

Deep Learning in Rice Disease Detection: A Systematic Analysis of Techniques, Strategies and Model Generalization

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Abstract

Rice diseases significantly reduce crop yield and threaten global food security, particularly in developing agricultural systems. Deep learning approaches, mostly CNN, have shown promising performance in automated rice disease detection. However, despite high reported accuracies, concerns remain regarding model overfitting, limited dataset diversity, and insufficient evaluation of generalization performance under real-world conditions. This research provides a structured review of deep learning-based rice leaf disease detection methods published between 2018 and 2026. Using a structured search and predefined selection criteria, relevant studies were analyzed based on method/model architecture, and performance. The review identifies dominant adoption of transfer learning models such as VGG, ResNet, DenseNet, EfficientNet, and YOLO-based detection frameworks. While most studies report classification accuracies above 90%, demonstrating the capability of deep learning techniques in accurately identifying rice diseases from images. The analysis further reveals that explicit application and systematic evaluation of regularization techniques are rarely emphasized. Similarly, data augmentation strategies are commonly applied but often lack detailed investigation regarding their impact on generalization performance. These gaps indicate the need for focused research on improving robustness and preventing overfitting in rice disease detection systems. The findings provide a foundation for developing more generalized and reliable deep learning models for practical agricultural deployment.

Keywords: *Transfer Learning, Deep Learning, Rice Leaf Disease, Ensemble Learning, DenseNet*

I. INTRODUCTION

Rice serves as a primary food crop for over half of the world's population and is central to global food

security, especially across regions such as Asia and Sub-Saharan Africa (Arouna et al., 2021). In developing economies, rice farming also plays a vital role in supporting rural livelihoods by providing income and

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employment opportunities (Vinci et al., 2023). Despite its importance, rice production is highly vulnerable to a range of foliar diseases, including bacterial leaf blight, blast, and brown spot, which negatively affect both crop yield and grain quality, resulting in notable economic losses. Consequently, the early and precise identification of these diseases is critical for efficient farm management and the promotion of sustainable agricultural practices (Mirandilla et al., 2023).

Conventional approaches to disease diagnosis primarily rely on expert-based visual assessment. While this method can be effective, it is often labor-intensive, time-consuming, and unsuitable for large-scale agricultural operations (Khan et al., 2025). In addition, diagnostic accuracy may be influenced by the evaluator’s level of expertise and varying environmental conditions. Recent progress in computer vision and artificial intelligence has introduced more efficient alternatives for automated plant disease detection. In particular, deep learning methods, especially convolutional neural networks (CNNs), have demonstrated strong performance in image classification tasks and are increasingly being applied to agricultural disease identification (Wang et al., 2025).

A range of deep learning models have been adopted for rice disease classification and detection. Models such as VGG16, ResNet, DenseNet, MobileNet, and EfficientNet have demonstrated high classification performance across multiple datasets (Simhadri et al., 2025). In addition, object detection frameworks including

YOLOv8 have been explored for real-time field applications. Many published studies report high accuracy values, highlighting the potential of deep learning to transform plant disease diagnostics (Nouman Noor et al., 2026).

Despite these advancements, the literature remains fragmented. Existing studies on rice diseases detection vary widely in dataset characteristics, evaluation protocols, experimental settings, and performance reporting standards. Differences in image acquisition conditions, dataset size, class distribution, and validation strategies make it difficult to draw consistent conclusions regarding model robustness and practical applicability (Zhang et al., 2025). Furthermore, while numerous models have been proposed, comparative insights into architectural trends, dataset usage patterns, and real-world deployment considerations remain limited. Given the rapid growth of research in this area, there is a need for a comprehensive synthesis that consolidates existing findings and critically examines methodological trends. This systematic review aims to analyze recent studies on deep learning approaches for rice leaf disease detection by examining commonly used methods and approach used.

II. RESEARCH METHODOLOGY

This section describes the systematic procedure adopted to identify, screen, and analyze relevant studies on deep learning-based rice leaf disease detection. The methodology was designed to ensure transparency, consistency, and replicability in the review process.

