Advancements in Deep Learning for Rice Disease Detection: A Comprehensive Review

Prabhat Kumar Suman
M.Tech Scholar
Department of Computer science & Engineering
Radharaman Engineering College, Bhopal, India.
Email: pksuman.pks.ps008@gmail.com

Rakesh Shivhare
Assistant Professor
Department of Computer science & Engineering
Radharaman Engineering College, Bhopal, India.
Email: rirtcollege@gmail.com

ABSTRACT: Rice, as a staple food for more than half of the global population, plays a crucial role in ensuring food security and sustaining agricultural productivity. However, its cultivation faces significant challenges due to various diseases that severely impact crop yield and quality. In recent years, advancements in artificial intelligence (AI) and particularly convolutional neural networks (CNNs) have revolutionized rice disease detection by enabling precise, early, and automated diagnosis. This review comprehensively analyzes of research studies conducted globally, focusing on the application of CNN-based deep learning techniques for rice disease identification. It examines diverse datasets collected across different geographic regions, highlighting how variations in climate, soil conditions, and agricultural practices influence disease patterns and data distribution. The paper explores preprocessing strategies, model architectures, transfer learning techniques, and hyperparameter optimization approaches, emphasizing their role in enhancing model performance. Performance metrics are critically evaluated to compare the effectiveness of different methodologies. Furthermore, the review identifies current challenges and outlines promising future research directions. By synthesizing insights from global research efforts, this paper underscores the potential of deep learning to advance smart agriculture and contribute to sustainable solutions for global food security.

Keywords: Rice disease detection, Deep learning, Convolutional Neural Networks (CNNs), Computer vision, Image classification, Federated learning, Explainable AI, Sustainable Agriculture.

1. Introduction

Plants are vital for life on Earth, providing oxygen, absorbing carbon dioxide, supporting biodiversity, and regulating climate. They serve as key sources of food, medicine, and raw materials while contributing to the economy and maintaining ecological balance, underscoring the need for their conservation [1–4]. Rice is a globally vital crop, serving as a staple food for over half the world's population and playing a crucial role in nutrition, food security, and economic sustainability. Rich in essential nutrients and a primary energy source, rice supports diverse culinary traditions and holds deep cultural significance. Its cultivation sustains millions of livelihoods, drives international trade, and contributes significantly to global economies. With its adaptability to varied agroclimatic conditions and preservation of biodiversity, rice remains indispensable for sustaining human life and ensuring global food security [5–8]. Rice is one of the most vital crops globally, serving as a staple food for over half of the world's population. Cultivated in diverse regions, rice plays a crucial role in ensuring food security and livelihoods for millions of people, particularly in Asia, where the majority of rice is grown and consumed. According to the Food and Agriculture Organization (FAO) of the United Nations, global rice production reached approximately 500 million metric tons in 2020, with Asia accounting for about 90 % of the total output [9]. China and India are the top rice-producing countries, with China leading at 149.0 million metric tons and India following closely at 118.0 million metric tons [10]. Additionally, Indonesia, Bangladesh, and Pakistan are among the largest rice-producing countries in Asia [11]. Rice is a crucial staple food for over half of the world's population, providing 60–70 % of caloric intake [12]. The demand for rice is continuously increasing, especially in regions like Asia and sub-Saharan Africa, where populations living in poverty heavily rely on rice as a primary food source [13]. Rice diseases significantly threaten global food security, economic stability, and farmer livelihoods. As a staple for over half the world's population, outbreaks reduce yield, affect grain quality, and disrupt international trade. They also impact soil health and sustainable agriculture, posing risks to environmental balance. Effective management requires innovative farming practices, scientific research, and global collaboration to ensure resilient rice production, food safety, and economic sustainability [14–16]. The global rice industry plays a crucial role in food security, trade, and economic sustainability. Major producers like China, India, Indonesia, Bangladesh, and Vietnam contribute significantly to global output, while countries such as India, Thailand, and Vietnam lead in exports. Key importers include nations across Africa, the Middle East, and parts of Asia. Rice cultivation supports the livelihoods of millions, particularly in Asia, and its trade has a substantial impact on international economies and market balances. Beyond agriculture, the industry influences employment, food security, and related sectors, making an understanding of global rice production and trade dynamics essential for shaping effective agricultural policies and economic stability [17–20]. Artificial intelligence (AI) has become increasingly significant in agriculture, particularly in rice disease detection. Among AI techniques, convolutional neural networks (CNNs) excel in analyzing image datasets to identify disease-related patterns with high accuracy and efficiency [21]-[29]. By training CNNs on images of healthy and diseased rice plants, these models enable rapid, reliable, and proactive disease management. While other algorithms like SVMs, decision trees, and random forests exist, CNNs remain the most effective for image-based detection. This paper distinguishes itself by providing a comprehensive analysis of datasets, preprocessing strategies, algorithms, and performance metrics based on insights from over 40 global studies. It emphasizes international collaboration, identifies existing challenges, and highlights future research opportunities in developing robust AI-driven solutions. By combining a forward-looking perspective with an in-depth methodological review, the study offers valuable insights for advancing AI-enabled rice disease detection and supporting sustainable agricultural practices [30]-[34].

