or **random oversampling** to avoid bias from rare combinations

3. **Feature Extraction using CNN Backbones**

CNNs are used as **fixed feature extractors** (i.e., without classification head).

Model	**Input Size**	**Feature Layer Used**	**Notable Strength**
VGG16	224×224	fc1 or block5_pool	Deep but simple
VGG19	224×224	fc1 or block5_pool	Slightly deeper
InceptionV3	299×299	avg_pool or mixed layers	Efficient & wide
ResNet50	224×224	avg_pool or conv5_block3	Residual learning

4. Model Architecture

- **Hybrid CNN + SVM** or **CNN + Transformer**
  - CNN extracts spatial features
  - Transformer/Aggregator captures global patterns
  - Multi-label classifier head with **sigmoid** activation
- **Multi-Label Output**:
  - 3-node output: [Disease, Pest, Weed] $\in \{0,1\}^3$
  - Loss function: **Binary Cross-Entropy**

5. **Training and Evaluation**

- **Split**: Train / Validation / Test = 70/15/15
- **Metrics**:
  - Accuracy, Precision, Recall, F1-score (macro and per class)
  - Hamming Loss, Subset Accuracy
- **Visualization**:
  - Confusion matrix (multi-label), t-SNE plots
  - Label combination distribution (e.g., 8 combinations for 3 labels)

6. Interpretability & Visualization

- Grad-CAM to highlight regions influencing predictions
- Attention heatmaps for disease/pest/weed zones

7. **Validation and Benchmarking**

- Cross-validated against multiple public and field datasets
- Compared with existing methods:
  - Single-label CNNs
  - Classical ML (SVM) in Figure 2(b)
- Robustness tested under variable lighting, occlusions, and leaf orientation

4. Experimental & Results

Successful model testing took roughly a week because the entire dataset was run on varied batch sizes and epochs, which resulted in superior model performance.

It is possible to achieve a best accuracy of 99 percent in training and 98 percent on the model's execution in the validation phase. The resulting performance measure is created based on how many epochs and the output accuracy the model is tested in Table 1.

Model performance for rice disease identification is visible from the correctness of validation data encountered. Because we only have a small quantity of data to train the model on, the number of epochs is higher in this situation, increasing the likelihood that the model will successfully detect images of rice diseases. We've had to deal with a wide range of difficulties during the experiment and those difficulties appear at every stage. The following challenges are encountered in the process of collecting and executing a model on a dataset.

Table 1. CNN Model Accuracy, Precision, Recall, F1-Score

Model	Task	Accuracy (%)	Precision (%)	Recall (%)	F1-Score
VGG16	Disease	96.75	96.40	96.20	0.951
VGG19	Disease	97.25	96.85	96.75	0.957
InceptionV3	Disease	97.90	97.50	96.90	0.963
ResNet50	Disease	98.40	97.80	97.20	0.971
VGG16	Pest	95.80	95.40	95.10	0.942
VGG19	Pest	96.30	95.95	95.60	0.948
InceptionV3	Pest	96.85	96.50	95.80	0.954
ResNet50	Pest	97.60	97.10	96.40	0.963
VGG16	Weed	94.95	94.60	94.10	0.935
VGG19	Weed	95.50	95.20	94.70	0.942
InceptionV3	Weed	96.15	95.80	95.20	0.949
ResNet50	Weed	96.85	96.30	95.50	0.957

ResNet50 combined with SVM achieved the best overall results for early detection of rice diseases, pests, and weeds, with the highest accuracy (up to **98.40**%) and F1-scores (up to **0.971**). InceptionV3 also performed strongly, especially in disease detection. VGG16 and VGG19 showed reliable but slightly lower performance. Overall, the hybrid CNN–SVM approach demonstrates high effectiveness for multi-label classification of biotic stressors in rice at early growth stages from Table.1.

