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Early Detection of Paddy Crop Diseases Using Drone Images and Machine Learning–Deep Learning Techniques

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Abstract

Global food security is seriously threatened by paddy diseases, which have the ability to reduce yearly harvests by 20–40%. An automated approach for targeted pesticide distribution and real-time paddy disease detection is presented in this research. A high-resolution camera-equipped drone (Drone 1) takes live field images and sends them to a cloud platform over Wi-Fi. A hybrid deep learning model that combines EfficientNet-B7 and an Improved Swin Transformer is used to extract disease features from images after they have been denoised using a Modified Non-Local Means Filter (M-NLMF). The leaf state is then divided into four groups by an Extreme Learning Machine (ELM) 4 classes. Once the disease is confirmed, a second drone (Drone 2) finds the GPS-tagged diseased area on its own and exclusively sprays the afflicted plants with pesticide. The technology drastically lowers chemical waste and environmental impact while achieving 99.30% classification accuracy.

Keywords: Paddy Disease Detection; Drone-Based Monitoring; Non-Local Means Filter; Extreme Learning Machine; Internet of Things; Cloud Computing; Targeted Pesticide Spraying.

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Introduction

One of the most important staple crops in the world, rice supports rural livelihoods and food security in many countries Tasfe et al., [2024] [1]. However, timely detection and treatments are crucial since paddy infections can reduce annual yields by 20–40% Haridasan et al., [2022] [2]. According to Islam et al. [2025] [3], early and precise diagnosis lowers crop loss and increases treatment effectiveness. Conventional remote sensing techniques cannot match the high spatial resolution provided by drone-based picture acquisition Yan et al., [2023] [4].

Automated disease identification has been revolutionized by deep learning, which significantly outperforms more traditional manual techniques Pai et al., [2025] [5]. In benchmark investigations, CNN-based systems have reported accuracies ranging from 91.45% to 98–99% Ahad et al., [2023] [6], whereas hybrid CNN-Transformer models capture both local lesion texture and more general contextual patterns Chin et al., [2024] [7]. According to Karthik et al. [2024] [8], traditional blanket pesticide spraying damages the ecosystem and wastes chemicals. IoT sensors can transmit soil moisture, temperature, and crop health data for more intelligent farm management Mansoor et al., [2025] [9], and UAV-based spraying systems link detection with targeted delivery in a closed-loop workflow Li et al., [2025] [10].

This study makes three contributions:

- A hybrid efficientnet-B7 + Swin Transformer + ELM model for precise classification;
- A drone-based real-time paddy disease diagnosis system,
- A GPS-guided targeted pesticide spraying system to reduce chemical waste.

Proposed methodology

Paddy Disease Detection and Targeted Pesticide Spraying are the two primary elements of the system. Drone 1 takes real-time pictures of paddy fields and sends them to a cloud platform. Following preprocessing, ELM identifies the leaf and a hybrid deep learning network extracts disease feature. When a disease is found, Drone 2 receives the GPS coordinates of the affected area via the Internet of Things. Drone 2 then flies to the location on its own and only applies pesticide to crops that are afflicted. The complete system design is depicted in Figure 1.