2. Rice Plant Diseases Type

Rice plant diseases Various pathogenic microorganisms destroy rice plants' leaves, leading to many losses in the rice fields . These microorganisms, such as fungi, viruses, bacteria, and amoebain many plants, cause biotic diseases. These diseases reduce the quantity and quality of rice products. The most common rice diseases are discussed below. Fig. 1 illustrated some examples of the images of rice leaf diseases.

- Bacterial Leaf Blight (BLB): It is the most dangerous rice leaf disease caused by "Xanthomonas oryzae" bacteria. The Japanese farmers first identified this disease in 18846 . It is widespread in various regions of Africa, northern Australia, and the United States . The leaf affected by this disease has a gray-green, takes the color of straw (yellow), and finally dies after withering. The lesions have sharp borders and infect the bottom.
- Blast (BL): It is the most harmful disease that affects rice production, and this causes a threat to food safety. Magnaporthe oryzae causes it8 . It is a fungal disease. The first symptom is a change from white to patches of grey-green color that are concise (pivot-shaped), after becoming dark-red color and finally dark-brown edges. This disease has fewer crystal shapes with sharp ends and big cores.
- Brown Spot (BS): It is a damaging and common rice leaf disease caused by fungi . Rice diseases have many large spots that harm and affect the leaf. The round, small leaf 's color turns into purple-brown dark brown lesions. These can be discovered early on, producing lesions that turn into elliptical shapes with a light brown color to gray core with a reddish-brown perimeter caused by the fungi's blights.
- Tungro (TU): It is a very dangerous rice disease because of the virus10. It is found because the two viruses mix and are increased by green leafhoppers. It causes the slow development of rice plants, leaf discoloration, partially or sterile-filled grains, and fewer tillers. This disease affected cultivated rice, wild rice cousins, and other grassy weeds.
- Sheath Blight (SB): It is a widespread and dangerous rice disease caused by soilborne fungus. This disease is named 'snakeskin disease' and 'rotten foot stalk'11. Firstly, the Sheath blight symptom is a water-soaked lesion on leaves. After two or three days, this lesion has a grayish-white center surrounded by a dark color. After BL disease, this is the second most frequent rice disease and the most significant commercially12.
- Leaf Smut (LS): Leaf smut (LS) is caused by a fungus named Entyloma oryzae13. Even though it is not a serious disease, it can lead to other diseases by making an environment favorable to other fungi's growth. This disease's symptoms are tiny spots scattered through the leaf in a non-uniform shape. The lesions of leaf smut are reddish brown circular.

Various rice diseases affect the growth and productivity of crops, causing many ecological and economic problems. For this reason, it is very significant to identify these diseases. Correcting and identifying rice diseases can be performed manually or using computer-aided systems. Plant pathologists perform manual predication, which can be lengthy, tiresome, and expensive and may cause fatigue errors. Therefore, new advancements like machine learning and deep learning-based artificial intelligence have great attention in computer vision algorithms that are used in plant disease identification. Computer-aided rice leaf disease detection and classification systems face many challenges. These challenges can be classified into three main categories. First, there is insufficient size and variety of datasets because collecting images for rice leaves is very expensive and demands agricultural expertise for precise plant disease detection and identification.

Second, some rice leaf diseases have similar symptoms; even professionals or experts fail to identify them by eye. One symptom may vary because of geographic locations, weather conditions, and crop development. Third, there are many problems in rice leaves images like noise, illumination, and low contrast. There is a great advancement in image preprocessing and computer vision techniques in various fields which help in detection and classification rice plant diseases

a b c d e f

Figure 1. Different rice plant diseases (a) BLB, (b) BL, (c) BS, (d) TU, (e) SB, and (f) LS.