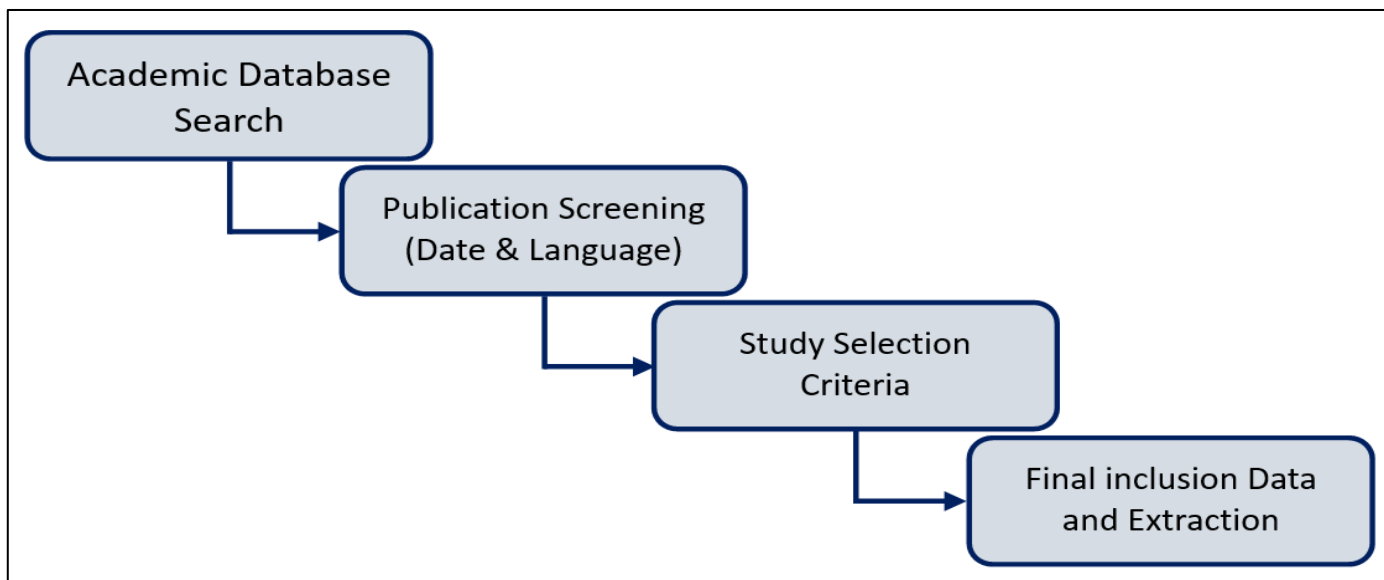


Fig 1 Study Selection Criteria

➤ Review Design

A well-defined systematic review methodology was adopted to integrate and analyze existing studies on deep learning methods applied to rice leaf disease detection. The review specifically considers peer-reviewed publications from 2018 to 2026, a timeframe characterized by rapid advancements in the use of deep learning for agricultural image analysis. Emphasis was placed on widely utilized model architectures and their reported

performance outcomes. Through the use of a structured and methodical approach, this study seeks to deliver an unbiased and comprehensive assessment of recent progress in deep learning-based rice disease detection.

➤ Search Strategy

An extensive literature search was performed to locate studies focused on deep learning applications in rice disease detection. To achieve comprehensive coverage,

several major academic databases were examined, including IEEE Xplore, Elsevier ScienceDirect, SpringerLink, and Google Scholar. These platforms were chosen because they provide broad access to publications in computer science, artificial intelligence, and agricultural informatics. To enhance search accuracy, carefully defined queries incorporating rice-specific keywords were applied. The main search expression utilized Boolean logic, combining terms such as “*rice leaf disease*,” “*rice plant disease*,” and “*paddy leaf disease*” with “*deep learning*,” “*convolutional neural network*,” “*CNN*,” and “*transfer learning*,” along with “*classification*,” “*detection*,” or “*recognition*.”

The search process was limited to English-language studies published between 2018 and 2026, a period selected due to the rapid advancement of deep learning techniques in agricultural image analysis. Furthermore, the reference lists of the selected papers were manually reviewed to identify additional relevant studies that satisfied the inclusion criteria.

➤ *Study Selection Criteria*

Clearly defined selection criteria were established to ensure the inclusion of studies that are both relevant and methodologically robust. To qualify, studies needed to specifically address rice leaf disease detection using deep learning approaches and present measurable experimental outcomes. Only peer-reviewed articles from journals and conferences, published in English between 2018 and 2026, were considered. Furthermore, each selected study was required to include detailed methodological information, such as the model architecture and the evaluation metrics used to assess performance.