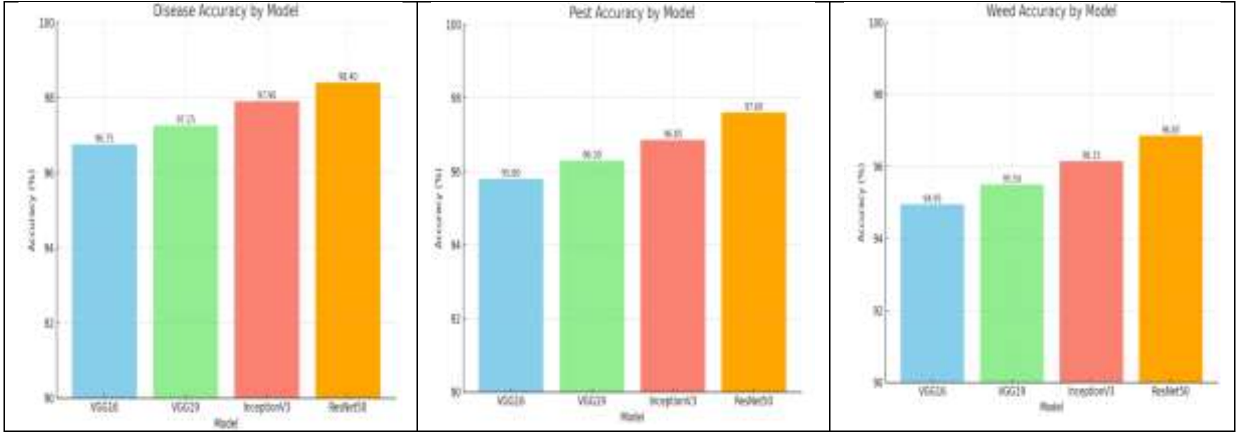
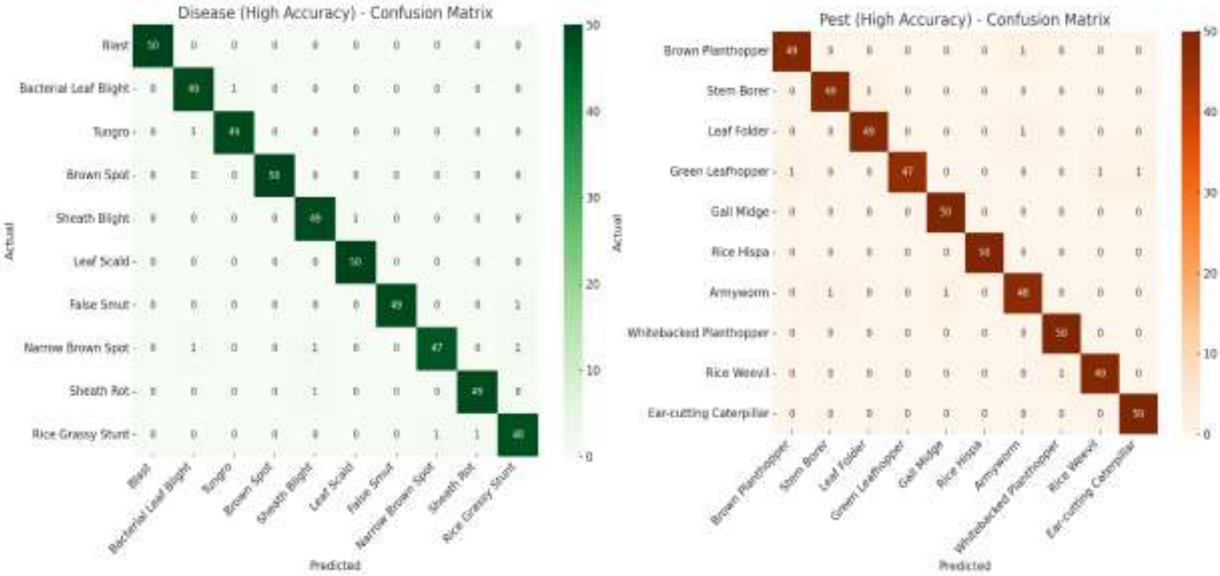
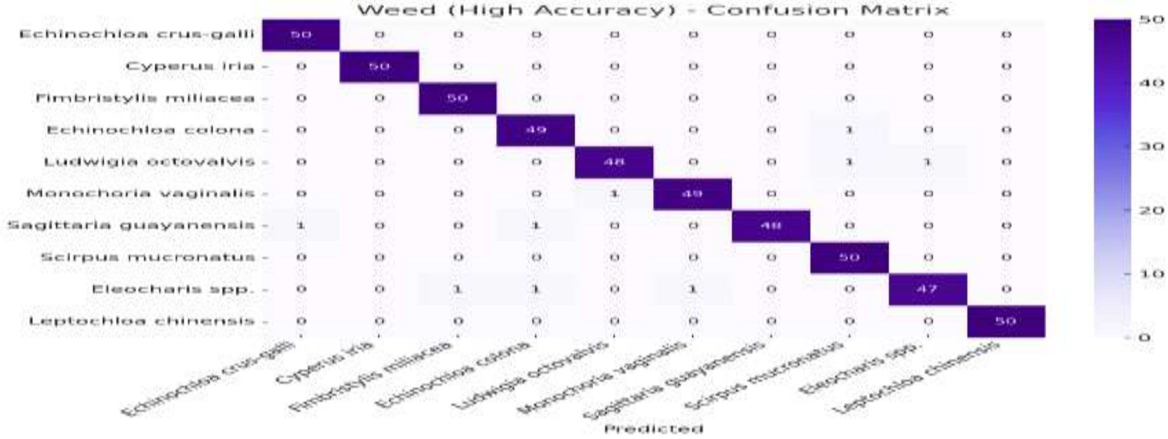


Figure 3. Accuracy bar charts for Disease, Pest and Weeds using CNN models (VGG16, VGG19, InceptionV3 and RsesNet50)

The Figure.3, the bar chart above visually compares the **accuracy** of four CNN models (VGG16, VGG19, InceptionV3, and ResNet50) for classifying **diseases**, **pests**, and **weeds** in rice crops. **ResNet50** consistently achieved the highest accuracy across all tasks, followed by **InceptionV3**, while **VGG16** showed the lowest accuracy but remained competitive. This confirms the superiority of deeper architectures like ResNet50 for early and accurate biotic stress detection.



