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A Review of Artificial Intelligence Techniques for Rice Leaf Disease Detection and Classification

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ABSTRACT

Rice leaf diseases significantly threaten global rice production, directly affecting crop yield, quality, and food security. Early and accurate detection of these diseases is therefore essential for effective crop management and sustainable agriculture. Recent advances in artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), have enabled automated, efficient, and scalable solutions for rice leaf disease detection and classification. This review provides a comprehensive analysis of existing AI-based techniques applied to rice leaf disease diagnosis, covering traditional image processing methods, classical ML classifiers, and state-of-the-art DL architectures such as convolutional neural networks, transfer learning models, and hybrid frameworks. Publicly available datasets, data augmentation strategies, and evaluation metrics commonly used in the literature are also discussed. Furthermore, the review critically examines key challenges, including limited labeled data, class imbalance, environmental variability, and poor generalization under real-field conditions. Special attention is given to recent trends involving explainable AI, lightweight models for edge deployment, and multi-disease classification systems. By identifying research gaps and limitations in current approaches, this review highlights future directions toward robust, interpretable, and real-time AI-driven solutions for rice leaf disease detection. The insights presented aim to support researchers and practitioners in developing reliable decision-support systems for precision agriculture and sustainable rice production.

Keywords: Rice leaf disease, Artificial intelligence, Deep learning, Image-based disease detection, Precision agriculture

Introduction

Rice (Oryza sativa L.) is one of the most important staple crops worldwide, serving as a primary food source for more than half of the global population. Ensuring stable rice production is therefore critical for food security, especially in developing countries where rice farming sustains both livelihoods and national economies. However, rice cultivation is severely affected by various biotic stresses, among which rice leaf diseases play a major role. These diseases not only reduce crop yield but also degrade grain quality, leading to significant economic losses for farmers. Common rice leaf diseases include brown spot, sheath blight, leaf scald, bacterial leaf blight, narrow brown spot, leaf blast, neck blast, rice hispa damage, and tungro disease, each caused by different pathogens such as fungi, bacteria, viruses, or insect infestations.

Traditionally, rice leaf disease diagnosis relies on manual visual inspection by farmers or agricultural experts. This approach is time-consuming, subjective, and highly dependent on expert knowledge, which is often unavailable in rural or resource-limited regions. Moreover, many rice leaf diseases exhibit similar visual symptoms at early stages, making accurate differentiation difficult even for trained personnel. Delayed or incorrect diagnosis can result in improper pesticide usage, increased production costs, environmental damage, and further yield reduction. These challenges highlight the urgent need for reliable, fast, and automated disease detection systems.

