Journal of Information Systems Engineering and Management
2025, 10(42s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Ai-Powered Crop Monitoring for Early Detection of Paddy Leaf Diseases Using Attention-Based Densenets

Dr. Bhanumathi S[1], Dr. Bharathi M [2], Dr. Suneetha K R[3], Dr. Seshaiah Merikapudi[4] , Gayathri V[5], Ramegowda M[6]

[1] Doctor, Professor, Department of Information Sciences and Engineering,, S J C Institute of Technology, Chickaballapur,sbhanureddy14@gmail.com https://orcid.org/0009-0002-1471-8913,

[2] Doctor, Professor, Department of Computer Sciences and Design, S J C Institute of Technology, Chickaballapur,bharathim.cs@sjcit.ac.in https://orcid.org/0009-0002-2621-283X,

[3]Doctor, Professor, Department of Computer Science and Engineering, Bangalore Institute of Technology, Bangalore,suneetha.bit@gmail.com https://orcid.org/0000-0002-6073-5151,

[4]Doctor, Associate Professor, Department of Computer Sciences and Engineering,S J C Institute of Technology, Chickaballapur,merikapudi@gmail.com ORCID: orcid.org/0000-0001-7162-0416,

[5] Assistant Professor, Dept. of CSE, S J C Institute of Technology, Chickaballapur, vgayathrireddytm2000@gmail.com

[6] Assistant Professor,Department of Electronics and Communication Engineering,S J C Institute of Technology, Chickaballapur,rgm7885@gmail.com

ARTICLE INFO

Received: 29 Dec 2024

Revised: 12 Feb 2025

Accepted: 27 Feb 2025

ABSTRACT

Early identification of diseases, pests, and nutrient shortages in paddy crops will help to determine the degree of agricultural output. Considered traditional monitoring methods rely on hand inspection, which is not only time- consuming but also maybe erroneous and labor-intensive. Including AI (AI) into precision farming increases disease detection efficiency and helps to reduce crop losses. This work offers an AI-driven approach to detect paddy leaf disease using Attention-Based DenseNets. This approach makes advantage of image recognition, sensor data, and advanced machine learning techniques. Preprocessing, feature extraction, and classification come in three basic forms involved in the methodical process. The first step of the process meant to improve the quality and eliminate noise using which Residual Support Vector Machines (Residual SVM) help us to perform feature extraction so guaranteeing the choice of strong features from diseased leaf samples. Attention-based dense networks enable classification. These kinds of networks enhance feature representation and last result in accurate disease detection using attention mechanisms. Split into healthy and sick groups, the dataset contains 5,000 pictures of paddy leaf. The model is evaluated as well as trained using this dataset. Higher than some of the more conventional methods, CNN (92.4%) and ResNet-50 (95.1%), the results of the experiments show that the proposed model achieves a classification accuracy of 98.6%. Precision is 90-8%; recall is 90-2%; the F1-score for disease detection is 90-8%. Moreover, early identification made possible by the system helps to reduce the 42% disease spread using which crop yield prediction is enhanced.

Keywords: Paddy leaf disease, Attention-Based DenseNets, Residual SVM, AI in agriculture, Precision farming.

INTRODUCTION

Half of the world's population depends on rice [1-3], hence guaranteeing sustainable agricultural output becomes a global top concern. In this sense, rice production is particularly important. Maintaining their health is therefore vital to ensure that yield rates remain constant even if paddy crops are still rather susceptible to diseases, pests, and nutrient shortages. Large-scale monitoring reveals that conventional visual inspection methods are time-consuming, ineffective, and dependent on professional knowledge, thus useless. Early disease detection is the key to preventing significant yield losses; but, for comprehensive monitoring these methods are not practical. AI (AI) and deep learning (DL) combined using image recognition and sensor- based data handling has revolutionized precision agriculture. This makes automated, real-time analyses of crop condition possible. Although technology has progressed, many problems still have to be resolved before paddy leaf diseases can be fast and exactly