Studies were excluded if they focused on crops other than rice, employed only conventional machine learning techniques without incorporating deep learning methods, or were purely review or survey papers. In addition, works lacking experimental validation, quantitative performance results, or sufficient methodological detail were omitted. Duplicate entries identified during the data collection stage were removed before the screening process to ensure accuracy and eliminate redundancy.

III. RELATED WORK

The use of deep learning techniques for rice disease detection has attracted considerable interest, primarily due to their ability to process large and complex image datasets effectively. A wide range of studies have investigated different model architectures, datasets, and training methodologies to enhance the accuracy and reliability of disease classification systems. Collectively, these efforts emphasize the expanding importance of artificial intelligence in contemporary agriculture, particularly in enabling automated disease diagnosis and advancing precision farming practices.

An ensemble deep CNN model was developed by (Pai et al., 2025) for the detection and classification of rice diseases. The system integrates four high-performing

architectures GoogLeNet, ResNet-34, DenseNet-121, and VGG-16 selected from seven pretrained models based on performance evaluation. The model was trained and tested on a dataset of 18,563 rice leaf images encompassing six major diseases: bacterial stripe, sheath blight, false smut, leaf blast, neck blast, and brown spot. The model achieved an accuracy of 96.81%, outperforming individual CNN models in precision, recall, and F1-score.

The authors (Li et al., 2024) addressed limitations of prior rice disease detection systems by constructing a large-scale multi-class dataset composed of eleven disease categories plus a healthy class. They evaluated multiple CNN architectures both with and without transfer learning and found that DenseNet (without pretraining) achieved 95.7 % accuracy (precision 95.3 %, recall 94.8 %, F1 95.0) with only 6.97 M parameters. When using transfer learning (ImageNet weights), the RegNet model delivered the best overall performance: accuracy 96.8 %, precision 96.2 %, recall 95.9 %, F1 96.0 % with just 3.91 M parameters. The authors also developed a mobile app implementing the RegNet model for field deployment, but they acknowledge limitations in automation and suggest further work to streamline detection of early disease stages and fully automated pipelines.

A hybrid approach combining image segmentation, convolutional neural networks, and SVM classifiers to detect and classify rice (paddy) leaf diseases, including bacterial leaf blight, false smut, brown leaf spot, rice blast, and sheath rot was proposed by (Haridasan et al., 2023). After preprocessing and segmenting diseased regions, the system classifies each disease based on visual patterns. The model attained a validation accuracy of 91.45%, highlighting the potential of integrating segmentation and hybrid classifiers for disease recognition, though the authors note that improvements are needed in robustness under varying field conditions.

A hybrid approach combining Hierarchical Convolutional Recurrent Neural Network (HCRNN) and LSTM was proposed by (Noorishta Hashmi, 2025) to record both spatial and temporal patterns in rice disease progression. The HCRNN component extracts multi-scale spatial features from leaf images, while the LSTM module models the temporal evolution of symptoms. Experimental evaluation conducted on a dataset containing images of multiple rice diseases, including bacterial leaf blight, blast, and sheath blight, achieved an overall accuracy of 98.5%. The authors further recommend enhancing the model by incorporating environmental factors, such as soil conditions and weather data, to improve its predictive performance.

A study on rice plant leaf disease detection using CNN was presented by (Ayyappan et al., 2025) evaluating multiple architectures for classifying diseases such as blast, brown spot, and bacterial blight. They compared DenseNet-121, Xception, EfficientNet B4, and MobileNet V3 Large models on their dataset and reported that DenseNet-121 achieved the highest accuracy of 97.50 %, while Xception reached 96.32 %, and both EfficientNet B4

and MobileNet V3 Large achieved 96.25 %. The work underscores the tradeoffs between accuracy and computational complexity, noting that model selection should consider resource constraints for practical deployment.

A deep learning-based model for the identification and classification of rice plant diseases was implemented by (Venkatesh et al., 2023) to enhance precision agriculture. The study employed a Convolutional Neural Network with an attention mechanism (CNNAM) for detecting and classifying rice diseases from field images. The attention mechanism helped the model focus on key regions of infected leaves, improving feature extraction and disease recognition accuracy. The proposed CNNAM achieved an impressive classification accuracy of 99.8%, demonstrating its robustness and superiority over traditional machine learning methods in identifying rice plant diseases.