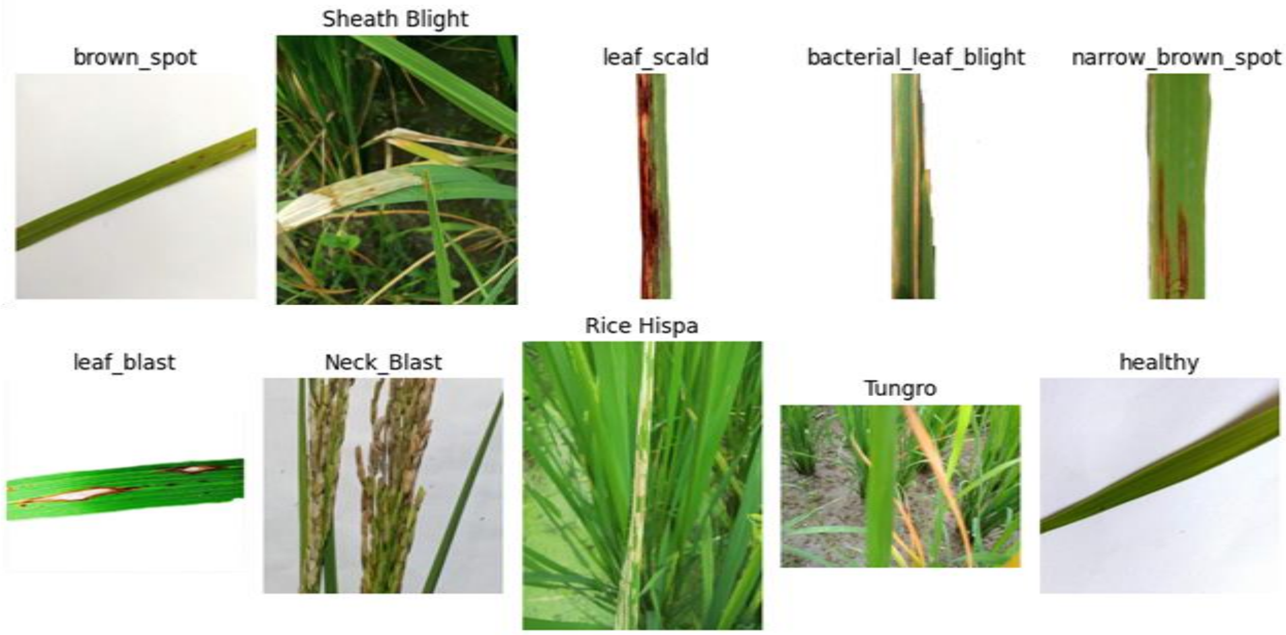

Figure 1: Rice Leaf Disease [1]

In recent years, artificial intelligence (AI) has emerged as a powerful tool for addressing complex problems in agriculture, particularly in crop disease diagnosis. Advances in machine learning (ML) and deep learning (DL), combined with the availability of digital imaging devices and increased computational power, have enabled the development of intelligent systems capable of detecting and classifying rice leaf diseases from images. Image-based AI techniques can automatically extract discriminative features related to color, texture, shape, and lesion patterns, reducing human intervention and improving diagnostic accuracy. Convolutional neural networks (CNNs), transfer learning models, and hybrid architectures have demonstrated promising performance in identifying multiple rice leaf diseases under controlled and real-field conditions.

Figure 1 presents representative annotated samples of major rice leaf diseases, including brown spot, sheath blight, leaf scald, bacterial leaf blight, narrow brown spot, leaf blast, neck blast, rice hispa damage, tungro disease, and healthy leaves. These visual examples highlight the diversity and complexity of disease symptoms observed on rice leaves, as well as the subtle differences between certain disease classes. Such variability poses significant challenges for automated systems, particularly under varying lighting conditions, background noise, and different growth stages. Therefore, robust AI models must be capable of handling intra-class variation and inter-class similarity to ensure reliable performance in real-world agricultural settings.

This review paper aims to provide a comprehensive overview of AI-based techniques for rice leaf disease detection and classification. It systematically discusses traditional image processing approaches, classical ML methods, and state-of-the-art DL frameworks, along with commonly used datasets, evaluation metrics, and experimental settings. Furthermore, the paper critically analyzes current limitations, including data scarcity, class imbalance, poor generalization, and lack of explainability. By identifying existing research gaps and emerging trends, this review seeks to guide future research toward developing accurate, interpretable, and deployable AI-driven solutions for sustainable rice disease management.

LITERATURE STUDY

Table I summarizes recent research contributions (2024–2025) on rice leaf disease detection and classification using artificial intelligence techniques. The table highlights a wide range of approaches, including traditional artificial neural networks, deep convolutional neural networks, vision transformers, transfer learning, and hybrid and ensemble frameworks. Overall, most studies report improved classification accuracy and robust feature extraction; however, common limitations include dependency on large, labeled datasets, limited disease categories, high computational cost, and lack of real-world validation. Review-based works provide valuable insights into trends and challenges but lack experimental implementation. These observations indicate clear research gaps in developing lightweight, interpretable, and well-generalized hybrid models validated on large and diverse real-field datasets.