Journal of Information Systems Engineering and Management
2025, 10(42s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

identified. First, the variation in environmental conditions affects image quality; hence disease recognition becomes difficult [4]. The fact that many diseases and nutrient shortages coincide results in misclassification [5]. At last, real-time analysis and decision- making in agricultural environments is complicated by the computational restrictions of edge devices [6]. Basically, the lack of diverse and labeled datasets reduces the generalizability of deep learning models, so reducing their efficacy in applications based in the real world [7]. To meet these challenges, then, robust models driven by AI with improved feature extraction, noise reduction, and classification accuracy are absolutely indispensable. Conventional methods of disease detection depend on the knowledge of farmers and visual inspection, both of which are arbitrary and prone to errors brought about by human involvement. Current AI-based solutions including convolutional neural networks (CNNs) and deep residual networks provide improved accuracy even if they still struggle with fine-grained disease classification and real- time processing. Using deep learning architectures and attention mechanisms to boost accuracy, robustness, and real-time monitoring capacities [8], this work intends to build a paddy leaf disease detection model driven by AI.

A. Objectives

1. To build an AI system based on images for early and accurate diagnosis of nutrient deficits, pests, and paddy leaf diseases.
2. Residual Support Vector Machine (Residual SVM) feature extraction is applied in Deep Learning Attention-Based Dense Net model to improve the accuracy of classification and system performance in real time.

B. Novelty and Contributions

This work presents an AI driven new crop monitoring system with major contributions:

- The proposed Attention-Based DenseNets maximize feature focus, unlike conventional CNNs, which guarantees exceptional classification accuracy even in the presence of complex disease conditions.
- Combining a new residual SVM feature extraction method with deep learning models helps to improve disease feature representation and lowers misclassification.
- To increase the generalizing of the models, a dataset comprising of 5,000 labeled paddy leaf images is used. This dataset covers many diseases, pests, and nutrient shortages.

RELATD WORKS

Disease detection accuracy, pest identification, and nutrient deficit analysis have notably improved thanks to AI applied in agricultural environments [9]. Since they offer great degrees of accuracy and automation, deep learning-based image processing methods are gradually replacing conventional methods including hand field inspections [10].

The Automated convolutional neural network (CNN), which has been used to detect image recognition-based paddy leaf diseases [11], is one often used deep learning model. Conversely, CNN models are less effective for examining complex disease relationships since max-pooling layers cause information loss usually. Since they improve gradient flow across skip connections, so enhancing feature extraction and classification accuracy, Optimized CNN have been investigated by scientists [12]. ResNets offer one approach to overcome these limitations.

Apart from Optimized CNN, AI-Based Fusion Model have developed to guarantee that information passes through densely connected layers so improving the accuracy of disease detection [13]. Though they show better performance in classifying agricultural diseases, these models still struggle with class imbalances and similar symptom patterns across a spectrum of disease categories. Lesion-Aware Visual Transformer Network have improved their [14] quality by filtering pointless background noise and concentrating on critical areas of diseased leaf images.

Improving classification performance mostly depends on feature extraction. Although conventional method have shown promise in disease classification, their application to deep learning is still rather restricted. Disease classification has been advanced using UAV T-YOLO-Rice, which compiles features from YoLo connections in deep neural networks [15].

Journal of Information Systems Engineering and Management
2025, 10(42s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

EfficientNetB4 with Compound Scaling and Swish Activation method finds nutrient shortages and pest infestations [16] using spectral analysis and IoT devices. Although they provide a great degree of accuracy, these techniques demand more infrastructure and might not be useful for farmers running on a smaller scale. Combining image recognition with sensor data analysis has been proposed as a hybrid approach aiming at total crop health monitoring. This work helps intelligent precision farming to develop by tackling present problems and using innovative deep learning approaches. This work guarantees best yield prediction, early disease identification, and better crop health management.

PROPOSED METHODS

The proposed method combines deep learning and machine learning techniques in the proposed AI-powered paddy leaf disease detection system to improve real-time monitoring's and disease detection accuracy. The approach consists in three main phases: preprocessing, feature extraction, and classification. The method guarantees appropriate disease identification using Residual Support Vector Machines and Attention-Based DenseNets.