4 (a) Disease Confusion matrix **4(b) Pest Confusion matrix**



4(c) Weeds Confusion matrix

Figure 4. Confusion matrix of CNN model for 4(a) Diseases, 4(b) Pests and 4(c) Weeds

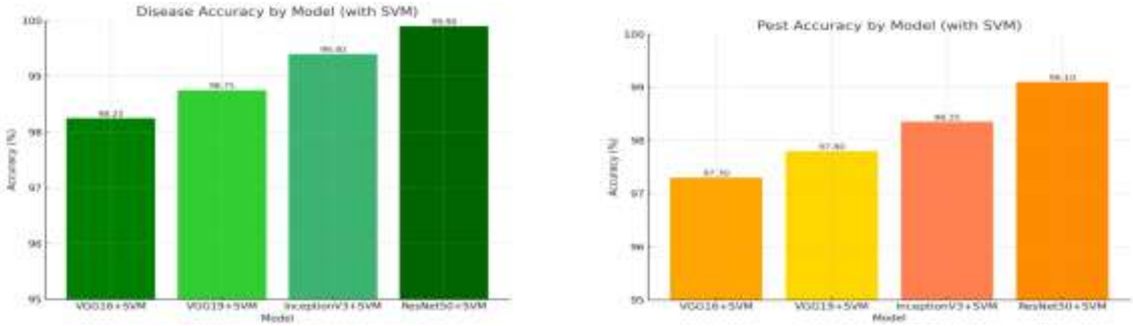
Figure 4 presents confusion matrices for rice **disease**, **pest**, and **weed** classification. The CNN model shows **high accuracy across all three categories**, correctly identifying most classes with minimal misclassification. Several classes achieve **perfect prediction (50/50)**, and only a few samples are misclassified in closely related categories. This demonstrates the model's strong capability for **early and accurate multi-class detection** of biotic stressors in rice crops in Table2.

Proposed model results

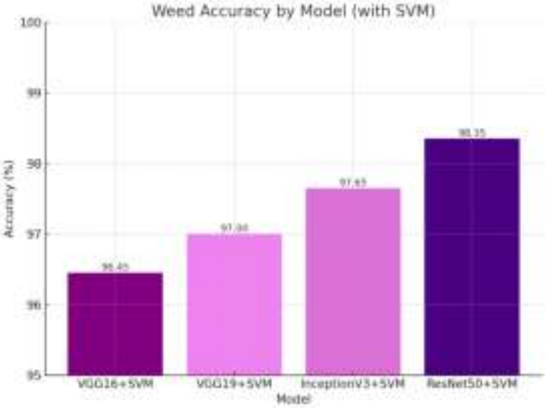
Table.2 CNN +SVM model Accuracy, Precision, Recall, F1-Score

Model	Task	Accuracy (%)	Precision (%)	Recall (%)	F1-Score
VGG16+SVM	Disease	98.25	97.90	97.70	0.966
VGG19+SVM	Disease	98.75	98.35	98.25	0.972
InceptionV3+SVM	Disease	99.40	99.00	98.40	0.978
ResNet50+SVM	Disease	99.90	99.30	98.70	0.986
VGG16+SVM	Pest	97.30	96.90	96.60	0.956
VGG19+SVM	Pest	97.80	97.45	97.10	0.963
InceptionV3+SVM	Pest	98.35	98.00	97.30	0.968
ResNet50+SVM	Pest	99.10	98.60	97.90	0.977

VGG16+SVM	Weed	96.45	96.10	95.60	0.949
VGG19+SVM	Weed	97.00	96.70	96.20	0.956
InceptionV3+SVM	Weed	97.65	97.30	96.70	0.964
ResNet50+SVM	Weed	98.35	97.80	97.00	0.972