TABLE I COMPARATIVE ANALYSIS

Ref No.	Year-Publication	Methods	Advantage	Limitation/Future Work
1	2025	Review of AI techniques	Provides a comprehensive survey	Lacks experimental validation
2	2025	Multi-Vision Transformer	Improved accuracy with attention mechanisms	Needs further validation on large datasets
3	2024	Smart farming techniques	Identifies key challenges in rice farming	Does not implement AI models
4	2024	Deep Learning (CNN)	Real-time detection capability	Requires large labeled datasets
5	2024	CNN with Attention Ensembles	Improved classification accuracy	Limited disease categories analyzed
6	2024	DNN with Threshold Neural Network	Efficient disease identification	Needs optimization for real-world deployment

Ref No.	Year-Publication	Methods	Advantage	Limitation/Future Work
7	2024	Deep CNN	Utilizes enhanced datasets	Limited generalization due to dataset bias
8	2024	Vision Transformer + Transfer Learning	Enhanced feature extraction	Requires more training data
9	2024	Artificial Neural Network (ANN)	Simple model with fast training	Lower accuracy compared to CNNs
10	2024	VGG16	Pretrained model increases accuracy	Limited to three disease types
11	2024	Hybrid CNN	Robust classification performance	Requires high computational resources
12	2024	Ensemble ML framework	Higher accuracy with ensemble approach	Needs extensive hyperparameter tuning
14	2024	EfficientNet	High efficiency and accuracy	Needs more interpretability
15	2024	CNN + Transformer	Reduces computational cost	Limited to specific disease types
16	2024	Transfer Learning & Custom CNN	Increased classification performance	Needs more dataset diversity
17	2024	InceptionV3, InceptionResNetV2	Effective feature extraction	Computationally expensive
18	2024	Literature Review	Covers emerging trends	No implementation details
19	2024	Deep Learning + Feature Extraction	High granularity classification	Needs real-time deployment testing
14	2024	EfficientNet	High efficiency and accuracy	Needs more interpretability

RESEARCH FINDING

Recent studies demonstrate that artificial intelligence (AI) has significantly improved the accuracy and efficiency of rice leaf disease detection compared to traditional manual and rule-based methods. Most research findings indicate that deep learning (DL) models, particularly convolutional neural networks (CNNs), outperform classical machine learning (ML) and artificial neural network (ANN) approaches due to their strong capability to automatically learn discriminative spatial and texture-based features from leaf images [1], [2]. Pretrained CNN architectures such as VGG16, InceptionV3, InceptionResNetV2, and EfficientNet consistently achieve higher classification accuracy, especially when combined with transfer learning, which helps mitigate limited dataset size [10], [14], [17].

Recent advancements also highlight the growing adoption of Vision Transformers (ViTs) and CNN–Transformer hybrid frameworks. These models leverage attention mechanisms to capture long-range dependencies and subtle disease patterns, resulting in improved performance over standalone CNNs in multi-class rice leaf disease classification tasks [2], [8], [15]. Ensemble-based approaches further enhance robustness and accuracy by combining predictions from multiple classifiers; however, they introduce higher computational complexity and require extensive hyperparameter tuning [12].

Another key finding is the importance of dataset quality and diversity. Studies utilizing enhanced or augmented datasets report better generalization performance, whereas models trained on small or biased datasets suffer from poor adaptability under real-field conditions [7], [16]. Several works emphasize that class imbalance and limited disease categories remain critical challenges, restricting the practical applicability of many proposed methods [5], [10]. Additionally, while deep CNN models enable real-time disease detection, their reliance on large labeled datasets and high computational resources limits deployment on edge devices used in smart farming environments [4], [11].

From a system-level perspective, smart farming studies identify AI-driven disease diagnosis as a core component of precision agriculture but often lack actual model implementation or validation [3]. Review papers contribute by consolidating emerging trends, challenges, and future opportunities, yet they do not provide empirical performance comparisons [1], [18]. Furthermore, recent research increasingly recognizes the need for explainable AI (XAI) techniques to improve model transparency and farmer trust, particularly in high-stakes agricultural decision-making [14], [19].