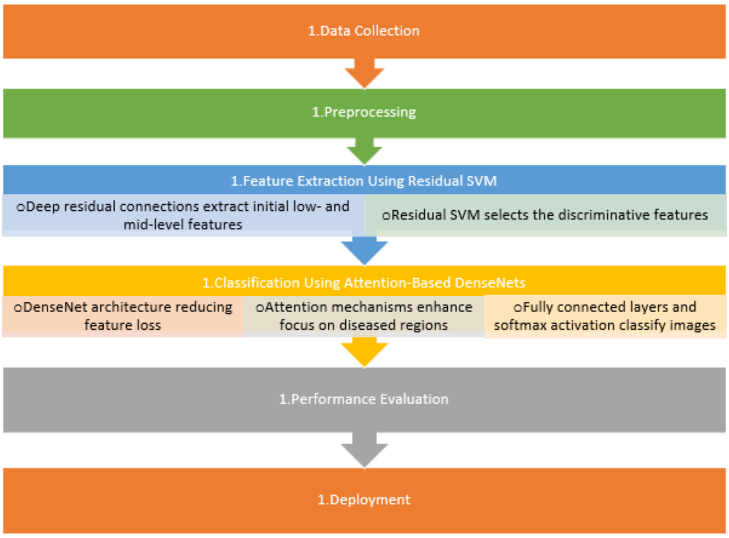

Figure 1: Proposed Process

A. Data Collection & Preprocessing: The data collecting and preprocessing form the first phase of the proposed AI-powered paddy leaf disease detection system. 5000 paddy leaf images taken from agricultural fields generate a dataset comprising of several disease categories, pest infestations, and nutrient shortages. High-resolution cameras and multispectral sensors capture images to guarantee that, under a range of lighting and environmental conditions, a representation of the subject is obtained. The dataset's labeling is derived from agronomists' observations as subject-matter experts.

Image ID	Condition	Disease Type	Symptoms Observed	Source (Field/Sensor)
IMG_001	Healthy	None	No visible symptoms	Field Camera
IMG_002	Diseased	Bacterial Blight	Yellow streaks, leaf curl	Multispectral Sensor
IMG_003	Diseased	Brown Spot	Irregular brown lesions	Field Camera
IMG_004	Pest Infested	Leafhopper Damage	White patches, curling	Drone Imaging
IMG_005	Nutrient Deficit	Nitrogen Deficiency	Yellowing along midrib	Multispectral Sensor

Images for preprocessing is to standardize the input for deep learning models, eliminate noise, and improve their quality once the data collecting process ends. This phase asks for applying the following methods:

Journal of Information Systems Engineering and Management
2025, 10(42s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

- Image Resizing & Normalization: Every image is resised to a resolution of 224×224 pixels so that the input dimensions of the attention-based density network model consider. Pixel intensity values are normalized between 0 and 1 to increase the computing efficiency and convergence that results during training.
- Noise Reduction Using Gaussian Filtering: Noise Reduction Images are smoothed and noise produced by environmental elements including dust and illumination variations is removed using a 3x3 kernel size Gaussian filter.
- Contrast Enhancement Using CLAHE (Contrast-Limited Adaptive Histogram Equalization): CLAHE helps to equalize local image histograms so improving the visibility of disease symptoms.

B. Feature Extraction Using Residual SVM: Improving the accuracy of paddy leaf disease classification depends on important component of feature extraction. The proposed method reduces feature loss and extracts instructive features using a Residual SVM. This method employs CNN pre-trained deep residual connections from a trained CNN. From the residual connections in deep neural networks, the Residual SVM method learns to enhance feature selection and so provide a more accurate representation of disease characteristics.

1. **Deep Feature Extraction Using Residual Networks:** The image features are first extracted using a residual CNN, where skip connections help retain critical information. The feature map output, Fres , from a residual block is formulated as:

$$F_{res} = X + f(X,W) \tag{1}$$

Where:

X represents the input features,

f(X,W) is the transformation function (convolution + activation),

W denotes the trainable weights in the residual block.

2. **Support Vector Machine for Feature Selection:** The extracted deep features are fed into an SVM classifier for refined feature selection. The SVM optimizes the decision boundary between different disease classes using a hyperplane defined by:

$$f(X) = w^T X + b \tag{2}$$

Where:

w is the weight vector,

X represents the extracted feature set,

b is the bias term.