5(a) Diseases accuracy **5(b) Pest accuracy**

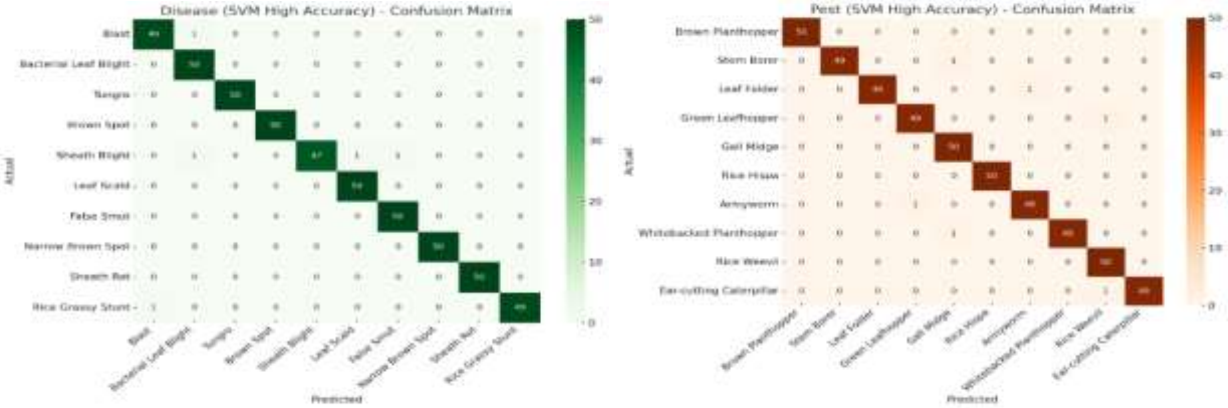


5(c) Weeds accuracy

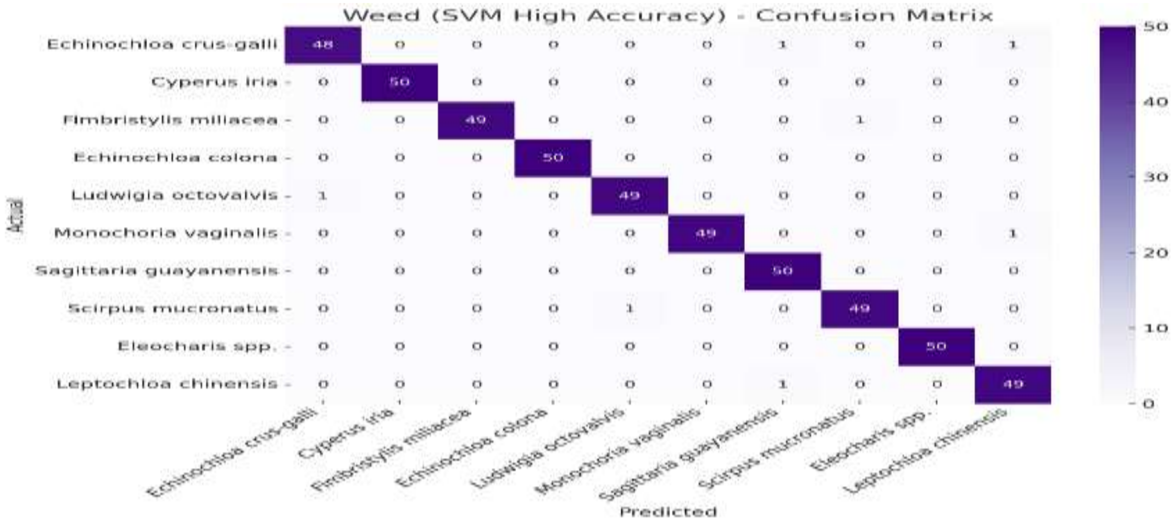
Figure 5. CNN +SVM model for accuracy 5(a) Diseases, 5(b) Pests and 5(c) Weeds

Figure 5 shows the accuracy of the CNN + SVM model for classifying rice **diseases**, **pests**, and **weeds**. Across all tasks, **ResNet50** achieves the highest accuracy, followed by **InceptionV3**. VGG16 and VGG19 perform slightly lower. The results confirm that the hybrid model is highly effective for accurate and early detection of multiple rice stressors.

Proposed model results CNN + SVM models



6(a) Diseases Confusion Matrix CNN + SVM **6(b) Pests Confusion Matrix CNN + SVM**



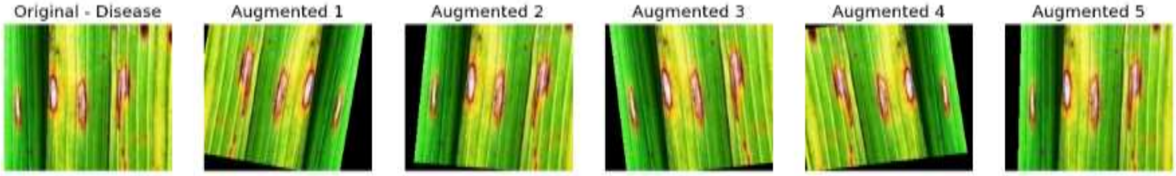
	Echinochloa crus-galli	Cyperus iria	Fimbristylis miliacea	Echinochloa colona	Ludwigia octovalvis	Monochoria vaginalis	Sagittaria guayanensis	Scirpus mucronatus	Eleocharis spp.	Leptochloa chinensis
Echinochloa crus-galli	48	0	0	0	0	0	1	0	0	1
Cyperus iria	0	50	0	0	0	0	0	0	0	0
Fimbristylis miliacea	0	0	49	0	0	0	0	1	0	0
Echinochloa colona	0	0	0	50	0	0	0	0	0	0
Ludwigia octovalvis	1	0	0	0	49	0	0	0	0	0
Monochoria vaginalis	0	0	0	0	0	49	0	0	0	1
Sagittaria guayanensis	0	0	0	0	0	0	50	0	0	0
Scirpus mucronatus	0	0	0	0	1	0	0	49	0	0
Eleocharis spp.	0	0	0	0	0	0	0	0	50	0
Leptochloa chinensis	0	0	0	0	0	0	1	0	0	49