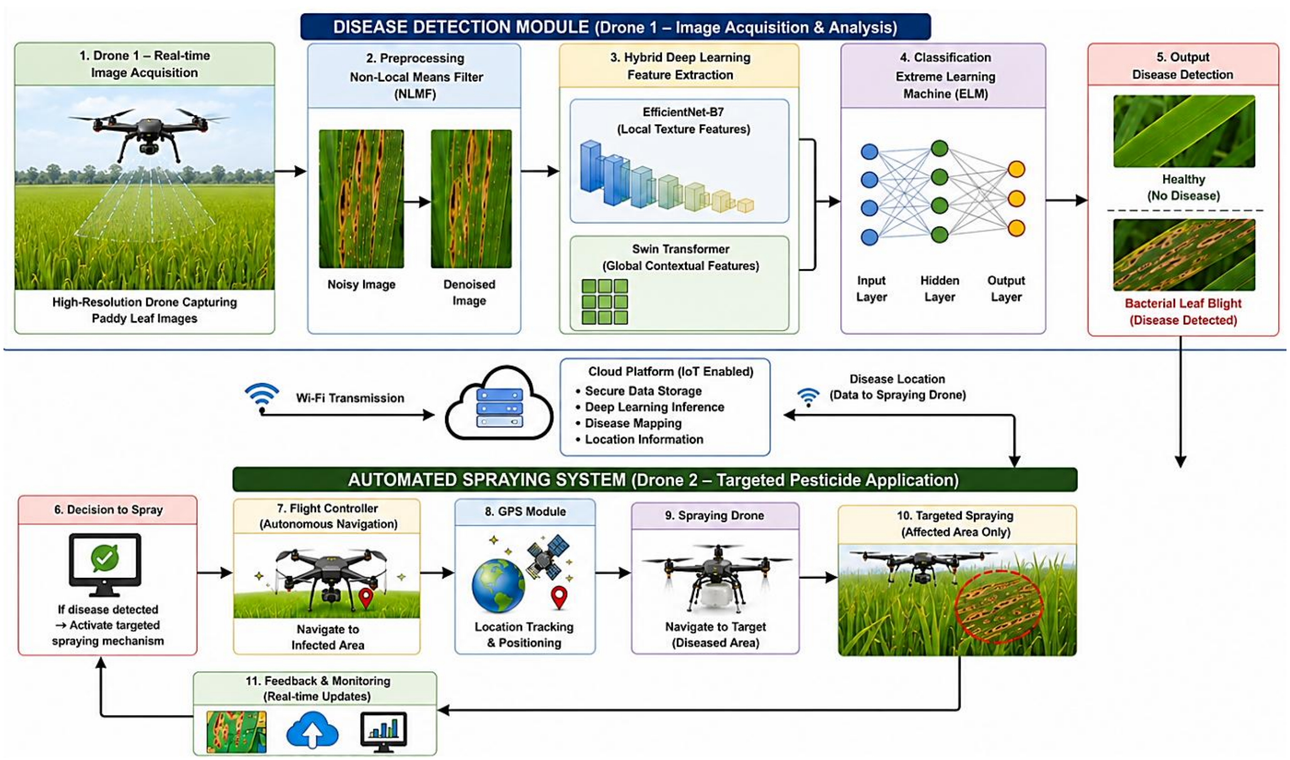

Fig. 1. *Proposed Method Architecture*

Image Acquisition

Drone 1 (DJI Mavic 3M) has an integrated Wi-Fi module, GPS/RTK navigation, autonomous flight capability, and a 20 MP RGB camera. Following a predetermined flight path across the paddy field, it continuously takes pictures of the leaves, which are then promptly sent to an IoT-enabled cloud platform for processing.

Preprocessing

Modified Non-Local Means Filter (M-NLMF) carefully preserves crucial visual characteristics associated with disease while detecting and eliminating noise, such as random pixel distortions brought on by illumination, camera shake, or compression. The technique preserves disease-related characteristics, including lesions, spots, and textural changes, while eliminating noise from collected pictures. The Median Absolute Deviation (MAD) is initially used to estimate noise:

$$\sigma^2 = | I(x_i) - \text{median}(I(x_i)) | \qquad (1)$$

where σ^2 is the estimated noise variance, and $I(x_i)$ is the pixel intensity. After that, the filter creates a clean image with all important visual elements intact by performing weighted averaging over similar image patches.

Feature extraction

This approach uses an Improved Swin Transformer and EfficientNet-B7 as part of a hybrid deep learning model to extract both local and global features from the pre-processed images. Local disease characteristics are the main focus of EfficientNet-B7. In order to find fine-grained patterns like discolouration, spots, and changes in surface texture, it applies a sequence of convolutional procedures to the input image, scanning tiny pixel patches. The process of convolution is written as:

$$F(i,j) = \sum_m \sum_n I(i+m, j+n) \times K(m,n) \qquad (2)$$

where F is the final feature map, K is the convolution filter kernel, and I is the input image. The Improved Swin Transformer then uses a self-attention mechanism to record global patterns throughout the leaf: Q, K, and V are query, key, and value matrices,

$$Attention(Q,K,V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \qquad (3)$$

The model produces a rich and thorough feature representation that significantly increases the accuracy of disease classification by combining EfficientNet-B7 with Improved Swin Transformer.

