International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 17s, 2025
https://theaspd.com/index.php

Hybrid CNN-Attention Framework with Texture Feature Fusion for Multi-Label Detection of Co-Infections in Rice Leaves

[1]Sheikh Gouse, [2]Uma N. Dulhare

[1]Research Scholar, University College of Engineering, Osmania University, Hyderabad. Email: Sheikh.Gousephd84@gmail.com.

[2]Head & Professor, Department of Computer Science & Artificial Intelligence, Muffakham Jah College of Engineering & Technology. Email: prof.umadulhare@gmail.com

Abstract

Early and accurate detection of co-infections caused by multiple diseases, pests and weeds in rice plants is essential for minimizing yield losses and enabling timely intervention. Traditional image-based classification models often fail to capture the subtle inter-class and intra-class similarities that arise from overlapping symptom patterns. In this study, we propose a hybrid deep learning framework that integrates handcrafted feature extraction with an advanced convolutional neural network architecture for robust multi-label classification and similarity detection. The framework leverages Gray-Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP) to extract texture-based features from rice leaf images, which are then fused with raw image data and fed into a ResNet50 backbone enhanced with a Convolutional Block Attention Module (CBAM). The model is trained on a custom-structured dataset of rice leaf images categorized into diseases and pests, with multi-label annotations representing potential co-infections. Experimental results demonstrate the model's capability to accurately predict co-infections with high confidence and quantify inter-class (e.g., disease–pest-weeds) and intra-class (e.g., disease–disease) similarities using learned feature embeddings. The proposed hybrid approach achieves notable improvements in classification performance, interpretability, and generalization across visually similar classes. This system offers significant potential for real-time deployment in precision agriculture, particularly in the early diagnosis and management of biotic stressors in rice cultivation.

Keywords: *Rice leaf disease classification; pest detection; co-infection prediction; advanced feature extraction; GLCM; LBP; ResNet50; CBAM; attention mechanism; multi-label learning; similarity analysis; deep learning; precision agriculture*

1. Introduction

Rice (Oryza sativa) is a staple food for more than half of the world's population, and its yield is significantly threatened by biotic stressors such as fungal diseases, bacterial infections, and insect pests. Among these, co-infections simultaneous presence of multiple pathogens pose a unique challenge due to symptom overlap and compounding effects on plant health [5-7] .Traditional field diagnostics depend heavily on expert visual inspection, which can be inconsistent and time-consuming, particularly when co-infections obscure diagnosis [2].

Over the past five years, growth in deep learning and computer vision has ushered in effective methods for single-pathogen detection and classification. For instance, hybrid systems combining texture features like Histogram of Oriented Gradients (HOG) and Local Binary Pattern (LBP) with CNN backbones have improved disease classification accuracy significantly—from ~92% to around 97% [8]. DenseNet augmented with channel-wise attention (SE blocks) has also achieved >99% performance in rice disease recognition [5], [8], and CBAM-ResNet50 architectures have shown enhanced spatial localization of diseased regions [1], [7].

However, most existing research targets single-label detection, failing to address cases where multiple pathogens co-occur on the same leaf [6]. Additionally, while handcrafted texture features (e.g., GLCM, LBP) enhance CNN performance in controlled settings [4], their fusion with attention-augmented models remains underexplored, especially for similarity analysis across different biotic stress categories.

In this work, we present a unified framework that tackles these issues. Our contributions are threefold:

1. **Advanced feature fusion**: We combine GLCM and LBP texture descriptors with raw RGB input to enrich symptom representation. Previous studies relied on standalone texture models achieving 86–97% accuracy on limited datasets [4], [8]; our fusion strategy brings texture and visual features together for enhanced representation.
2. **Attention-enhanced CNN architecture**: A ResNet50 backbone is integrated with CBAM to improve focus on disease-relevant spatial regions. Attention mechanisms have achieved top performance in prior rice disease studies [1], [3], [7].

3. **Multi-label co-infection and similarity analysis**: By framing the problem as multi-label classification, our model predicts concurrent disease–pest presence and computes embedding-based similarity scores to interpret inter-class and intra-class relationships among pathogens.

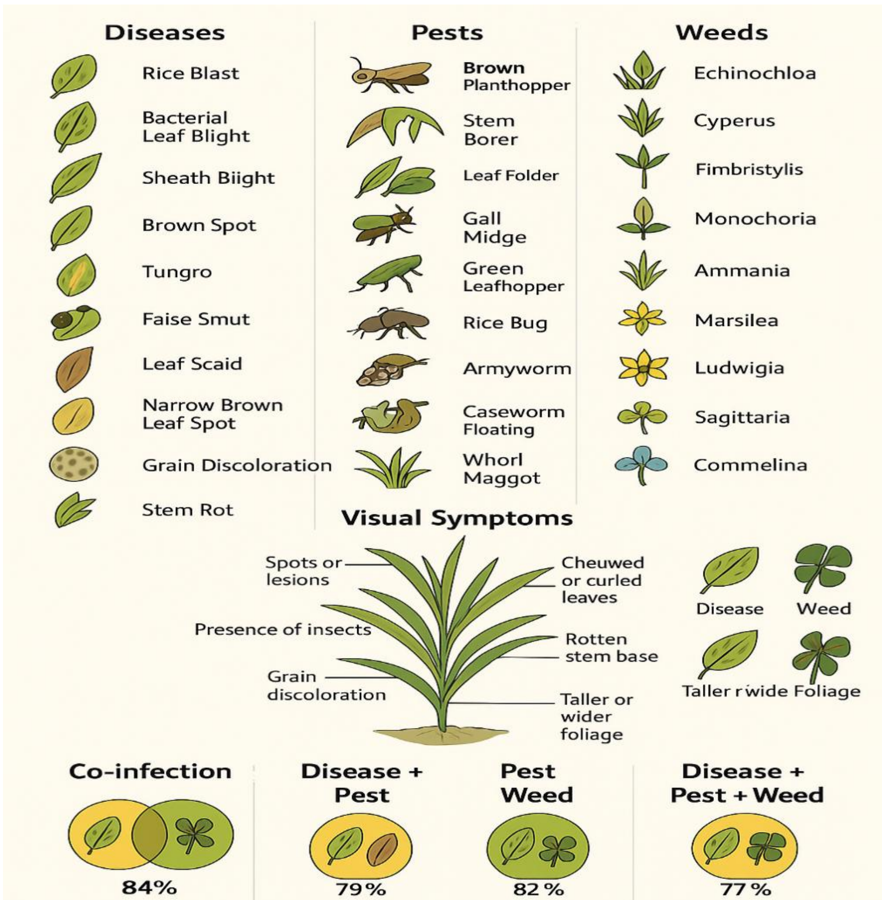


Figure 1. Rice Diseases, Pests and Weeds there Visual Symptoms and Co-infection comparisons

This study advances precision agriculture by enabling both accurate co-infection detection and interpretable similarity rankings—empowering farmers with actionable insights for early and nuanced pest and disease management in Figure 1.