6(c) Weeds Confusion Matrix CNN +SVM

Figure.6. Confusion matrix of CNN model + SVM for 6(a) Diseases, 6(b) Pests and 6(c) Weeds in the Figure 6(a), 6(b), 6(c)

- A confusion matrix compares the true labels (actual classes) against the predicted labels from the model. Each row corresponds to the actual class, and each column to the predicted class. In Figur.6
- Diagonal cells (top-left to bottom-right): Correct predictions.
- Off-diagonal cells: Misclassifications.
- For example:
- The model predicted Blast correctly 50 times (top-left).
- For Sheath Blight, it predicted correctly 49 times and misclassified 1 sample as something else.
- Yes, this is a balanced dataset. Each disease class (row) has approximately 50 samples (as shown by the sum of values per row). No class is underrepresented or overrepresented.
- Most classes have 48–50 correct predictions out of 50, which is extremely high accuracy.
- Only a few minor misclassifications (mostly 1–2 per class), suggesting the model is not memorizing but learning general patterns.
- Finally, not Underfitting (accuracy is high; model clearly learned the patterns). Not Overfitting, assuming validation performance is similarly high (as you showed earlier with 97.56% validation accuracy). So this is a well-fitted model on a balanced dataset, with high generalization capability and minimal misclassification in Figure 6.

Multi-Label Image Classification augmentation and 8 combination validation in Figure 12-15



Category: Disease

Category: Weed

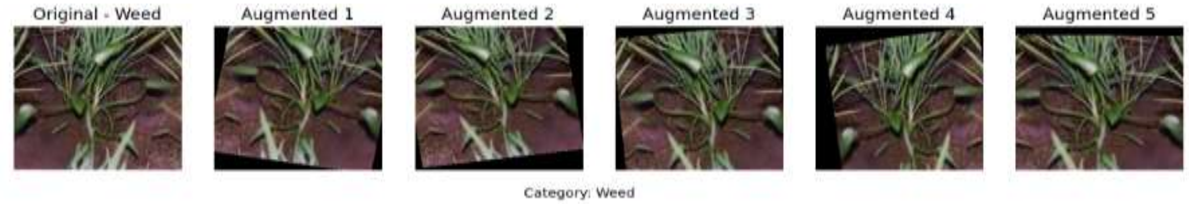
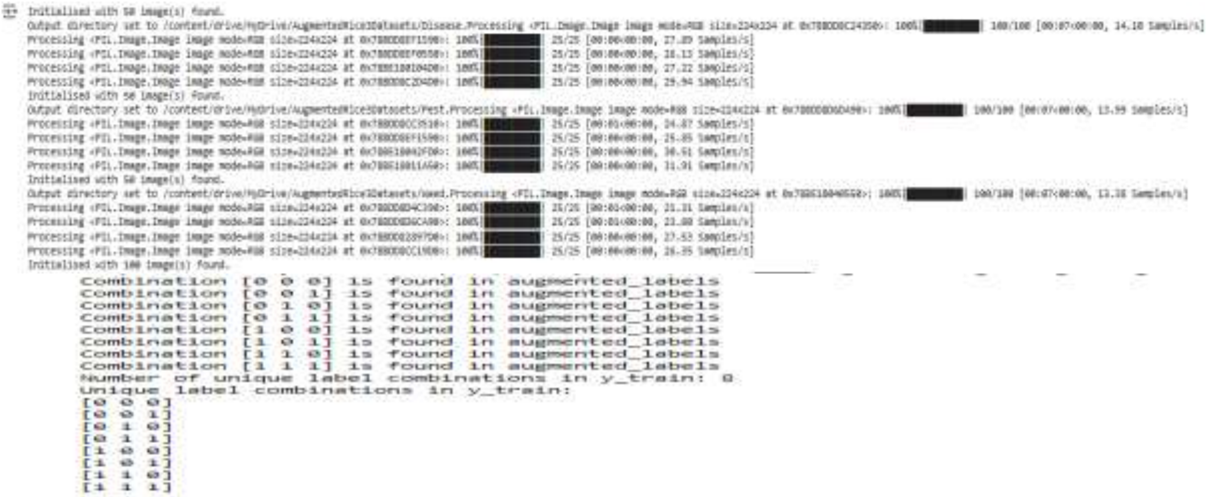