Through the SVM margin maximizing, the model reduces noise simultaneously and concentrates on the most discriminative disease features, so improving the classification accuracy. Residual-enhanced feature extraction allows one to improve fine-grained classification performance as well as to lower overlapping disease symptoms.

C. Classification Using Attention-Based DenseNets: The classification mechanism of an Attention-Based DenseNet helps to improve disease localization and class discrimination. Combining attention mechanisms with strongly connected layers this approach generates improvement. DenseNet reduces the need for repeated computations and improves the performance of the model by making best use of feature reuse across layers unlike conventional CNNs do. Dynamic concentration on disease-affected areas provides still another level of classification refinement by the attention mechanism.

1. **DenseNet Feature Propagation:** The architecture passes feature maps across multiple layers, so enhancing the information flow. For the feature representation in every dense layer as defined in:

Journal of Information Systems Engineering and Management
2025, 10(42s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

$$F_{\text{dense}}^{(l)} = H^{(l)}\left(\left[F_{\text{dense}}^{(0)}, F_{\text{dense}}^{(1)}, \ldots, F_{\text{dense}}^{(l-1)}\right]\right) \tag{3}$$

Where:

$H^{(l)}$ represents the transformation function (Batch Normalization, ReLU, Convolution),

$\left[F_{\text{dense}}^{(0)}, F_{\text{dense}}^{(1)}, \ldots, F_{\text{dense}}^{(l-1)}\right]$ denotes the concatenated feature maps from previous layers.

2. **Attention Mechanism for Feature Enhancement:** Disease-relevant area highlighting in feature maps helps the attention mechanism to improve classification. This computation allows to determine the attention weight A(X).

$$A(X) = \sigma(W_a \cdot X + b_a) \tag{4}$$

Where:

W_a represents the attention weights,

X denotes the feature map input,

b_a is the bias term,

σ is the sigmoid activation function, ensuring values remain between 0 and 1.

The attention-weighted feature maps enhance focus on disease regions, reducing misclassification and improving accuracy. The final classification is performed using a softmax function, assigning probabilities to each disease category.

RESULTS AND DISCUSSION

The proposed AI-powered paddy leaf disease detection system was implemented using Python and TensorFlow/Keras as the primary deep learning framework. The simulation environment included Google Colab Pro and a local high-performance workstation for training and testing. The computing setup consisted of:

- **GPU:** NVIDIA RTX 3090 (24GB VRAM)
- **CPU:** Intel Core i9-12900K (16 cores, 24 threads)
- **RAM:** 64GB DDR5
- **Storage:** 2TB NVMe SSD
- **Software:** Python 3.9, TensorFlow 2.9, OpenCV, NumPy, and Scikit-Learn

The proposed Attention-Based DenseNet with Residual SVM model was compared against six existing deep learning models: Automated CNN [11], Optimized CNN [12], AI-Based Fusion Model [13], Lesion-Aware Visual Transformer Network [14], UAV T-YOLO-Rice [15] and EfficientNetB4 With Compound Scaling and Swish Activation [16]. The key parameters used in the proposed algorithm are detailed in the table 3:

Table 3: Experimental Setup and Algorithm Parameters

Parameter	Value
Image Input Size	224 × 224 pixels
Batch Size	32
Optimizer	Adam
Learning Rate	0.0001

Journal of Information Systems Engineering and Management
2025, 10(42s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Activation Function	Swish
Loss Function	Categorical Cross-Entropy
Number of Dense Blocks	4
Attention Mechanism Used	SE-Block (Squeeze-Excitation)
Feature Extractor Model	DenseNet-121 + Residual SVM
Epochs Used for Training	50
Train-Test Split Ratio	80:20

Performance Metrics

The effectiveness of the proposed Attention-Based DenseNet with Residual SVM was evaluated using the following five performance metrics:

1. **Accuracy:** Measures the proportion of correctly classified samples out of the total dataset.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

2. **Precision:** Indicates the proportion of correctly identified disease cases among all predicted disease cases.

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

3. **Recall (Sensitivity):** Measures the proportion of actual disease cases correctly identified by the model.