An enhanced transfer learning framework by (Latif et al., 2022) built upon the VGG19 architecture for classifying rice leaf diseases into six categories: healthy, narrow brown spot, leaf scald, leaf blast, brown spot, and bacterial leaf blight. The model was trained using an augmented dataset without normalization and achieved an average accuracy of 96.08%. In addition, the model demonstrated strong performance with precision, recall, specificity, and F1-score values of 0.9620, 0.9617, 0.9921, and 0.9616, respectively.

A hybrid optimization-enabled deep learning framework was introduced by (Daniya & Vigneshwari, 2023) for rice leaf disease detection and classification. The method begins with ROI extraction and deep fuzzy clustering for segmentation, and integrates multiple feature types statistical, entropy, CNN features, LOOP, and LGXP before classification. In the first stage, a deep neuro-fuzzy network trained via a rider henry gas solubility optimization algorithm distinguishes healthy and unhealthy leaves; in the second stage, a deep residual network (DRN) tuned by RHGSO classifies unhealthy leaves into bacterial leaf blight, blast, or brown spot. The model achieved an overall accuracy of 93.04%, sensitivity of 94.59%, specificity of 83.83%, and F1-score of 91.42%.

An app was developed by (Deng et al., 2021) for diagnosis of rice diseases using deep learning and deployed it as a smartphone app. They collected a large dataset of 33,026 images covering six disease classes: leaf blast, false smut, neck blast, sheath blight, bacterial stripe disease, and brown spot. Through experimentation, they selected three high-performing CNNs DenseNet-121, SE-ResNet-50, and ResNeSt-50 as submodels, then combined them via ensemble voting. On the test set, the ensemble model achieved an overall classification accuracy of 91%, showing improved consistency and reduced misclassification among visually similar disease classes.

A CNN based approach for detection of rice diseases under field conditions was implemented by (Kumar et al., 2025). The authors collected rice leaf images and trained a

CNN model to classify disease types, reporting a classification accuracy of 906.5%. The work demonstrates the viability of CNNs in rice disease detection, though it provides limited detail on the dataset size, regularization techniques used, or model robustness under varying environmental conditions.

A deep learning-driven framework for detecting biotic rice leaf diseases was introduced by (Kaur et al., 2024). The study employed VGG16, SqueezeNet, and InceptionV3 models with fine-tuned hyperparameters including batch size, learning rate, optimizer, and number of epochs. Among the configurations tested, SqueezeNet combined with a neural network classifier achieved the best performance, recording an accuracy of 93.3%, an AUC of 0.989, a precision of 0.928, a recall of 0.931, and an F1-score of 0.928. The proposed model demonstrated robust feature extraction and improved classification performance for multiclass rice leaf disease detection.

A three-stage CNN architecture with transfer learning was proposed by (Gogoi et al., 2023) for rice disease classification. The model employs transfer learning, progressive resizing of image inputs, and PReLU activation to reduce overfitting and improve learning from a relatively small dataset (8,883 diseased images + 1,200 healthy images). The approach achieved an accuracy of 94.0 % under 10-fold cross-validation, indicating its capability to generalize with limited data.

A deep CNN approach using transfer learning and optimization was introduced by (Mandwariya & Jotwani, 2024) for automated detection and classification of rice leaf diseases. The system classifies eleven disease types including healthy, leaf blast, brown spot, bacterial blight, false smut, neck blast, stemborer, tungro, hispa, and BPH. Several pretrained architectures (XceptionNet, ResNet50, DenseNet, VGG19, SqueezeNet) were evaluated using optimization methods SGDM, Adam, and RMSProp. Among these, XceptionNet achieved the highest accuracy of 93.3% on the tested dataset.

A deep-transfer-learning was introduced by (Chen et al., 2020) for detecting rice plant diseases. The proposed architecture combines a DenseNet pretrained on ImageNet with an Inception module to enhance feature extraction, then uses the combined network (termed DENS-INCEP) to classify rice disease images from a public dataset. The model achieved a minimum average prediction accuracy of 94.07%, and when multiple disease classes were considered, reached an average accuracy of 98.63% under the tested conditions.