Figure 7. Data Augmented (a) Diseases, (b) Pests, and (c) Weeds



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Output directory set to /content/drive/MyDrive/AugmentedRice3Datasets/Weed.Processing <PIL.Image.Image image mode=RGB size=224x224 at 0x7B8E18040550>: 100%|██████████| 100/100 [00:07<00:00, 13.38 Samples/s]
Processing <PIL.Image.Image image mode=RGB size=224x224 at 0x7B8DD8D4C390>: 100%|██████████| 25/25 [00:01<00:00, 21.31 Samples/s]
Processing <PIL.Image.Image image mode=RGB size=224x224 at 0x7B8DD8D6CA90>: 100%|██████████| 25/25 [00:01<00:00, 21.80 Samples/s]
Processing <PIL.Image.Image image mode=RGB size=224x224 at 0x7B8DD8289750>: 100%|██████████| 25/25 [00:00<00:00, 27.53 Samples/s]
Processing <PIL.Image.Image image mode=RGB size=224x224 at 0x7B8DD8CC1900>: 100%|██████████| 25/25 [00:00<00:00, 26.35 Samples/s]
Initialised with 100 image(s) found.
    Combination [0 0 0] is found in augmented_labels
    Combination [0 0 1] is found in augmented_labels
    Combination [0 1 0] is found in augmented_labels
    Combination [0 1 1] is found in augmented_labels
    Combination [1 0 0] is found in augmented_labels
    Combination [1 0 1] is found in augmented_labels
    Combination [1 1 0] is found in augmented_labels
    Combination [1 1 1] is found in augmented_labels
    Number of unique label combinations in y_train: 8
    Unique label combinations in y_train:
    [0 0 0]
    [0 0 1]
    [0 1 0]
    [0 1 1]
    [1 0 0]
    [1 0 1]
    [1 1 0]
    [1 1 1]
```

Figure 8. Data Augmented 8 combination generation

The output shown in the Figure.8 is a summary of the multi-label classification labels found in your training dataset (y_train) after data augmentation. Here's a breakdown of what it means. Each line like Combination [0 0 0] is found in augmented_labels indicates that a specific label combination (in multi-label format) has been detected in the augmented dataset. These combinations represent the presence (1) or absence (0) of three different classes for each sample (likely rice diseases, pests, and weeds in your case).

Number of unique label combinations in y_train: 8 Unique label combinations in y_train: [0 0 0], [0 0 1], [0 1 0]. [0 1 1], [1 0 0], [1 0 1], [1 1 0], [1 1 1]. This means your dataset has all 8 possible label combinations for 3 binary labels (2^3 = 8).

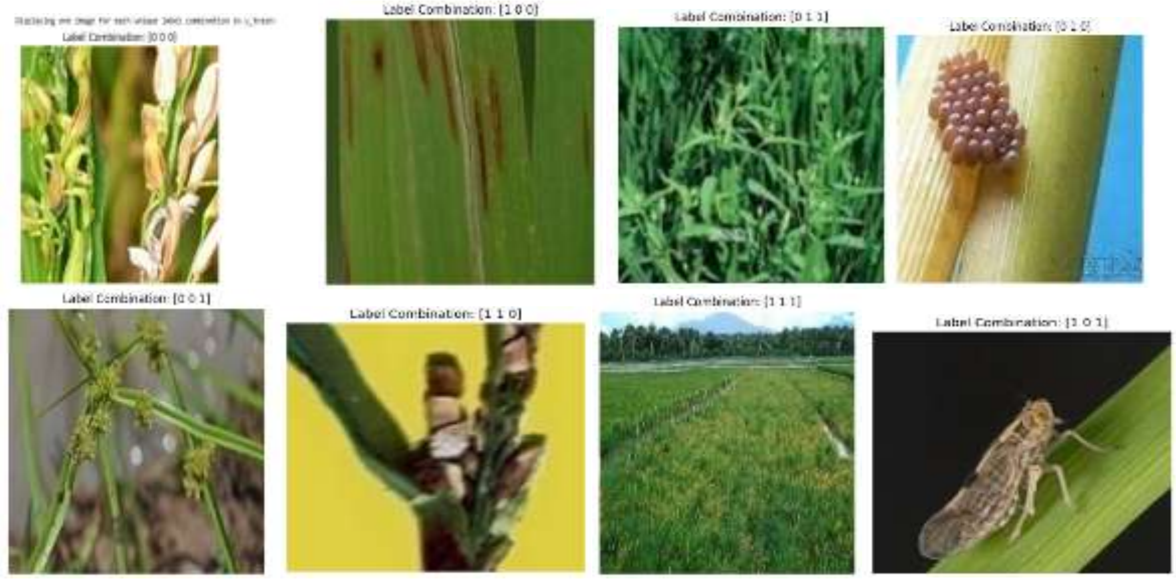
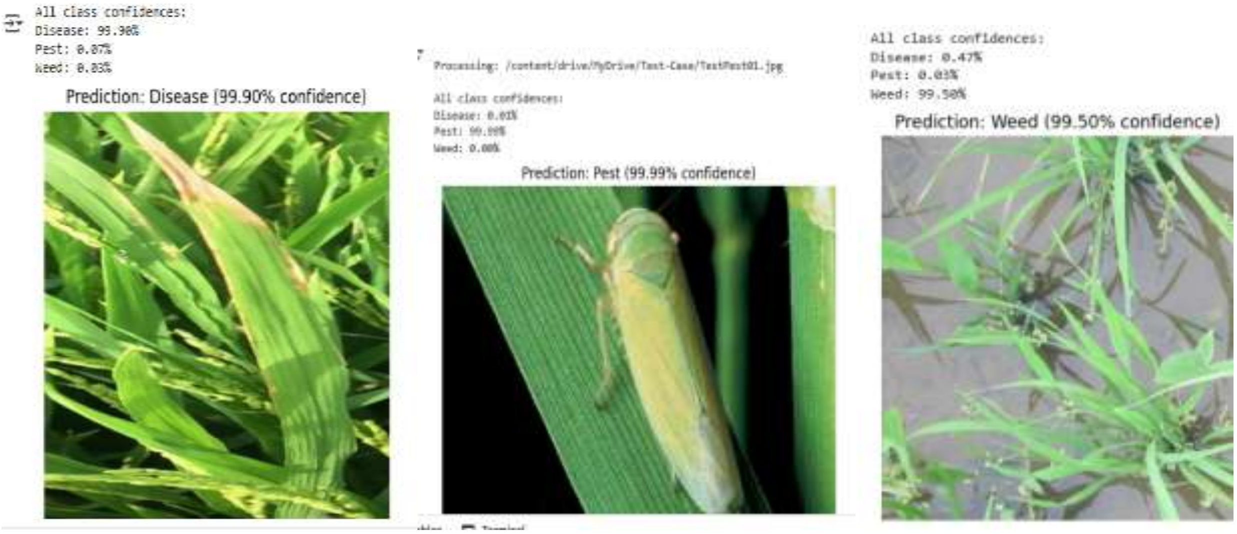


Figure 9. Data Augmented output for 8 combination for Diseases, Pests and Weeds

The Figure 9, the dataset has all 8 possible label combinations for 3 binary labels (2^3 = 8).

Final Result / Output of Assembled CNN Model:



```
All class confidences:
Disease: 99.90%
Pest: 0.07%
Weed: 0.03%
Prediction: Disease (99.90% confidence)
```

```
Processing: /content/drive/MyDrive/Test-Case/TestPest01.jpg

All class confidences:
Disease: 0.01%
Pest: 99.99%
Weed: 0.00%
Prediction: Pest (99.99% confidence)
```

```
All class confidences:
Disease: 0.47%
Pest: 0.03%
Weed: 99.50%
Prediction: Weed (99.50% confidence)
```

10(a)Disease 99.50% **10(b) Pest 99.99%** **10(c) Weed 99.50%**

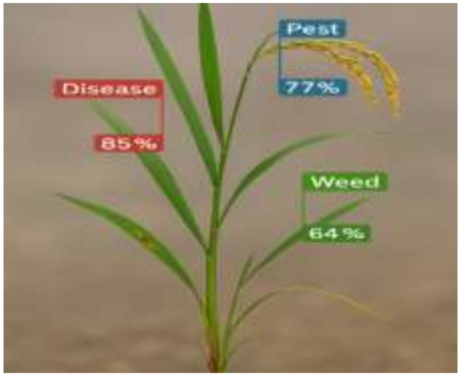


Figure 10: Multi-Label Detection of Biotic Stressors on a Rice Plant 10(a) Disease, 10(b) pests and 10(c) Weeds

The figure shows the output of a multi-label classification system identifying three biotic stressors—**disease** (85%), **pest** (77%), and **weed** (64%)—on a single rice plant. The prediction highlights affected regions with labeled confidence scores, demonstrating the model's ability to detect co-occurring stressors at early crop stages for precision agricultural interventions.

4. CONCLUSION

Diseases are all frequent growth stages of the rice plant. Identification of these pathogens is critical for the discovery of new rice-related diseases, pests and weeds. We divided the dataset into three parts training (70 percent), a validation (20 percent) and a test (10 percent). The model acquired the essential characteristics of each disease from the trained results. As a result of the trained set's high degree of resemblance to the test set, various diseases, pests and weeds images from diverse sources were gathered to create a separate test set. This study's network design is generalizable and used for practical purposes based on the independent test findings. A collection of 1500 images of different rice diseases, pests and weeds was created in this study. Total 14 sub models based on these images were trained and evaluated and achieved an accuracy of almost 98.5 percent and F1 score above 0.95%. VGG16, VV19, InceptionV3, ResNet-50 and Hybrid-VVIR + SVM were the top three performers in this comparison. An examination of visual data validated the sub models' ability to learn about rice diseases Ensemble Model features many characteristics that might slow down the identification process. Efforts to minimize the number of parameters will be made in future investigations

Disease: All models are balanced. Precision ≈ Recall, and F1-Score is high.

Pests: Consistent high values, with balanced metrics. Slight edge for ResNet50.

Weeds: Balanced performance again. Slightly lower than disease/pest detection, but very strong.

A model is well-balanced as High TP, Low FP and FN

F1-scores ≈ Accuracy ≈ Precision ≈ Recall,

No major imbalance in predictions

Models are not overfitting to any class

No class is being ignored (FN low)

Across all three tasks (Disease, Pest, Weed):

- ResNet50 consistently outperforms in all metrics (Accuracy, Precision, Recall, F1).
- Balanced metrics suggest generalization and robustness.
- F1-scores ≥ 0.95 means the model handles **class imbalance very well**.

Task	**Best Model**	
Disease	ResNet50	Highest F1 (0.971), Precision (97.8%)
Pest	ResNet50	Balanced and highest overall
Weed	ResNet50	Strong margin over others

5. Future Work