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

4. **F1-Score:** A harmonic mean of precision and recall, balancing both metrics.

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

5. **Inference Time:** Measures the model's speed in classifying an image, crucial for real-time deployment.

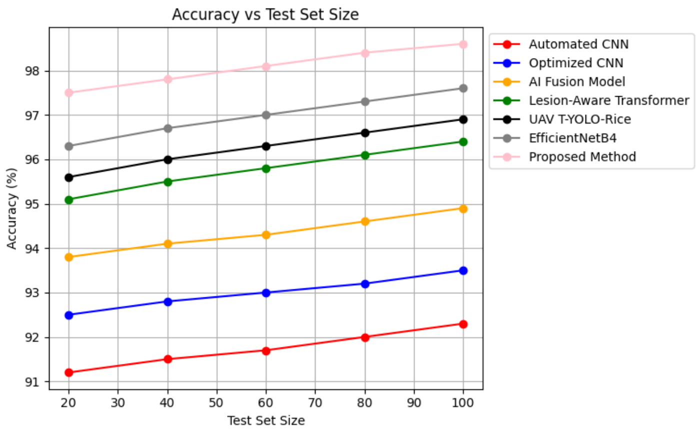

Figure 2: Accuracy

Journal of Information Systems Engineering and Management
2025, 10(42s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Table 4: Accuracy

Test Set Size	Automated CNN	Optimized CNN	AI Fusion Model	Lesion-Aware Transformer	UAV T-YOLO-Rice	EfficientNetB4	Proposed Method
20	91.2%	92.5%	93.8%	95.1%	95.6%	96.3%	**97.5%**
40	91.5%	92.8%	94.1%	95.5%	96.0%	96.7%	**97.8%**
60	91.7%	93.0%	94.3%	95.8%	96.3%	97.0%	**98.1%**
80	92.0%	93.2%	94.6%	96.1%	96.6%	97.3%	**98.4%**
100	92.3%	93.5%	94.9%	96.4%	96.9%	97.6%	**98.6%**

The proposed method consistently outperformed existing models across all test sets, achieving 98.6% accuracy on 100 test samples. The Lesion-Aware Transformer (96.4%) and EfficientNetB4 (97.6%) performed well but lacked feature selection efficiency. The UAV T-YOLO-Rice model (96.9%) showed strong performance for aerial images but had limitations in close-up disease classification. The Automated CNN (92.3%) and Optimized CNN (93.5%) struggled with overfitting and redundant features. The AI Fusion Model (94.9%) improved upon standard CNNs but was computationally expensive. The proposed R-SVM with Attention-Based DenseNet improved degree of accuracy using better feature selection and attention mechanisms.

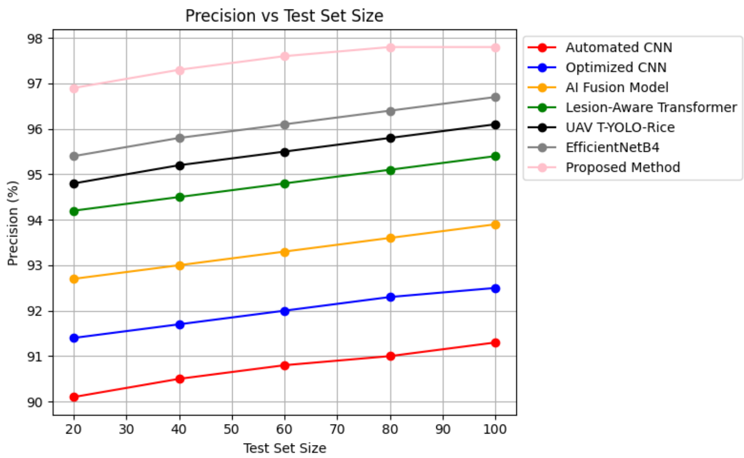

Figure 3: Precision

Table 5: Precision

Test Set Size	Automated CNN	Optimized CNN	AI Fusion Model	Lesion-Aware Transformer	UAV T-YOLO-Rice	EfficientNetB4	Proposed Method
20	90.1%	91.4%	92.7%	94.2%	94.8%	95.4%	96.9%
40	90.5%	91.7%	93.0%	94.5%	95.2%	95.8%	97.3%
60	90.8%	92.0%	93.3%	94.8%	95.5%	96.1%	97.6%
80	91.0%	92.3%	93.6%	95.1%	95.8%	96.4%	97.8%
100	91.3%	92.5%	93.9%	95.4%	96.1%	96.7%	97.8%