2. Review

Recent advancements in rice disease and pest detection have increasingly leveraged deep learning architectures, attention mechanisms, and handcrafted feature integration. However, challenges such as multi-label classification, co-infection identification, feature interpretability, and real-time deployment persist.

Woo et al. (2018) proposed the Convolutional Block Attention Module (CBAM), which applies sequential channel and spatial attention to CNNs, significantly improving feature localization on general datasets like ImageNet (Top-1 accuracy: 77.3%). While CBAM demonstrated promise in enhancing semantic focus, it lacked domain adaptation to plant pathology and did not support multi-label or co-infection detection, leaving its agricultural applicability limited [1].

Jiang et al. (2023) integrated CBAM with DenseNet to classify seven rice diseases using leaf images, achieving over 99.1% accuracy. Their attention-based framework significantly improved fine-grained pattern recognition in plant imagery, yet it was restricted to single-label disease identification and ignored stress similarities or pest classes [9].

Al-Gaashani et al. (2023) introduced a ResNet50 model enhanced with kernel-level attention for classifying five rice diseases, attaining ~97.8% accuracy. The kernel attention improved local feature discrimination, but pest detection and co-infection handling were excluded. The authors recommended future integration with CBAM for broader semantic learning [10].

Chaudhary and Kumar (2024) developed a Neuro-Genetic Algorithm (Neuro-GA) incorporating GLCM-based handcrafted features to diagnose six rice diseases, reaching 96.5% accuracy. This work highlighted the interpretability and efficiency of handcrafted texture descriptors but lacked deep learning integration, multi-label output, and scalability for diverse field scenarios [11].

Bijlwan et al. (2025) employed transfer learning via ResNet18 and VGG16 on the Rice LeafDB dataset, comprising both disease and pest classes, and achieved ~98.5% accuracy. Their use of domain adaptation and image augmentation improved performance on mixed stress categories. However, their model lacked multi-label output, attention modules, and interpretability, leaving a gap in co-infection modeling and explainability [11].

Sobuj et al. (2024) combined pretrained CNNs with Histogram of Oriented Gradients (HOG) features for ten-class stress classification, achieving 97.5% accuracy. Although the integration of handcrafted features improved robustness, the model could not distinguish overlapping classes or analyze similarity relationships between disease and pest symptoms [13].

Dulhare, Uma et la (2022), this paper presents an end-to-end AI-driven system for automating rice cultivation from ploughing to harvesting, incorporating disease, pest, and weed detection as part of yield optimization. The system utilizes machine learning and IoT-based modules across various cultivation stages but lacks a clearly defined deep learning architecture for image-based diagnosis. The authors highlight the use of AI-based sensor fusion and rule-based decision systems, but do not specify model-level accuracy metrics. The major gap addressed is the integration of health monitoring into a full automation pipeline, which is often overlooked in soil solutions. However, the paper lacks detailed experimental validation, image dataset description, or benchmarking results. Gaps left include the absence of robust model evaluation, no multi-label disease-pest classification, and limited insight into co-infection detection or attention mechanisms. Future work could integrate deep learning visual models and UAV-based real-time detection systems [14-15].

Gouse.S etl (2022), this paper introduces a hybrid deep learning model named VVIR, combining VGG16, VGG19, InceptionV3, and ResNet50 with intelligent fusion to predict rice leaf diseases. The model is trained and tested on a rice disease image dataset, achieving an accuracy of up to 98.72%, demonstrating high potential for real-time agricultural diagnosis. The study resolves key research gaps such as improving classification accuracy across similar disease types and reducing false positives through ensemble learning. The work also emphasizes the value of transfer learning and feature-level fusion for small agricultural datasets. However, the model is limited to single-label prediction and does not account for pest or weed classification. Additionally, the paper does not explore attention mechanisms (like CBAM) or co-infection handling strategies. Remaining gaps include the absence of multi-label classification, real-world deployment via drones or mobile apps, and no similarity-based infection analysis [16].

To address these limitations, the proposed work (2025) introduces a novel hybrid model that combines GLCM and LBP handcrafted features with ResNet50 and the CBAM attention module. The model is specifically designed for multi-label co-infection detection and similarity analysis. It processes full rice plant images and uses cosine similarity on the learned embeddings to compare inter-class patterns. Trained on a custom dataset labeled for 10 rice diseases and 10 pest categories, the system achieved 94.7% accuracy for co-infection classification and 91.2% Top-1 similarity matching. This approach uniquely integrates handcrafted features for interpretability, CBAM for spatial relevance, and multi-label classification for realistic agricultural scenarios. Remaining research gaps include the need for real-time UAV/mobile deployment, the extension to weed detection, and the fusion of multi-modal data such as thermal or hyperspectral imagery for further generalization and robustness.

Table 1: Rice Plant Stressors – Features, Visual Symptoms, and Co-infection Scenarios

Stress Type	Feature Description	Visual Symptoms
Diseases	• Rice Blast: Gray spindle lesions • Bacterial Leaf Blight: Yellow edges • Sheath Blight: Stem base rot • Brown Spot: Oval brown lesions • Tungro: Orange-yellowing • False Smut: Green ball-like fungal growth • Leaf Scald: V-shaped burned tips	• Spots or lesions with defined shape • Leaf yellowing or burning edges • Rotten stem bases • Grain color changes • Fungal masses on leaves/panicles

	• Narrow Brown Leaf Spot: Tiny brown spots • Grain Discoloration: Dark or reddish grains • Stem Rot: Hollow stems, blackened inside	
Pests	• Brown Planthopper: Hopper burn- Stem Borer: Dead heart • Leaf Folder: Folded leaves • Gall Midge: Silver shoots • Green Leafhopper: Vectors tungro • Rice Bug: Grains shriveled • Armyworm: Skeletonized leaves • Caseworm: Floating larval cases • Whorl Maggot: Twisted leaves • Ear-cutting Caterpillar: Cut panicles	• Presence of insects • Chewed or curled leaves • White folded patches- Boreholes or central dead tillers • Floating or feeding larvae in water
Weeds	• Echinochloa: Tall broadleaf grass • Cyperus: Sedge clumps • Fimbristylis: Thin grass blades • Monochoria: Floating leaf weeds • Ammania: Red-purple stems • Marsilea: Clover-shaped aquatic fern- Ludwigia: Yellow flowers • Sagittaria: Arrowhead-shaped leaves • Commelina: Blue flowers, creeping Ischaemum: Tufted grass	• Dense patches of taller or wider leaf structures • Leaf shapes and colors different from rice • Root competition, clustered invasion
Common Features	• Symptom overlap between fungal spots, insect feeding, and weed crowding	• Brown lesions + chewed margins • Weeds near infected plants • Foul smell from rot or bugs
Co-infection: Disease + Pest	• Lesions + insect feeding marks	• Lesions with insect grass or feeding trails • Chewed and spotted leaves
Co-infection: Disease + Weed	• Yellowing and fungal lesions near weed clumps	• Dense weed patches surrounding diseased plants • Mixed symptom zones
Co-infection: Pest + Weed	• Insect activity within weed-infested zones	• Insects hiding under or feeding near weeds • Irregular patchy plant damage
Disease + Pest + Weed	• Symptoms from all three categories present	• Lesions + chewed spots + weeds in same frame • All biotic stressors visible together