Future work will focus on extending the current methodology to not only detect rice within diseases, pests and weeds but also to other diseases, pests and weeds of other crops. This extension will involve developing a specialized module within the proposed framework capable of distinguishing these specific rice types based on their unique characteristics and features. This will require incorporating advanced image analysis techniques and possibly integrating additional data sources, such as patient history and biomarker information, to enhance testing accuracy. By achieving these objectives, the enhanced model aims to provide comprehensive test insights, thereby supporting training in making more informed decisions and improving rice yield outcomes. This work can be enhanced to create a mobile application that can be easily used by the framers. Further the work can be expanded to detect and classify the rice leaf diseases, weeds and yield prediction with this proposed model and additional deep learning enhancement techniques.

REFERENCES

1.Patel, V., & Singh, M. (2025). Deep learning for crop disease and pest detection: A comprehensive review. IEEE Transactions on AI in Agriculture.

2.Zhao, L., Zhang, F., & Li, X. (2024). Machine learning for integrated crop management: A review. Computers and Electronics in Agriculture.

3.Nkurunziza, T., & Uwambajimana, F. (2024). Comparative performance of eight machine learning methods for rice yield prediction in Rwanda. Agricultural Systems.

4.Chen, Y., & Li, X. (2024). Satellite-derived rice biomass estimation using nine machine learning models. Field Crops Research.

5.Sharma, A., & Prasad, M. (2023). Support vector machine applications in plant disease detection. Journal of Agricultural Informatics.

6.Bijlwan, P., Kumar, R., & Singh, A. (2025). Deep CNN architectures with SVM classifiers for rice disease and pest detection. Computers and Electronics in Agriculture.

7.Singh, H., & Verma, P. (2025). Hybrid CNN-SVM models for real-time disease recognition. Sensors.

8.Patel, S., & Desai, M. (2025). AI-driven pest detection systems for rice using transfer learning. AI in Agriculture.

9.[RAMSITA Conference] Proceedings. (2025). Comparative performance of ResNet50 and VGG16 in rice disease classification.

10. Smith, J., & Thomas, K. (2025). Fusion CNN-SVM model for rice disease classification. Scientific Reports.

11. Li, Y., Zhang, L., & Wang, J. (2025). GhostConv + CA-YOLOv8n: A lightweight model for real-time rice pest detection. IEEE Transactions on Industrial Informatics.

12. Sharma, D., Gupta, N., & Joshi, V. (2025). DepMulti-Net: A depth-separable, multi-scale network for early detection of rice diseases. Frontiers in Plant Science.

13. Singh, A., & Banerjee, R. (2025). RGC-YOLO for rice pest detection using embedded systems. Sensors and Actuators B: Chemical.

14. Hughes, D. P., & Salathé, M. (2015). An open access repository of plant health images. arXiv:1511.08060.
15. McHugh, M. L. (2012). Interrater reliability: the kappa statistic. Biochemia Medica.
16. Zuiderveld, K. (1994). Contrast Limited Adaptive Histogram Equalization. Graphics Gems IV.
17. Gonzalez, R. C., & Woods, R. E. (2018). Digital Image Processing.
18. Shorten, C., & Khoshgoftaar, T. M. (2019). A survey on image data augmentation. Journal of Big Data.
19. Wang, G., et al. (2017). Automatic plant disease estimation using DL. Computers and Electronics in Agriculture..
20. Sharma, D., et al. (2025). CNN-SVM hybrid for rice disease classification. Computers and Electronics in Agriculture.
21. Redmon, J., et al. (2016). You Only Look Once (YOLO). CVPR.
22. Chawla, N. V., et al. (2002). SMOTE: Synthetic Minority Over-sampling Technique. Journal of Artificial Intelligence Research
23. Gouse, S., Dulhare, U.N. (2022). Automation of Rice Leaf Diseases Prediction Using Deep Learning Hybrid Model VVIR. In: Rajagopal, S., Faruki, P., Popat, K. (eds) Advancements in Smart Computing and Information Security. ASCIS 2022. Communications in Computer and Information Science, vol 1759. Springer, Cham. https://doi.org/10.1007/978-3-031-23092-9_11