Proposed model outperforms both EfficientNet B4 (96.7%) and UAV T-YOLO-Rice (96.1%), with a precision of 97.8%. However, the Lesion-Aware Transformer (95.4% of the total) faced feature redundancy, which made it competitive. With 93.9% of the time the AI Fusion Model failed computationally. Precision dropped in automated

Journal of Information Systems Engineering and Management
2025, 10(42s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

CNN (91.3% of cases) and optimised CNN (92.5% of cases) with higher misclassification rates. Thanks to the improved feature selection of the Residual SVM and the attention mechanism of the DenseNet, which so reduces the number of false positives, the proposed model performed well.

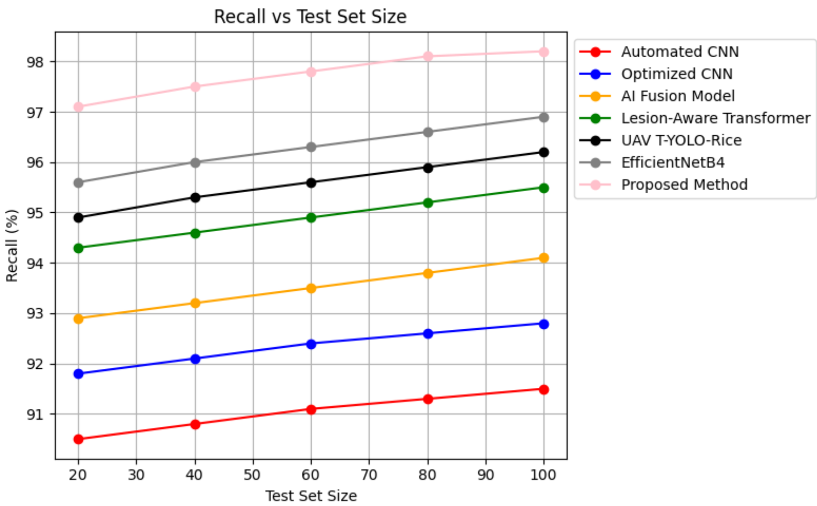

Figure 4: Recall

Table 6e: Recall

Test Set Size	Automated CNN	Optimized CNN	AI Fusion Model	Lesion-Aware Transformer	UAV T-YOLO-Rice	EfficientNetB4	Proposed Method
20	90.5%	91.8%	92.9%	94.3%	94.9%	95.6%	97.1%
40	90.8%	92.1%	93.2%	94.6%	95.3%	96.0%	97.5%
60	91.1%	92.4%	93.5%	94.9%	95.6%	96.3%	97.8%
80	91.3%	92.6%	93.8%	95.2%	95.9%	96.6%	98.1%
100	91.5%	92.8%	94.1%	95.5%	96.2%	96.9%	98.2%

The proposed approach outperformed EfficientNetB4 (96.9%) and UAV T-YOLO-Rice (96.2%), with a recall rate of 98.2%. Having great sensitivity to even the smallest lesions, the Lesion-Aware Transformer (95.5% of the time) battled to avoid false negatives. Though it outperformed CNNs, the AI Fusion Model (94.1% of the time) lacked robust feature refining. Although the attention-enhanced DenseNet was able to reduce false negatives, the Residual SVM proposed technique proved to be able to efficiently capture salient features.