Image Classification with ELM

The obtained features are used by an Extreme Learning Machine (ELM) classifier to identify the disease category. A type of feedforward neural network with a single hidden layer, ELM is well known for its exceptionally fast training speed and potent classification skills. Unlike normal neural networks, which require extensive recurrent training, ELM assigns input weights and biases at random and then analytically computes the output weights in a single step, making it highly effective for real-time applications.

A single-hidden-layer neural network called the Extreme Learning Machine (ELM) is capable of fast and precise disease classification. Random initialization is used for input weights (W) and biases (b); the hidden layer output is calculated as $H = g(XW + b)$; output weights are calculated analytically as $\beta = H\ T$; and Class = argmax(Y), where $Y = H\beta$, is used to give the final class. Bacterial Leaf Blight (BLB), non BLB, other disease, and Healthy are the four categories into which the system divides leaves. The binary output for BLB detection 1 (True) for BLB and 0 (False) otherwise—allows for quick, automated illness alerts.

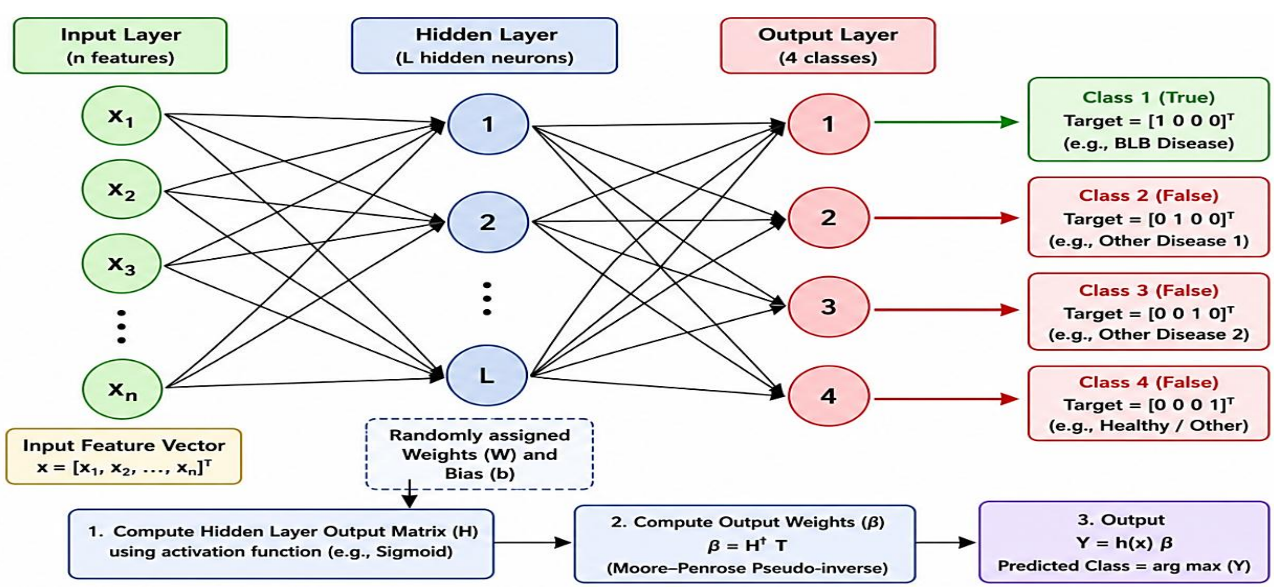

Fig. 2. *Extreme Learning Machine Architecture*

Algorithm 1: Extreme Learning Machine (ELM)

1. Initialize random input weights W and bias b.
2. Compute hidden layer output:

$$H = g(XW + b)$$

3. Calculate output weights:

$$\beta = H^{\dagger}T$$

where $H^{\dagger}$ is the Moore–Penrose pseudo-inverse and T is the target matrix.