3. Literature Review

3.1 Traditional techniques

Yang et al. [12] proposed a microscopy-based method for detecting rice smut and rice blast diseases, which are among the most significant threats to rice production. Due to the small size and structural similarity of the spores, traditional microscopic detection is challenging. To address this, the authors utilized a combination of Histogram of Oriented Gradients (HOG), contour analysis, and texture feature extraction. They also introduced a distance transformation, Gaussian filtering, and watershed algorithm to separate overlapping spores, improving detection accuracy by approximately 10%. Four shape features (area, perimeter, ellipticity, and complexity) and three texture features (entropy, homogeneity, and contrast) were selected for classification using a decision-tree model. The confusion-matrix method was applied to assess performance, achieving a global accuracy of 82%, a Kappa coefficient of 0.81, and a detection accuracy of 94%. Similarly, Gayathri et al. [13] developed an automated rice leaf disease detection system using image processing techniques to address the significant yield losses (20–30%) caused by common rice diseases in India. The proposed framework involved four stages: image acquisition, preprocessing, segmentation, and classification. A hybrid feature extraction approach combining Discrete Wavelet Transform (DWT), Scale Invariant Feature Transform (SIFT), and Gray Level Co-occurrence Matrix (GLCM) was used to capture both spatial and textural details. The extracted features were classified using multiple algorithms, including K-Nearest Neighbor (KNN), backpropagation neural networks, Naïve Bayes, and multi-class Support Vector Machines (SVM). Experimental results, implemented in MATLAB, demonstrated that multi-class SVM achieved the highest accuracy of 98.63%, outperforming other classifiers significantly. Puspitasari et al. [14] introduced a color and shape-based approach for detecting rice blast disease. The methodology focused on extracting dominant color features using histogram analysis and converting images from the RGB to HSV color space for better green-channel representation. Shape-based features, including area, diameter, and perimeter, were calculated using morphological closing techniques, and Canny edge detection was applied after grayscale conversion to enhance boundary detection. The proposed model was evaluated on a dataset of 267 images with 74 testing samples divided into two categories: blast-infected and healthy leaves. The experimental results showed a detection accuracy of 85.71% using color features, 71.42% using shape features, and 85.71% when combining both color and shape features, indicating the effectiveness of multimodal feature integration for accurate disease identification.

Traditional AI techniques like SVM, Decision Trees, KNN, and feature-based image processing methods (e.g., color histograms, GLCM, shape descriptors) were initially used for rice disease detection and achieved good results in controlled settings. However, these methods relied heavily on handcrafted features, were sensitive to environmental changes, and lacked adaptability across different rice varieties, diseases, and growth stages. They also required complex preprocessing and segmentation, limiting their practicality for real-time applications. To address these challenges, researchers have shifted toward deep learning, especially CNNs, which automatically extract features, improve accuracy, enhance robustness, and enable scalable, field-ready systems for early and precise rice disease detection.

3.2 CNN-Based Transfer Learning Approaches

Transfer learning-based CNN architectures have shown significant success in rice disease classification. Megha et al. [17] employed a CNN-VGG model using transfer learning to identify brown spot, leaf blast, and leaf blight, achieving 95.6% accuracy compared to 85.62% without transfer learning. Rani et al. [31] compared multiple CNN models, including VGG16, Inception, MobileNetV2, DenseNet, and Xception, concluding that Xception performed best, achieving 86.90% training accuracy and 75% testing accuracy. Similarly, Upadhyay et al. [24] proposed a modified SqueezeNet with multi-scale feature aggregation (MFA), achieving 99.3% accuracy with extremely high precision (0.972–1.000) and recall (0.980–1.000). Tababa et al. [25] utilized ResNet50 to classify 14 rice diseases with a 99% accuracy, outperforming MobileNet (87%) and EfficientNet (91%). In addition, Islam et al. [32] improved pre-trained CNN performance by integrating Histogram of Oriented Gradients (HOG), where EfficientNet-B7 achieved 97% accuracy, highlighting the effectiveness of feature extraction in improving classification. Finally, Sharma et al. [26] applied ResNet50 on a large dataset of 600,000 rice images for variety identification, obtaining 96% training and 80.5% testing accuracy.