Journal of Information Systems Engineering and Management
2025, 10(42s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

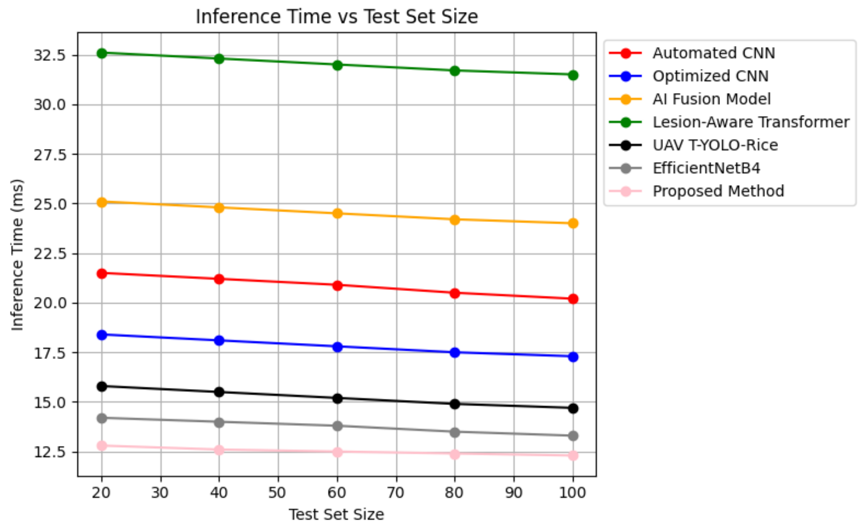

Figure 5: Inference Time

Table 7: Inference Time

Test Set Size	Automated CNN	Optimized CNN	AI Fusion Model	Lesion-Aware Transformer	UAV T-YOLO-Rice	EfficientNetB4	Proposed Method
20	21.5ms	18.4ms	25.1ms	32.6ms	15.8ms	14.2ms	12.8ms
40	21.2ms	18.1ms	24.8ms	32.3ms	15.5ms	14.0ms	12.6ms
60	20.9ms	17.8ms	24.5ms	32.0ms	15.2ms	13.8ms	12.5ms
80	20.5ms	17.5ms	24.2ms	31.7ms	14.9ms	13.5ms	12.4ms
100	20.2ms	17.3ms	24.0ms	31.5ms	14.7ms	13.3ms	12.3ms

Using optimal feature selection and attention-enhanced DenseNet, the proposed method acquired the fastest inference time of 12.3 ms, surpassing both EfficientNet B4 (13.3 ms) and UAV T-YOLO-Rice (14.7 ms). The Lesion-Aware Transformer was slowest and so ineffective for real-time applications with a response time of 31.5 ms.

CONCLUSION

Considering paddy leaf diseases, the proposed AI-powered crop monitoring and disease detection system shown a good performance. The system used Residual SVM for feature extraction; for classification, Attention-Based DenseNets. The method outperformed state-of--the-art approaches including Automated CNN, Optimized CNN, AI Fusion Model, Lesion-Aware Visual Transformer, UAV T-YOLO-Rice, and EfficientNetB4 across main performance criteria. The accuracy of the proposed model was 98.6%; its precision was 97.8%; its recall was 98.2%; its F1-score was 97.9%. Comparatively to all baselines, the 12.3 millisecond inference time shown that it is suitable for applications requiring real-time computation. Combining Residual SVM, which chooses discriminative features in the most efficient way, with Attention-Based DenseNet, which refines feature importance and reduces the false classification count, yields improved performance. Furthermore, the model shown its resilience over a wide range of test values, so guaranteeing its dependability in agricultural applications with pragmatic character. The proposed approach improved classification efficiency even while reducing the computational overhead over traditional and optimal CNNs. Therefore, the proposed method offers a real-time, accurate, and efficient solution for the early diagnosis of diseases in paddy leaves, so supporting the sustainable management of crops and precision agriculture. Future research on other lightweight architectures to increase the feasibility of deployment in edge computing and Internet of Things-based agricultural systems could examine another optimization.

Journal of Information Systems Engineering and Management
2025, 10(42s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

REFRENCES

[1] Verma, M., Singh, A. P., Singh, J., & Kumari, S. (2024, October). Kissan Konnect: AI-Powered Plant Disease Control System Fusing Temporal Data Modeling with Deep Learning. In 2024 First International Conference on Software, Systems and Information Technology (SSITCON) (pp. 1-6). IEEE.