4. Compute network output:

$$Y = H\beta$$

5. Assign class using:

$$\text{Class} = \arg\max(Y)$$

6. If Class = BLB, output 1 (True); otherwise output 0 (False).

End.

Result and discussions

The entire pipeline was used to process the field images from Drone 1. The model was able to correctly detect BLB-affected leaves and distinguish them from healthy tissue after M-NLMF preprocessing made disease-related color differences evident in the feature maps. The stages of image processing and detection results are depicted in Figure 3.

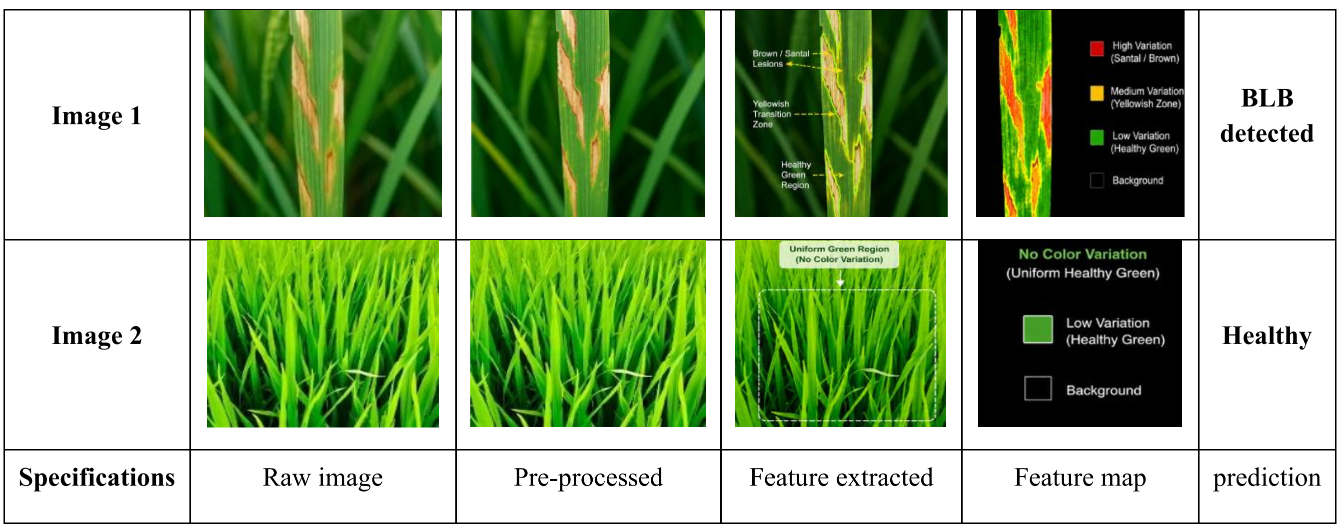

Fig. 3. *Image Results – Raw, Pre-processed, Feature Map, Detection*

Table 1. *MNLMF Performance Comparison*

Image	Noise Level	Noisy Image PSNR (dB)	Noisy Image FSIM	AITF PSNR (dB)	AITF FSIM	Proposed MNLMF PSNR (dB)	Proposed MNLMF FSIM
Image 1	10%	28.20	0.3270	31.86	0.7214	42.63	0.9610
Image 2	30%	18.33	0.1735	24.57	0.6081	38.44	0.9420
Average	–	20.62	0.2503	28.22	0.6648	40.54	0.9515

When compared to AITF and noisy images, the suggested MNLMF technique performs better with the highest average PSNR (40.54 dB) and FSIM (0.9515), demonstrating improved noise reduction and image quality retention.

Performances of the classification

The Hybrid AI-ELM model accurately classifies almost all paddy leaf samples with few misclassifications, according to the confusion matrix. Figure 3: Confusion Matrix and ROC Curve AUC values above 0.99 were obtained from ROC curve analysis for each of the four disease classifications, indicating exceptional detection reliability. Table 2 is Comparison With 99.30% accuracy, 98.00% precision, 97.00% recall, and 98.05% F1-score, the suggested Hybrid AI Model outperformed SVM (92.40%), Random Forest (95.10%), and solo ELM (97.60%). These findings show that combining EfficientNet-B7, the Improved Swin Transformer, and ELM into a single pipeline results in significantly better performance.