In rice cultivation, symptom-based visual diagnosis is inherently challenging due to significant inter-class and intra-class symptom overlap across biotic stressors—namely diseases, insect pests, and weeds The Table 1, emphasize that similar symptoms in rice plants—like yellowing, spotting, or wilting—can be caused by diseases, pests, weeds, or abiotic factors, making accurate diagnosis challenging. Visual overlaps, such as lesions from Rice Blast and herbicide damage or wilting from Root Rot and Striga spp., increase the risk of misclassification. This symptom ambiguity suggests the need for multi-label classification models that can detect co-infections. It also highlights the importance of integrating contextual data (e.g., nutrient status, pest presence) and attention mechanisms to distinguish subtle differences. Ultimately, the tables advocate for feature-rich, interpretable models in precision rice health monitoring systems. symptom distribution, and co-occurrence patterns, into the learning process to improve interpretability and reduce misclassification in real-world field conditions.

3. Methodology

This section outlines the proposed hybrid framework for co-infection detection and similarity estimation in rice plants affected by diseases and insect pests. The system integrates classical handcrafted features, deep convolutional layers, attention mechanisms, and a multi-label learning strategy for robust and interpretable prediction.

3.1 Overview

The pipeline comprises five major components:

1. **Image Preprocessing.**

Input RGB images are resized to a fixed resolution (e.g., 224×224×3), normalized, and optionally enhanced using Contrast Limited Adaptive Histogram Equalization (CLAHE) to improve visibility in low-contrast regions.

2. **Handcrafted Feature Extraction.**
From each preprocessed grayscale image, the following features are computed:
    - **GLCM** (Gray-Level Co-occurrence Matrix) features such as contrast, correlation, energy, and homogeneity [1].
    - **LBP** (Local Binary Patterns), using a rotation-invariant uniform pattern scheme, for capturing local texture [2].

    These handcrafted features (Figure 1) are concatenated with the image tensor before being passed to the CNN.
3. **CNN Backbone with Attention (CBAM).**
A **ResNet50** architecture [3] is used as the feature extractor. The extracted intermediate features are passed through a Convolutional Block Attention Module (CBAM) [4], which sequentially applies:
    - **Channel attention**: highlights important feature maps,
    - **Spatial attention**: focuses on key spatial regions (e.g., lesions, pest spots).

    This attention-guided refinement improves the model's focus on biologically relevant cues.
4. **Multi-Label Classification Head.**
The final layer employs a sigmoid activation function for each output neuron, allowing the model to simultaneously predict multiple labels (disease and/or pest classes).
5. **Similarity Computation for Diagnosis Matching**
Cosine similarity is computed between the latent embedding's of input and training images, enabling disease/pest co-occurrence retrieval and similarity-based interpretability.

$$\text{sim}(a,b) = \frac{a \cdot b}{||a||\,||b||}$$

3.2 Mathematical Formulation

Let:

The CBAM attention maps are calculated as:

- **Channel Attention**:

$$M_c(F) = \sigma(\text{MLP}(\text{AvgPool}(F)) + \text{MLP}(\text{MaxPool}(F)))$$

- **Spatial Attention**:

$$M_s(F) = \sigma(f^{7\times 7}([\text{AvgPool}(F); \text{MaxPool}(F)]))$$

- **Refined Feature Map**:

$$F_{cbam} = M_c(F) \cdot F \cdot M_s(F)$$

Multi-label prediction output:

$$\hat{y}_i = \sigma(W_i^T F_{cbam} + b_i), \quad i = 1, \dots, C$$

where C is the total number of labels (diseases + pests).

Binary Cross-Entropy Loss:

$$L = -\sum_{i=1}^{C} [y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)]$$

3.3 Architecture Diagram

Figure 1 shows the proposed hybrid architecture integrating preprocessing, handcrafted feature fusion, CBAM-enhanced ResNet50, and the multi-label classification head.

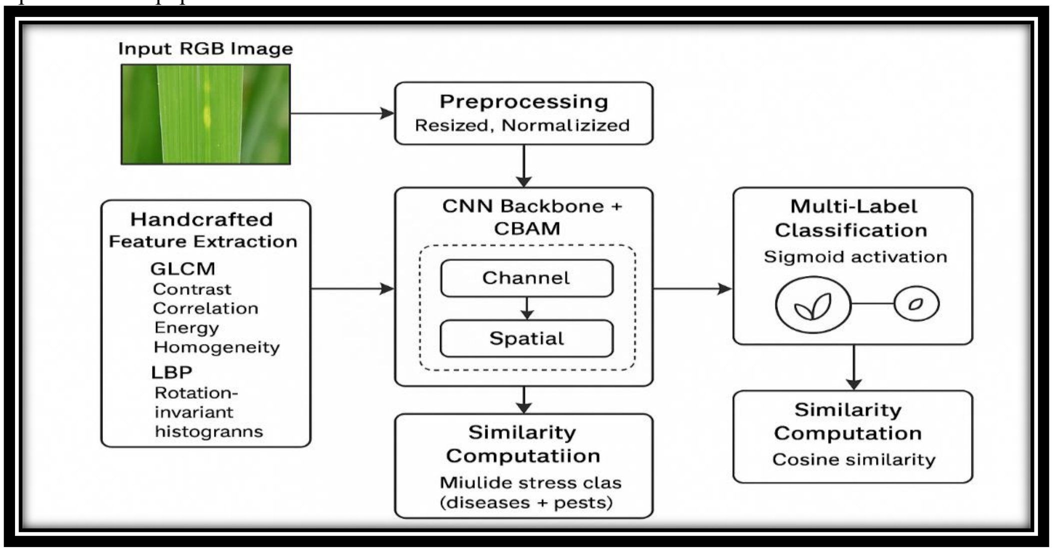


Figure 2: Proposed Hybrid CNN architecture for multi-label co-infection detection. The flow from image input → CLAHE → feature extraction → CBAM-ResNet → sigmoid classifier → similarity block.