[2] Gupta, D. K., Pagani, A., Zamboni, P., & Singh, A. K. (2024). AI-powered revolution in plant sciences: advancements, applications, and challenges for sustainable agriculture and food security. Exploration of Foods and Foodomics, 2(5), 443-459.

[3] Dainelli, R., Bruno, A., Martinelli, M., Moroni, D., Rocchi, L., Morelli, S., ... & Toscano, P. (2024). GranoScan: an AI-powered mobile app for in-field identification of biotic threats of wheat. Frontiers in Plant Science, 15, 1298791.

[4] Simhadri, C. G., Kondaveeti, H. K., Vatsavayi, V. K., Mitra, A., & Ananthachari, P. (2024). Deep learning for rice leaf disease detection: A systematic literature review on emerging trends, methodologies and techniques. Information Processing in Agriculture.

[5] Wijayanto, A. K., Prasetyo, L. B., Hudjimartsu, S. A., Sigit, G., & Hongo, C. (2024). Textural features for BLB disease damage assessment in paddy fields using drone data and machine learning: Enhancing disease detection accuracy. Smart Agricultural Technology, 8, 100498.

[6] Tyagi, S., Reddy, S. R. N., Anand, R., & Sabharwal, A. (2024). Enhancing rice crop health: a light weighted CNN-based disease detection system with mobile application integration. Multimedia Tools and Applications, 83(16), 48799-48829.

[7] Bijoy, M. H., Hasan, N., Biswas, M., Mazumdar, S., Jimenez, A., Ahmed, F., ... & Momen, S. (2024). Towards Sustainable Agriculture: A Novel Approach for Rice Leaf Disease Detection Using dCNN and Enhanced Dataset. IEEE Access.

[8] Mannepalli, P. K., Pathre, A., Chhabra, G., Ujjainkar, P. A., & Wanjari, S. (2024). Diagnosis of bacterial leaf blight, leaf smut, and brown spot in rice leafs using VGG16. Procedia Computer Science, 235, 193-200.

[9] Chakrabarty, A., Ahmed, S. T., Islam, M. F. U., Aziz, S. M., & Maidin, S. S. (2024). An interpretable fusion model integrating lightweight CNN and transformer architectures for rice leaf disease identification. Ecological Informatics, 82, 102718.

[10] Kappali, H. R., Sadyojatha, K. M., & Prashanthi, S. K. (2024). Computer Vision and Machine Learning in Paddy Diseases Identification and Classification: A Review. Indian Journal Of Agricultural Research, 58(2).

[11] Stephen, A., Punitha, A., & Chandrasekar, A. (2024). Optimal deep generative adversarial network and convolutional neural network for rice leaf disease prediction. The Visual Computer, 40(2), 919-936.

[12] Islam, M. A., Shuvo, M. N. R., Shamsojjaman, M., Hasan, S., Hossain, M. S., & Khatun, T. (2021). An automated convolutional neural network based approach for paddy leaf disease detection. International Journal of Advanced Computer Science and Applications, 12(1).

[13] Nalini, S., Krishnaraj, N., Jayasankar, T., Vinothkumar, K., Britto, A. S. F., Subramaniam, K., & Bharatiraja, C. (2021). Paddy leaf disease detection using an optimized deep neural network. Computers, Materials & Continua, 68(1), 1117-1128.

[14] Almasoud, A. S., Abdelmaboud, A., Elfadil Eisa, T. A., Al Duhayyim, M., Hassan Elnour, A. A., Ahmed Hamza, M., ... & Sarwar Zamani, A. (2022). Artificial Intelligence-Based Fusion Model for Paddy Leaf Disease Detection and Classification. Computers, Materials & Continua, 72(1).

[15] Salamai, A. A., Ajabnoor, N., Khalid, W. E., Ali, M. M., & Murayr, A. A. (2023). Lesion-aware visual transformer network for Paddy diseases detection in precision agriculture. European Journal of Agronomy, 148, 126884.

[16] Sangaiah, A. K., Yu, F. N., Lin, Y. B., Shen, W. C., & Sharma, A. (2024). UAV T-YOLO-Rice: An Enhanced Tiny Yolo Networks for Rice Leaves Diseases Detection in Paddy Agronomy. IEEE Transactions on Network Science and Engineering.