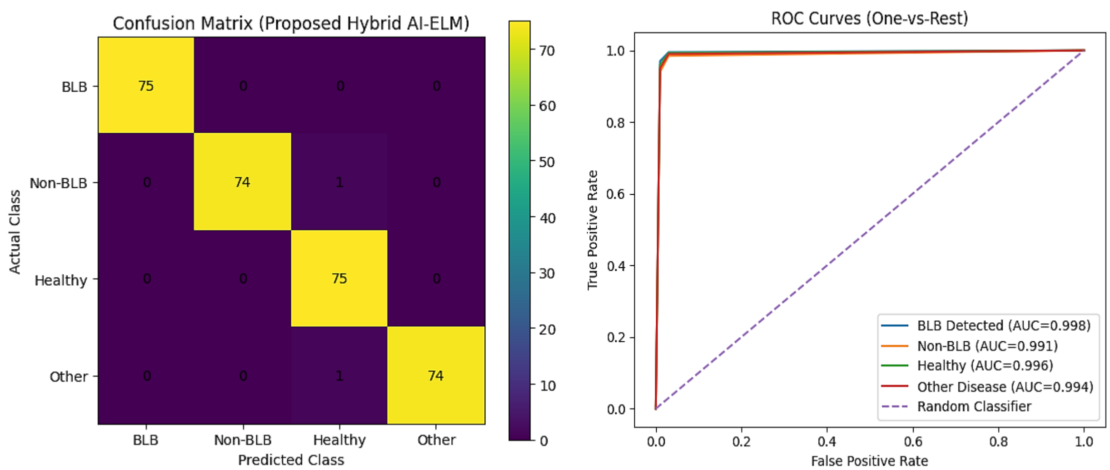

Fig. 3. *Confusion Matrix and ROC Curve*

Table 2. *Comparison with Other Classification Methods*

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Support Vector Machine (SVM)	92.40	91.20	90.50	90.85
Random Forest (RF)	95.10	94.30	93.80	94.05
Extreme Learning Machine (ELM)	97.60	96.50	95.90	96.20
Proposed Hybrid AI Model	99.30	98.00	97.00	98.05

Automated spraying system

Once the disease is diagnosed, Drone 2 (DJI Agras T25) uses precision pesticide spraying. It has a 20–25 kg cargo capacity, autonomous flight capability, and GPS/RTK navigation. The stages of the spraying procedure are as follows:

- Disease Location Generation: Drone 1's coordinates of affected crops are mapped via the cloud platform.
- Decision to Spray: A spraying job is created if the illness severity surpasses the threshold. Bitox (streptocycline copper oxychloride) is an insecticide that effectively combats bacterial leaf blight.
- Data Transmission: Using IoT-enabled Wi-Fi, Drone 2 receives GPS coordinates and spraying instructions.
- Autonomous Navigation: Drone 2 uses its flight controller and GPS module to fly to the destination without human assistance.
- Targeted Spraying: Only disease affected crop areas receive pesticide treatment; healthy plants are spared.
- Feedback and Monitoring: Drone 2 updates disease management data and creates a real-time monitoring report by sending the sprayed location, task status, and timestamp back to the cloud.

Conclusion

An integrated intelligent system for early paddy disease detection and precise pesticide distribution was presented in this research. Drone-captured pictures are efficiently cleaned by the M-NLMF preprocessing module, which achieves an average PSNR (40.54 dB) and FSIM (0.9515). Comprehensive disease features are captured by the hybrid EfficientNet-B7 and Improved Swin Transformer model, and the ELM classifier outperforms SVM, Random Forest, and standalone ELM with 99.30% accuracy. By ensuring that chemical (Bitox) only reaches diseased areas, the GPS-guided Drone 2 minimizes waste and environmental damage. These elements work together to provide a real-time, scalable system for intelligent paddy field management. Future research could investigate multispectral imaging for more profound health insights and expand the technique to identify other crop illnesses, thereby improving yield.

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