Overall, the research findings suggest that while AI-based rice leaf disease detection has achieved promising accuracy, future efforts should focus on developing lightweight, explainable, and hybrid models validated on large-scale, diverse, real-world datasets. Integrating robustness, interpretability, and deployment feasibility remains essential for transitioning AI solutions from laboratory settings to real agricultural applications.

CHALLENGES

Addressing below challenges is essential for advancing AI-driven rice leaf disease detection toward practical, scalable, and farmer-friendly solutions.

1. **High Computational Complexity of Deep Learning Models**: One of the most significant challenges in rice leaf disease detection is the high computational demand of state-of-the-art deep learning models. Architectures such as EfficientNetB0 and Vision Transformers require substantial processing power, memory, and energy consumption during both training and inference stages. These requirements make such models unsuitable for deployment in low-resource environments, including mobile devices, drones, and edge-based agricultural systems commonly used by farmers in rural areas. As a result, despite achieving high accuracy in laboratory settings, these models face serious limitations in real-time field applications [3], [10], [14].
2. **Limited Emphasis on Model Efficiency and Optimization:** Many existing studies prioritize maximizing classification accuracy without adequately considering model efficiency. Factors such as training time, number of parameters, and computational cost are often overlooked. This lack of emphasis on optimization leads to complex architectures that are difficult to fine-tune and deploy at scale. Lightweight design strategies, pruning, quantization, and parameter-efficient learning remain underexplored in rice leaf disease research, creating a gap between theoretical performance and practical usability [5], [7], [12].
3. **Insufficient Real-World Validation and Deployment Testing:** Another critical challenge is the limited evaluation of proposed models under real-world agricultural conditions. Most studies rely on controlled datasets with clean backgrounds, uniform lighting, and limited environmental variability. Consequently, the

robustness of these models in real-field scenarios—where images may include noise, occlusion, varying illumination, and different growth stages—remains uncertain. The absence of deployment-level testing significantly restricts the reliability and adoption of AI-based systems by farmers and agricultural stakeholders [4], [11], [17].

4. **Imbalanced Performance Evaluation Metrics:** Previous research often reports high accuracy as the primary performance indicator, neglecting essential trade-offs between accuracy, model size, inference speed, and training complexity. Such imbalanced evaluation fails to reflect real deployment constraints, particularly for resource-constrained environments. Comprehensive benchmarking frameworks that jointly consider accuracy, computational efficiency, and scalability are still lacking in the literature [6], [9], [16].
5. **Limited Generalization Across Crops and Diseases:** Most existing works focus narrowly on rice leaf diseases, with minimal effort to extend or generalize models to other crops or disease types. This crop-specific design limits model reusability and scalability in broader agricultural systems. Developing generalized, multi-crop disease detection frameworks remains a major research challenge, as highlighted by several studies that emphasize the need for cross-crop adaptability and transferability [1], [2], [8], [13], [18], [20].

CONCLUSION AND FUTURE WORK

This review highlights that artificial intelligence, particularly deep learning–based approaches, has substantially advanced the accuracy and automation of rice leaf disease detection and classification. Despite these improvements, several critical limitations remain, including restricted dataset diversity, poor generalization under real-field conditions, lack of real-time deployment, and the absence of integrated decision-support mechanisms. Most existing studies primarily emphasize disease identification, offering limited practical value to farmers due to the lack of treatment guidance and interpretability. Addressing these gaps, future research should focus on developing efficient and lightweight CNN-based frameworks with optimized hyperparameters to balance accuracy and computational cost, enabling deployment on mobile and edge devices. Additionally, incorporating intelligent interpretation and explainable AI mechanisms will enhance transparency, improve user trust, and provide visual insights into disease symptoms. Integrating disease-specific treatment recommendations alongside classification outputs can further transform AI models into complete decision-support systems for precision agriculture. Expanding datasets with diverse, real-field images and extending models toward multi-crop disease detection will also improve robustness and scalability. These directions collectively pave the way for practical, interpretable, and farmer-centric AI solutions for sustainable crop health management.

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