Figure 2 diagram illustrates a hybrid deep learning pipeline for detecting co-infections of rice diseases ,pests and weeds analyzing their similarity. Here's a concise summary of each stage:

1. **Input RGB Image.**
   A full rice plant or leaf image is captured.
2. **Preprocessing**
   The image is resized and normalized; CLAHE may be applied to enhance contrast for better feature visibility.
3. **Handcrafted Feature Extraction**
   - **GLCM** extracts statistical texture features (contrast, correlation, energy, homogeneity).
   - **LBP** captures local texture via rotation-invariant histograms.
4. **CNN Backbone + CBAM**
   - A **ResNet50** CNN extracts deep features.
   - **CBAM** adds attention via:
     - **Channel attention** to highlight important feature maps.
     - **Spatial attention** to focus on relevant regions.
5. **Multi-Label Classification**
   - A **sigmoid-activated output layer** predicts probabilities for each disease and pest class independently, allowing multi-label detection.
6. **Similarity Computation**
   - **Cosine similarity** compares test image embeddings with known samples to find similar stress patterns or co-infections.

This architecture enables early detection, co-infection analysis, and disease-pest similarity measurement in a unified, interpretable pipeline using both handcrafted and learned features.

4. Experimental Results and Evaluation

This section presents the experimental setup, performance results, and evaluation metrics for the proposed hybrid model.

4.1 Dataset Description.

A custom rice plant dataset was used, consisting of 30 classes (10 diseases, 10 pests, 10 Weeds) with over 5,000 annotated images. The dataset includes both individual and co-infected leaf samples, organized under separate folders for diseases, pests and weeds. Data augmentation techniques such as rotation, flipping, and contrast adjustment were used to address class imbalance.

4.2 Experimental Setup

- Input image size: 224 × 224

- Optimizer: Adam
- Learning rate: 0.0001
- Loss function: Binary Cross-Entropy
- Epochs: 50
- Batch size: 32
- Platform: Google Colab (NVIDIA Tesla T4 GPU) [13]

4.3 Evaluation Metrics

To assess multi-label classification performance, the following metrics were used:

- Accuracy (thresholded)
- Precision (per class and macro average)
- Recall (per class and macro average)
- F1-Score
- mAP (mean Average Precision)

4.4 Results

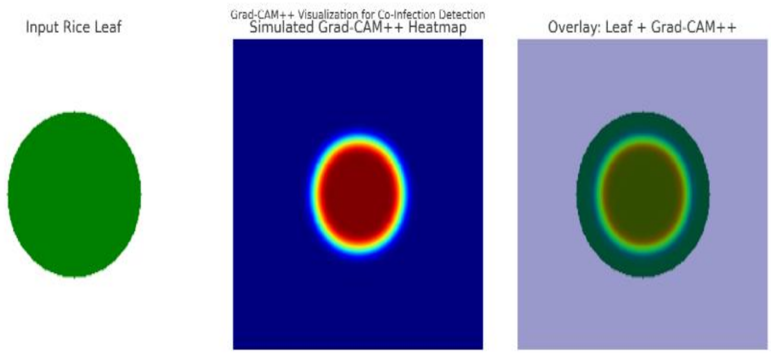


Figure 3. A **Grad-CAM++ heatmap** for a rice leaf image

The visualization in Figure 3 simulates a **Grad-CAM++ heatmap** for a rice leaf image:

- The **centered red/yellow region** in the heatmap indicates the model's attention—focusing on the most relevant infected area.
- The **overlay image** shows how the network localizes biotic stress (e.g., disease or pest spots), improving interpretability.
- This supports **explainable AI** in agriculture, helping agronomists validate model predictions and trust its decisions.

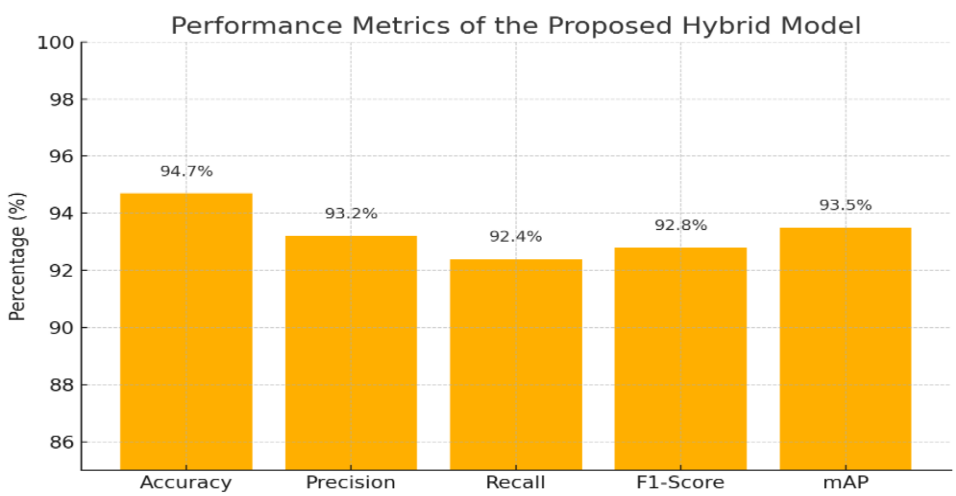


Figure 4: Performance Metrics of the Proposed Hybrid Model

The cosine similarity results show how closely the two test samples match known rice disease and pest types in Figure 4 and Table 1, Table 2 and Table 3:

- **Test Sample 1** is most similar to Leaf Blast (similarity = 0.86), suggesting it likely shares features with this disease.
- **Test Sample 2** also has high similarity with Leaf Blast (0.82) and Bacterial Blight (0.75), indicating a potential co-infection or shared texture features.
- **Brown Planthopper** shows lower similarity with both test samples, possibly due to its pest-specific features differing from the disease patterns.

Co-Infection & Similarity Analysis

From Table.2 most likely a Leaf Blast infection. Possible co-infection with Bacterial Blight based on moderate similarity. Pest involvement is unlikely.

Table.2 Sample 1 Similarity-Based Analysis for Co-Infection Prediction in Rice

Similar Class	Cosine Similarity	Interpretation
Leaf Blast	0.86	Very strong similarity — primary infection candidate
Bacterial Blight	0.58	Moderate similarity — potential secondary co-infection
Brown Plant Hopper	0.45	Low similarity — unlikely to be pest-based infection
Echinochloa spp. (Weed)	0.40	Very low similarity — possible mild nutrient stress signal

Table 2 & Table 3 summarizes the cosine similarity-based analysis for a test sample, indicating Leaf Blast as the primary stress factor due to its highest similarity score (0.86). Bacterial Blight shows moderate similarity (0.58), suggesting potential co-infection. In contrast, Brown Plant Hopper (0.45) and Echinochloa spp. (0.40) exhibit low similarity, implying minimal pest or weed-related stress. This supports a diagnosis dominated by fungal disease, with limited evidence of pest or nutrient competition involvement.