3.3 GAN-Based Data Augmentation

Data scarcity and imbalance are significant challenges in agricultural disease detection, and Ramadan et al. [18] addressed this by employing GAN-based data augmentation. Using simple GAN, CycleGAN, and DCGAN, they generated synthetic images to enrich datasets and improve CNN classification accuracy. Among these, the CycleGAN + MobileNet combination achieved the highest accuracy of 98.54%, demonstrating the potential of GANs to enhance dataset diversity, reduce overfitting, and improve detection performance.

3.4 Explainable Deep Learning Models

To address the "black-box" nature of CNNs, Lipsa et al. [22] introduced explainability techniques, integrating Layer-wise Relevance Propagation (LRP), SHAP, and LIME to interpret the model's decision-making process in rice disease classification. The model achieved 96.5% accuracy while improving transparency, enabling users to identify the most influential features for disease detection and fostering trust in AI-driven agricultural tools.

3.5 Multi-Architecture Comparisons

Several studies compare multiple deep learning architectures to identify the most effective models. Ayyappan et al. [19] evaluated CNN-based models, where DenseNet121 achieved 97.5% accuracy, followed by Xception (96.32%), EfficientNet B4 (96.25%), and MobileNet V3 Large (96.25%). Rahman et al. [20, 21] compiled a comprehensive dataset of 30,945 images across 35 plant diseases, applying nine CNN models. The study achieved 98% accuracy for rice using DenseNet121 and introduced a web and mobile application for real-time detection and treatment recommendations. Shafik et al. [23] proposed the IX-CNN model, combining inception and depthwise separable convolutions, achieving 99.79% accuracy on the Rice Disease dataset and over 99% on other datasets. Similarly, Shafik et al. [30] developed PDDNet-AE and PDDNet-LVE, two ensemble models integrating nine pre-trained CNNs, achieving 97.79% accuracy, demonstrating the superiority of ensemble learning over single-model approaches.

3.6 Transformer-Based Models

Recent advancements have seen the introduction of Vision Transformers (ViTs) for agricultural disease detection. Chitta et al. [33] compared custom CNNs and ViTs for rice leaf disease classification, finding that ViTs outperformed CNNs with an accuracy of 98.42% versus 96.33%. Similarly, Prommakhot et al. [28] proposed a two-stream CNN + BiLSTM + Transformer Network (TransNet), achieving 97.88% accuracy with enhanced feature mapping capabilities. These findings highlight the growing potential of transformer-based architectures for high-performance disease detection.

3.7 Federated and Distributed Deep Learning

Addressing privacy and scalability challenges, Pragya et al. [29] introduced the FDL-IWT framework (Federated Deep Learning with Intelligent Weight Transferring), which adapts local model weights based on Parallel MultiScale CNN (PMACNN). The model achieved 97.5% accuracy, outperforming seven state-of-the-art federated learning methods, showing its potential in collaborative and privacy-preserving agricultural applications.

3.8 Object Detection-Based Approaches

Beyond classification, Sambana et al. [27] implemented YOLOv7 and YOLOv8 models for real-time detection of plant diseases. YOLOv8 demonstrated superior performance with a mean Average Precision (mAP) of 91.05, precision of 91.22, and an F1-score of 89.40, making it highly effective for automated monitoring and early disease detection in large-scale agricultural settings.

3.9 High-Performance Disease Classification

Finally, Banerjee et al. [34] developed a high-performance rice disease classification model with consistently high precision (93–94%), recall (93–94%), and an F1-score of ~94%, achieving an overall accuracy of 98%. The study demonstrates the capability of deep learning models to achieve balanced and robust performance across multiple disease categories.

3.10 Hybrid Techniques

Several studies integrate multiple algorithms and modalities to enhance rice and plant disease detection accuracy. Padhi et al. [15] proposed a hybrid deep learning approach combining thermal imaging with CNN-based transfer learning. By evaluating eighteen CNN models, Darknet53 was identified as the best performer with 95.79% accuracy, which was further improved to 99.43% by replacing its dense layer with an SVM classifier. Similarly, Vijayan et al. [16] developed the Hybrid WOA_APSO algorithm, integrating the Whale Optimization Algorithm and Adaptive Particle Swarm Optimization for feature selection alongside CNN-based classification. Using the PlantVillage dataset, the proposed model achieved an impressive 97.5% accuracy, demonstrating the potential of hybrid bio-inspired optimization techniques in improving classification efficiency.