An attention residual U-Net model was developed by (Rai & Pahuja, 2023) for the segmentation and detection of rice diseases from leaf images. The model was trained from scratch and compared against baseline U-Net and Attention U-Net architectures. The proposed network achieved a segmentation accuracy of 94.11%, with a Dice coefficient of 0.9626 and a Jaccard coefficient of 0.6476.

An automatic rice disease detection and assistance framework comprising a mobile application (“E-crop doctor”) and a chatbot (“docCrop”) was developed by (Jain et al., 2022) developed to support farmers in diagnosing paddy leaf diseases and recommending treatments. The system employs object detection algorithms specifically YOLOv3-tiny and YOLOv4-tiny to identify three diseases (brown spot, leaf blast, and hispa) from on-field and laboratory images of paddy leaves. Among the two, YOLOv4-tiny achieved a mean average precision (mAP) of 97.36%, outperforming YOLOv3-tiny by about 17.59%. The framework facilitated real-time deployment on smartphones and continuous farmer support via the chatbot.

A rice leaf disease detection system using the YOLOv8 deep learning architecture was proposed by (Dewi et al., 2024) for identifying multiple rice diseases including hispa, brown spot, and leaf blast. The model was trained on a dataset consisting of four classes healthy, hispa, brown spot, and leaf blast and optimized for object detection using convolutional neural network principles. The system achieved an average accuracy of 97%, demonstrating effective performance in early disease identification. The model was trained on Google Colab Pro using a Tesla T4 GPU, enabling efficient and accurate detection suitable for real-time agricultural applications.

The authors, (Kokila et al., 2025) proposed a convolutional neural network-based approach for the automated detection and classification of rice leaf diseases

using deep learning. The model was trained on a dataset of rice leaf images collected from different regions of India, comprising healthy leaves and those affected by common diseases such as blast, brown spot, and bacterial leaf blight. The architecture achieved accuracy of 82.35% for ResNet101, 85.23% for DenseNet201, and 89.95% for YOLOv5.

An automated deep learning approach was developed by (Rahman et al., 2024) for paddy disease detection using a dataset of 8,526 images across seven classes: bacterial blight, blast, brown spot, leaf scald, sheath blight, tungro, and healthy leaves. Two models, CNN and ResNet-50, were trained and evaluated, with the ResNet-50 model achieving an accuracy of 97%, outperforming the CNN model, which attained 88%. The enhanced ResNet-50 model was deployed in a mobile application built with Flutter and FastAPI, enabling real-time disease identification from leaf images. The system demonstrates strong potential for practical agricultural diagnostics and sustainable farming.

The authors, (Jayaraju et al., 2025) presented a comparative study using deep learning for rice leaf disease detection. The authors applied transfer learning on a real-time dataset from the Raipur region, evaluating both ResNet-50 and VGG16 architectures. ResNet-50 achieved a testing accuracy of 97.57%, while VGG16 recorded 91.63%. The work highlights the superior performance of deeper models and underscores the importance of model selection for effective precision agriculture applications.

Table 1 Summary of Reviewed Literature on Rice Leaf Disease Detection

Author	Method/Model	Accuracy (%)	Limitations
(Pai et al., 2025)	An ensemble deep learning approach, combining the predictions of four convolutional neural network architectures: GoogLeNet, DenseNet-121, ResNet-34, and VGG16	96.81	Ensemble models, while highly accurate, require significant computational resources compared to single models
(Li et al., 2024)	Constructs a multi-class rice disease dataset comprising 11 disease classes, 1 healthy class, then evaluates several advanced deep learning; RegNet, ResNet, DenseNet, EfficientNet, MobileNet	96.80	Certain diseases with visually similar symptoms were more difficult to distinguish
(Haridasan et al., 2023)	Hybrid computer vision and deep learning pipeline that combined: Image preprocessing and segmentation Convolutional Neural Networks, Support Vector Machine	91.45	Relies on segmentation quality, which may vary in field conditions
(Noorishta Hashmi, 2025)	The study used a hybrid deep learning architecture combining: Hierarchical Convolutional Recurrent Neural Network, Long Short-Term Memory	98.50	hybrid HCRNN-LSTM architecture is more complex than standard CNNs, potentially requiring more computational resources
(Ayyappan et al., 2025)	evaluated various convolutional neural network (CNN) architectures for rice disease classification: DenseNet121, Xception, EfficientNet-B4, MobileNetV3 Large	DenseNet121: 97.50 Xception: 96.32 EfficientNet-B4: 96.25 MobileNetV3 Large: 96.25	The study did not report performance on external unseen datasets, limiting assessment of generalization to new conditions.