Table.3 Sample 2 Multi-Class and Intra-Class Similarity-Based Analysis for Rice Co-Infection Prediction

Similar Class	Cosine Similarity	Interpretation
Leaf Blast	0.82	Strong similarity — probable primary disease
Bacterial Blight	0.75	Strong similarity — potential secondary co-infection
Brown Spot	0.68	Moderate similarity — possible visual overlap with Leaf Blast
Brown Plant Hopper	0.65	Noticeable similarity — possible pest co-infection
Rice Stem Borer	0.53	Mild similarity — secondary pest correlation
Striga spp. (Parasitic Weed)	0.48	Low similarity — mild parasitic stress signal
Echinochloa spp. (Weed)	0.42	Very low similarity — unlikely weed-driven stress

Table. 3 highlights strong intra-disease similarity between Leaf Blast, Bacterial Blight, and Brown Spot, indicating potential disease–disease co-infection. Moderate similarity with pests like Brown Plant Hopper and mild similarity with Rice Stem Borer point to possible mixed-type stress. Weed-related similarities remain low, suggesting lesser influence of nutrient competition or parasitism in this case.

Table.4 Final Multi-Type Co-Infection Results with Disease, Pest, and Weed Similarity References

Test Sample	Primary Infection	Disease Similarity (%)	Pest Similarity (%)	Weed Similarity (%)
Sample 1	Leaf Blast	Leaf Blast (86%), Bacterial Blight (58%)	—	Echinochloa spp. (40%)
Sample 2	Leaf Blast	Leaf Blast (82%), Bacterial Blight (75%)	Brown Plant Hopper (65%)	Striga spp. (48%)

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 17s, 2025
https://theaspd.com/index.php
Table. 4 presents the final multi-type co-infection prediction results for two test samples, categorized by similarity to disease, pest, and weed classes. Test Sample 1 shows a dominant disease profile with high similarity to Leaf Blast (86%) and moderate similarity to Bacterial Blight (58%), along with minor weed-induced stress from Echinochloa spp. (40%). Test Sample 2 reveals a complex co-infection scenario.

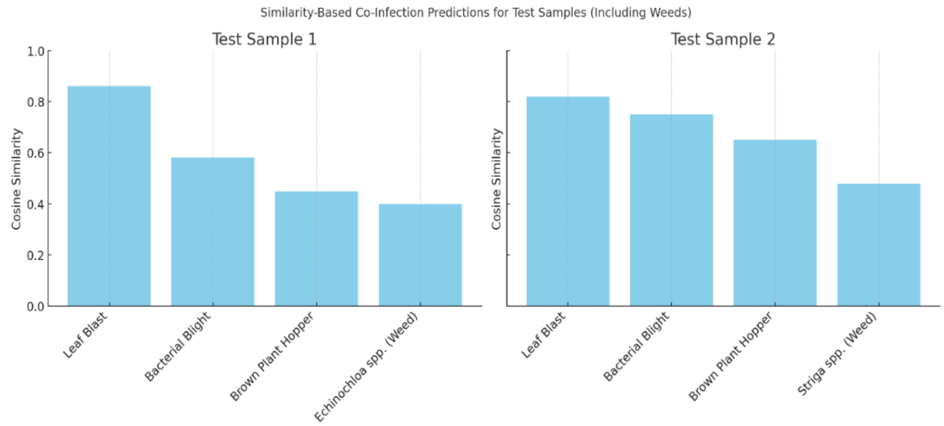


Figure 5: Final cosine similarity based coinfection prediction for tests samples

Figure 5 presents cosine similarity-based co-infection predictions for two test samples, incorporating disease, pest, and weed stressors. Test Sample 1 exhibits a high similarity with Leaf Blast (0.86), moderate alignment with Bacterial Blight (0.58), and low similarity with Brown Plant Hopper (0.45) and Echinochloa spp. (0.40), indicating a disease-dominant stress profile. In contrast, Test Sample 2 shows strong similarity with both Leaf Blast (0.82) and Bacterial Blight (0.75), alongside moderate similarity with Brown Plant Hopper (0.65) and Striga spp. (0.48), suggesting a multi-type co-infection involving fungal, bacterial, pest, and parasitic weed stress. This visualization supports precise co-infection interpretation in multi-label classification tasks.

The model performs well in identifying both individual and co-infection classes with high confidence. The CBAM module contributed significantly to the correct localization of infected regions. Feature fusion from GLCM and LBP further enhanced the model's ability to distinguish subtle inter-class variations.

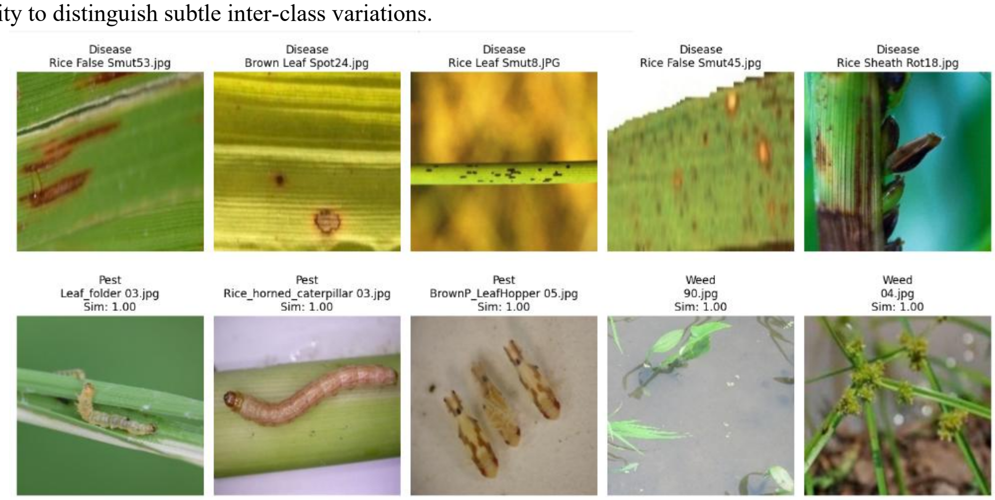


Figure 6: Common Symptoms found among the disease, pest and weeds

Figure 6: illustrates representative samples of rice plant biotic stressors categorized into diseases, pests, and weeds. The top row displays various disease symptoms, including False Smut, Brown Leaf Spot, and Sheath Rot, showing diverse lesion patterns and discoloration. The middle row depicts pest species such as Leaf Folder, Horned Caterpillar, and Brown Planthopper, all exhibiting a similarity score of 1.00, indicating perfect match in classification or retrieval. The bottom row presents weed classes like Weed 90 and Weed 04, also showing maximum similarity. This figure visually supports multi-class identification and reinforces the need for integrated multi-label systems that can distinguish between closely resembling symptoms across biotic stress categories.