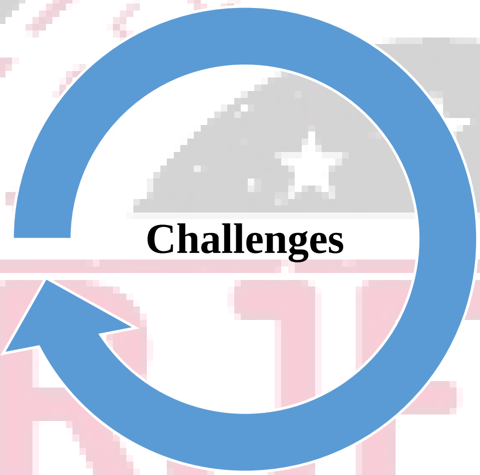
Table I. Recent Research Contributions

Study	Dataset	Model	Technique	Accuracy
Vijayan et al. [16]	PlantVillage dataset	CNN + WOA_APSO	Hybrid Bio-inspired Optimization	97.5%
Megha et al. [17]	1,800 rice images	CNN-VGG	Transfer Learning	95.6%
Rani et al. [31]	Rice disease dataset	Xception	Comparison of VGG16, Inception, MobileNet, DenseNet	86.9%
Islam et al. [32]	Rice disease dataset	EfficientNet-B7 + HOG	Feature Extraction Integration	97%
Sharma et al. [26]	600,000 rice images	ResNet50	Rice Variety Identification	96% train, 80.5% test
Ramadan et al. [18]	Rice leaf dataset	MobileNet + CycleGAN	GAN-based Data Augmentation	98.54%
Lipsa et al. [22]	Rice disease dataset	CNN + LRP, SHAP, LIME	Explainable AI	96.5%
Ayyappan et al. [19]	Rice disease dataset	DenseNet121	Comparison with Xception, EfficientNet, MobileNet	97.5%

Shafik et al. [30]	PlantVillage dataset	PDDNet-AE + PDDNet-LVE	Ensemble CNN Models	97.79%
Chitta et al. [33]	Rice leaf dataset	Vision Transformer	CNN vs ViT Comparison	98.42%
Prommakhot et al. [28]	PlantVillage dataset	CNN + BiLSTM + TransNet	Transformer-based Sequential Learning	97.88%
Pragya et al. [29]	Plant leaf datasets	PMACNN (FDL-IWT)	Federated Deep Learning	97.5%
Banerjee et al. [34]	Rice disease dataset	Custom CNN	High-Performance Classification	98%

4. Challenges and Future Direction

Despite the remarkable progress in applying deep learning for rice and plant disease detection, several limitations persist. Some of them are presented in fig 2. Future research should focus on building large-scale, diverse, and publicly available datasets that capture real-world variability.



- Insufficient large-scale, labeled rice disease datasets.
- Difficulty adapting models to diverse environmental conditions.
- Limited interpretability of CNN-based systems.
- High computational and hardware requirements for training and deployment.
- Development of unified, large-scale open-access rice disease datasets.
- Incorporation of explainable AI (XAI) for transparent decision-making.

5. Conclusion

This systematic review presents a comprehensive analysis of recent advancements in deep learning techniques for rice disease recognition, highlighting their potential to transform modern agricultural practices. As a staple food for over half of the global population, rice production faces significant threats from various diseases that cause substantial yield and quality losses. Deep learning, particularly convolutional neural networks (CNNs) and their variants, has emerged as a powerful tool for automating disease detection, enabling early diagnosis and effective crop management. By synthesizing findings from diverse studies, this review explores current trends, widely adopted model architectures, and data preprocessing strategies while providing an in-depth evaluation of commonly used datasets and their inherent limitations. The analysis underscores that while CNN-based approaches have achieved remarkable accuracy, challenges such as limited real-world datasets, overlapping disease symptoms, and lack of model interpretability remain significant barriers to large-scale deployment. Addressing these issues through multimodal data integration, explainable AI, lightweight architectures, and federated learning frameworks can further enhance model robustness and practical usability. Overall, this review serves as a valuable resource for researchers and practitioners, offering key insights to guide the development of efficient, scalable, and intelligent automated systems for rice disease detection and management, ultimately contributing to sustainable agriculture and global food security.

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