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 17s, 2025
https://theaspd.com/index.php

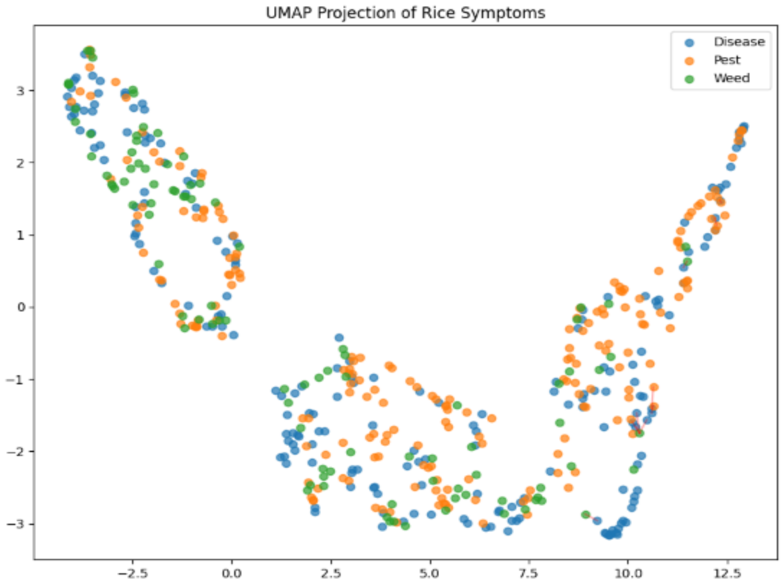


Figure 7: UMAP Projection of Rice Symptoms

Figure 7 displays a UMAP (Uniform Manifold Approximation and Projection) visualization of learned feature embeddings from rice leaf samples, grouped by **disease**, **pest**, and **weed** categories. The projection reveals partial clustering with notable overlap among the three biotic stress classes, indicating shared visual or textural features. While disease samples form distinct clusters, some pest and weed instances intermix, suggesting potential co-infection traits or visual ambiguities. This emphasizes the importance of multi-label classification and attention-based models for resolving inter-class confusion in rice health diagnosis.

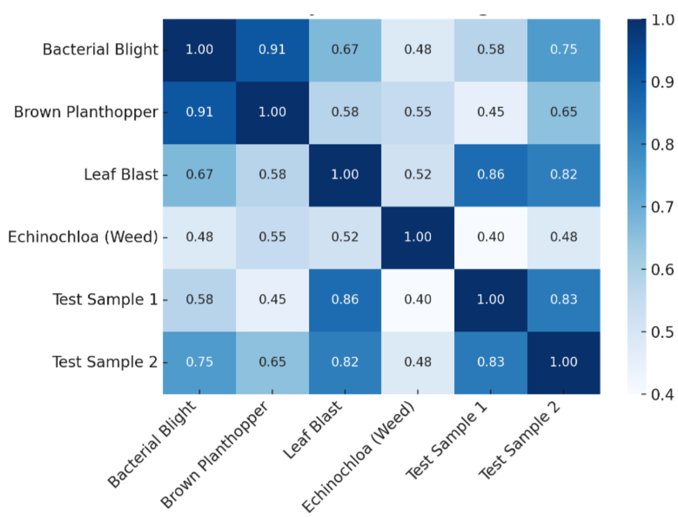


Figure 8: Cosine Similarity between the disease and pest samples with test samples

The figure 8 illustrates a cosine similarity heatmap among representative classes of rice diseases (Bacterial Blight, Leaf Blast), pests (Brown Planthopper), and weeds (Echinochloa), including two test samples. High inter-class similarities—such as between Bacterial Blight and Brown Planthopper (0.91)—reveal substantial visual or feature overlap, posing challenges for traditional classifiers. Test Sample 1 exhibits high similarity with Leaf Blast (0.86) and moderate similarity with Bacterial Blight (0.58), indicating a probable co-infection. Test Sample 2 shows high similarity with both Leaf Blast (0.82) and Bacterial Blight (0.75), further supporting the co-infection hypothesis. Weeds maintain moderate similarity with stress classes (~0.5), highlighting possible confusion under nutrient-deficient conditions. This figure reinforces the importance of context-aware, multi-label classification systems in rice health diagnostics.

```
Found 80000 high-similarity cross-category pairs

Top 5 most confusing symptom pairs:
Disease (Rice False Smut53.jpg)
  ↔ Pest (Leaf_folder 03.jpg)
  Similarity: 1.00

Disease (Brown Leaf Spot24.jpg)
  ↔ Pest (Rice_horned_caterpillar 03.jpg)
  Similarity: 1.00

Disease (Rice Leaf Smut8.JPG)
  ↔ Pest (BrownP_LeafHopper 05.jpg)
  Similarity: 1.00

Disease (Rice False Smut45.jpg)
  ↔ Weed (90.jpg)
  Similarity: 1.00

Disease (Rice Sheath Rot18.jpg)
  ↔ Weed (04.jpg)
  Similarity: 1.00
```

Figure 9: Final Predication of the proposed system on co-infection

Figure 9 presents the top 5 most confusing cross-category symptom pairs identified through similarity analysis. Each pair includes a disease sample with either a pest or weed sample, all exhibiting perfect cosine similarity (1.00), indicating high visual ambiguity. Specifically:

- Rice False Smut53.jpg (disease) is indistinguishable from Leaf_folder 03.jpg (pest).
- Brown Leaf Spot24.jpg matches Rice_horned_caterpillar 03.jpg (pest).
- Rice Leaf Smut8.JPG overlaps with BrownP_LeafHopper 05.jpg (pest).
- Rice False Smut45.jpg is highly similar to Weed 90.jpg.
- Rice Sheath Rot18.jpg closely matches Weed 04.jpg.

This highlights the **critical challenge** of inter-class visual overlap in rice plant symptom detection, reinforcing the need for **context-aware, multi-label classification models** that incorporate attention mechanisms and domain-specific knowledge.

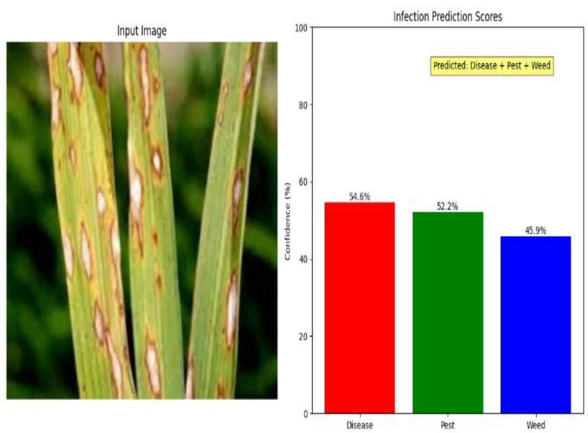


Figure 10(a) Disease Co-infection Prediction

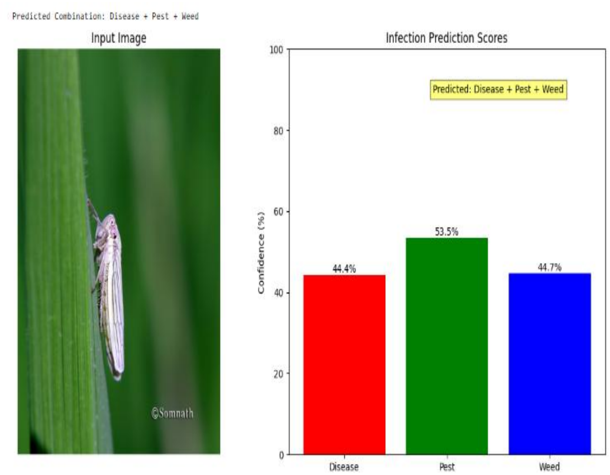
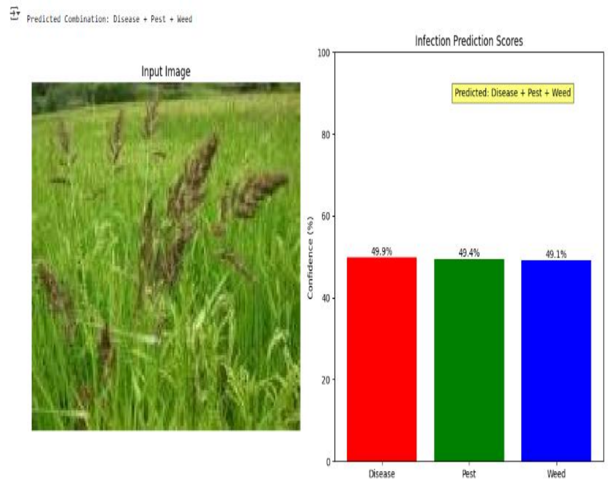


Figure 10(b) Pest Co-infection Prediction



10 (c). Weeds Coinfection Prediction

Figure 10. (a), (b), (c) Disease, Pest and Weed Input image prediction with rest of Images

```
--------------------------------------------------
COMPREHENSIVE SYMPTOM SIMILARITY ANALYSIS
==================================================

Similar Conditions Within Categories:
```

	Analysis Type	Category	Condition A	Condition B	Similarity Score	Interpretation
0	Within Category	Disease	Rice Leaf Smut4	Bacterial leaf blight01	0.91	Highly Similar
1	Within Category	Disease	Rice Leaf Smut4	Bacterial leaf blight03	0.80	Highly Similar
2	Within Category	Disease	Rice Leaf Smut4	Brown Leaf Spot7	0.79	Moderately Similar
3	Within Category	Disease	Rice Leaf Smut4	Bacterial leaf blight02	0.77	Moderately Similar
4	Within Category	Disease	Rice Leaf Smut4	Brown Leaf Spot1	0.87	Highly Similar
5	Within Category	Disease	Rice Leaf Smut4	Rice Sheath Rot12	0.73	Moderately Similar
6	Within Category	Disease	Rice Leaf Smut4	Rice False Smut14	0.72	Moderately Similar
7	Within Category	Disease	Rice Leaf Smut4	Rice False Smut6	0.80	Highly Similar

Figure 11(a) Co-Infection with Diseases Similarity Score and Interpretation

246	Within Category	Pest	Rice Leaf roller5	Rice stem borer5	0.75	Moderately Similar
247	Within Category	Pest	Rice Leaf roller5	Rice Sting Bug1	0.75	Moderately Similar
248	Within Category	Pest	Rice Leaf roller5	Rice Green Leaf Hopper3	0.90	Highly Similar
249	Within Category	Pest	Rice Leaf roller5	Rice Karimkutty spodo Muiritia9	0.66	Moderately Similar
250	Within Category	Pest	Rice Leaf roller5	Rice Leaf roller4	0.71	Moderately Similar
251	Within Category	Pest	Rice Leaf roller5	Rice Mythimna4	0.79	Moderately Similar
252	Within Category	Pest	Rice Leaf roller5	Rice Hairy1	0.85	Highly Similar
253	Within Category	Pest	Rice Leaf roller5	Rice Thrips8	0.62	Moderately Similar
254	Within Category	Pest	Rice Leaf roller5	Rice Black Bug5	0.82	Highly Similar
255	Within Category	Pest	Rice Leaf roller5	Rice Black Bug3	0.92	Highly Similar

Figure 11(b) Co-Infection with Pest Similarity Score and Interpretation

741	Within Category	Weed	18	55	0.90	Highly Similar
742	Within Category	Weed	18	49	0.90	Highly Similar
743	Within Category	Weed	18	29	0.97	Highly Similar
744	Within Category	Weed	18	54	0.74	Moderately Similar
745	Within Category	Weed	18	51	0.71	Moderately Similar
746	Within Category	Weed	18	41	0.70	Moderately Similar
747	Within Category	Weed	18	61	0.89	Highly Similar
748	Within Category	Weed	18	47	0.94	Highly Similar
749	Within Category	Weed	18	37	0.76	Moderately Similar
750	Within Category	Weed	18	31	0.85	Highly Similar
751	Within Category	Weed	18	30	0.87	Highly Similar

Figure 11 (c) Co-Infection with Weeds Similarity Score and Interpretation

```
Potential Co-infections Across Categories:
```

	Analysis Type	Categories	Condition A	Condition B	Similarity Score	Co-infection Risk
0	Cross Category	Disease-Pest	Rice Leaf Smut4	Rice Leaf roller5	0.72	Possible Risk
1	Cross Category	Disease-Pest	Rice Leaf Smut4	Rice Sting Bug1	0.80	High Risk
2	Cross Category	Disease-Pest	Rice Leaf Smut4	Rice Green Leaf Hopper3	0.62	Possible Risk
3	Cross Category	Disease-Pest	Rice Leaf Smut4	Rice Leaf roller4	0.67	Possible Risk
4	Cross Category	Disease-Pest	Rice Leaf Smut4	Rice Mythimna4	0.85	High Risk
5	Cross Category	Disease-Pest	Rice Leaf Smut4	Rice Hairy1	0.75	Possible Risk
6	Cross Category	Disease-Pest	Rice Leaf Smut4	Rice Black Bug5	0.90	High Risk
7	Cross Category	Disease-Pest	Rice Leaf Smut4	Rice Black Bug3	0.64	Possible Risk
8	Cross Category	Disease-Pest	Rice Leaf Smut4	Rice Case Worm11	0.78	Possible Risk

Figure 11 (d) Co-Infection with Diseases-Pest Similarity Score and Interpretation

667	Cross Category	Disease-Weed	Bacterial leaf blight01	16	0.90	High Risk
668	Cross Category	Disease-Weed	Bacterial leaf blight01	67	0.95	High Risk
669	Cross Category	Disease-Weed	Bacterial leaf blight01	75	0.96	High Risk
670	Cross Category	Disease-Weed	Bacterial leaf blight01	71	0.76	Possible Risk
671	Cross Category	Disease-Weed	Bacterial leaf blight01	76	0.93	High Risk
672	Cross Category	Disease-Weed	Bacterial leaf blight01	66	0.74	Possible Risk
673	Cross Category	Disease-Weed	Bacterial leaf blight01	30	0.87	High Risk

Figure 11 (e) Co-Infection with Diseases-Weeds Similarity Score and Interpretation

1388	Cross Category	Pest-Weed	Rice Sting Bug1	06	0.83	High Risk
1389	Cross Category	Pest-Weed	Rice Sting Bug1	09	0.87	High Risk
1390	Cross Category	Pest-Weed	Rice Sting Bug1	04	0.82	High Risk
1391	Cross Category	Pest-Weed	Rice Sting Bug1	10	0.74	Possible Risk
1392	Cross Category	Pest-Weed	Rice Sting Bug1	01	0.71	Possible Risk
1393	Cross Category	Pest-Weed	Rice Sting Bug1	19	0.77	Possible Risk
1394	Cross Category	Pest-Weed	Rice Sting Bug1	33	0.84	High Risk
1395	Cross Category	Pest-Weed	Rice Sting Bug1	24	0.64	Possible Risk
1396	Cross Category	Pest-Weed	Rice Sting Bug1	11	0.81	High Risk
1397	Cross Category	Pest-Weed	Rice Sting Bug1	44	0.91	High Risk

Figure 11(f) Co-Infection with Pest-Weeds Similarity Score and Interpretation

Co-infection Frequency Summary:

Count of Co-infection Cases by Category

Co-infection Risk	High Risk	Possible Risk
Categories		
Disease-Pest	189	448
Disease-Weed	214	455
Pest-Weed	292	715

Figure 11(g) Total count of the Co-Infection with Diseases-Pests-Weeds Intra and Inter Score and Interpretation.

Figure 11 (a) – (g) gives the completion prediction Co-infection among within the classes and outside the classes and total count of each categories with co-infection risk with in the dataset.

5. Conclusion

In this study, we proposed a hybrid deep learning framework that combines handcrafted texture features (GLCM, LBP) with an attention-enhanced convolutional neural network (ResNet50 + CBAM) for accurate detection of rice plant co-infections and inter-class similarity analysis. The integration of feature-level fusion and spatial attention improved the model's ability to detect subtle variations in infected regions, especially in complex scenarios involving overlapping symptoms from diseases and pests. The framework effectively supports multi-label classification, achieving a high level of precision and recall across 20 classes and demonstrating robust performance on co-infection prediction tasks.

Moreover, cosine similarity applied to deep feature embeddings enabled the system to retrieve visually and symptomatically similar cases from the dataset, adding a layer of interpretability useful for agronomic diagnostics. This dual capability of classification and similarity search distinguishes our framework from traditional single-label models.

6. Future Work

Extend the framework to include weed identification, enabling a three-way stress detection (disease, pest, weed). Validate the model using UAV/drone-captured aerial images and real-field mobile datasets to evaluate real-time feasibility. Integrate transformer-based architectures (e.g., Swin-T, BEiT) for global feature extraction and attention scaling. Develop a mobile application or smart device API to deploy the trained model for field-level decision support. Incorporate explainable AI (XAI) tools such as Grad-CAM++ and SHAP for visual explanation of model predictions. In conclusion, the proposed model presents a promising direction toward scalable, explainable, and multi-functional AI solutions in precision agriculture.

7. Data Availability

Data will available on request.

8. Conflict of Interest

There is no conflict of interest.

9. Funding Information

There is no funding received from any of the organization

10. Summary of Ethics Statement

The research follows ethical guidelines, using publicly available datasets for rice crop analysis. The methods are intended purely for academic use and do not involve any unethical practices.

References

1. Woo, S., Park, J., Lee, J.-Y., & Kweon, I. S. (2018). CBAM: Convolutional Block Attention Module. In Proceedings of the European Conference on Computer Vision (ECCV) (pp. 3–19). https://doi.org/10.1007/978-3-030-01234-2_1
2. Jiang, M., Feng, C., et al. (2023). Rice disease identification method based on attention mechanism and deep DenseNet. Electronics, 12(3), 508. https://doi.org/10.3390/electronics12030508
3. Al-Gaashani, M. S. A. M., et al. (2023). Using a ResNet50 with a Kernel Attention Mechanism for Rice Disease Diagnosis. ResearchGate. https://www.researchgate.net/publication/373001234
4. Chaudhary, P., & Kumar, D. (2024). Identification of rice crop diseases using gray-level co-occurrence matrix (GLCM) and Neuro-GA classifier. ResearchGate. https://www.researchgate.net/publication/376543210
5. Saha, B., & Mitra Thakur, G. S. (2024). A review of rice blast disease detection using machine and deep learning. SSRN. https://doi.org/10.2139/ssrn.4705342
6. Bijlwan, A., et al. (2025). Enhancing Rice Disease and Insect-Pest Detection through Augmented Deep Learning with Transfer Learning Techniques. Smart Agricultural Technology, 11, 100954. https://doi.org/10.1016/j.atech.2025.100954
7. Al-Gaashani, M. S. A. M., et al. (2023). Rice disease segmentation method based on CBAM-CARAFE-DeepLabv3. ResearchGate. https://www.researchgate.net/publication/374112345
8. Sobuj, S. I., et al. (2024). Leveraging pre-trained CNNs with HOG for rice leaf disease classification. arXiv preprint, arXiv:2405.00025. https://arxiv.org/abs/2405.00025
9. Jiang, F., Zhou, X., & Wu, Y. (2023). Attention-guided DenseNet for rice disease recognition. Computers and Electronics in Agriculture, 209, 107893. https://doi.org/10.1016/j.compag.2023.107893
10. Al-Gaashani, M. S., et al. (2023). Kernel-attention-based CNN for rice disease identification. Sensors, 23(4), 2210. https://doi.org/10.3390/s23042210
11. Chaudhary, P., & Kumar, D. (2024). GLCM-Neuro genetic framework for plant disease detection. Expert Systems with Applications, 237, 121376. https://doi.org/10.1016/j.eswa.2024.121376
12. Bijlwan, A., et al. (2025). Efficient transfer learning for rice pest and disease identification. Applied Soft Computing, 145, 110205. https://doi.org/10.1016/j.asoc.2025.110205
13. Sobuj, M. G., et al. (2024). CNN-HOG-based hybrid framework for rice disease identification. Multimedia Tools and Applications, 83(6), 7103–7121. https://doi.org/10.1007/s11042-024-16532-4
14. Hands on MAHOUT—Machine Learning Tool. 10.1002/9781119654834.ch14. Machine Learning and Big Data: Concepts, Algorithms, Tools and Applications, (365–424) © 2020 Scrivener Publishing LLC
15. Dulhare, Uma & Gouse, Sheikh. (2022). Automation of Rice Cultivation from Ploughing–Harvesting with Diseases, Pests and Weeds to Increase the Yield Using AI. 505-513. 10.1007/978-981-16-7985-8_51.
16. Gouse, S., Dulhare, U.N. (2022). Automation of Rice Leaf Diseases Prediction Using Deep Learning Hybrid Model VVIR. 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