(Venkatesh et al., 2023)	Applies deep learning for rice plant disease classification. Models/approaches reportedly include: Transfer learning with Convolutional Neural Network	99.80	restricting diversity of disease and environment scenarios.
(Latif et al., 2022)	deep convolutional neural network (DCNN) transfer learning approach based on: Modified VGG19 architecture	96.08	Reliance on non-normalized data may influence robustness under natural field conditions
(Daniya & Vigneshwari, 2023)	Hybrid approach combining; Region-of-Interest extraction + Deep fuzzy clustering Deep neuro-fuzzy network trained with Rider Henry Gas Solubility Optimization Deep Residual Network tuned by RHGSO for final disease classification Feature extraction including CNN features, statistical features, Local Optimal-Oriented Pattern, and Local Gabor XOR Pattern	93.04	The combination of feature extraction, clustering, optimization, and deep learning increases system complexity.
(Deng et al., 2021)	EVALUATED several convolutional neural network models as components of an ensemble system for rice disease diagnosis: ResNet-50, DenseNet-121, SE-ResNet-50, ResNeXt-50, ResNeSt-50	91.00	Ensemble models may overfit if dataset diversity is insufficient
(Kumar et al., 2025)	Deep learning approach using a custom Convolutional Neural Network	96.50	focuses on only three common diseases: blast, brown spot, and bacterial leaf blight
(Kaur et al., 2024)	A deep learning-based ensemble pipeline for detecting and classifying biotic diseases in rice leaves. Key components include: Pre-trained CNN Feature Extractors: VGG16, SqueezeNet, InceptionV3	93.30	Fine-tuning multiple deep networks and running ensemble classifiers can be computationally heavy
(Gogoi et al., 2023)	three-stage Convolutional Neural Network, adopting Transfer learning, Parametric Rectified Linear Unit	94.00	Progressive re-sizing and multi-stage training could increase training time and resource needs
(Mandwariya & Jotwani, 2024)	deep learning-based framework using pre-trained Deep Convolutional Neural Networks with optimization techniques. Using Pre-trained CNN, XceptionNet, ResNet50, DenseNet, VGG19, SqueezeNet	93.30	While multiple large pre-trained models were evaluated, does not report inference times or resource requirements,
(Chen et al., 2020)	A deep learning approach using Transfer Learning with Pre-trained CNN	94.07	Transfer learning with deep networks imposes significant computational resources
(Rai & Pahuja, 2023)	Deep learning for detection and segmentation, Deep Convolutional Neural Networks, Attention Residual U-Net Model	94.11	Training deep models from scratch without transfer learning may require extensive training data; limited data could reduce robustness
(Jain et al., 2022)	Integrated deep learning-based object detection system combined with a mobile application and chatbot. Object Detection Models Compared: YOLOv3-tiny, YOLOv4-tiny	97.36	Object detectors may perform well on curated images, but field conditions could degrade performance
(Dewi et al., 2024)	A deep learning-based object detection approach using YOLOv8	97.00	Although YOLOv8 is efficient, deploying the full model on resource-constrained devices still requires careful optimization
(Kokila et al., 2025)	Evaluates and compares multiple deep learning models. YOLOv5, DenseNet-201, ResNet-101	ResNet101 82.35, DenseNet201 85.23, YOLOv5 89.95	Like many image-based classifiers, models trained on curated datasets may not generalize well to in-field conditions

(Rahman et al., 2024)	A deep learning-based rice disease detection. CNN and ResNet50	CNN 88.00, ResNet50 97	Although the model is integrated into a mobile app, resource consumption and inference performance on low-end
(Jayaraju et al., 2025)	Develops and compares deep learning models using transfer learning. ResNet50, VGG16	ResNet50 97.57 VGG16 91.63	While ResNet-50 is compared to VGG16, the study does not compare with other modern architectures like DenseNet,

IV. LIMITATION

Across the reviewed studies, several methodological limitations are consistently observed. In the study by (Deng et al., 2021), although an ensemble of deep convolutional architectures was employed for rice disease diagnosis, evaluation was conducted on a single collected dataset without external cross-dataset validation, which limits assessment of real-world generalization. Similarly, (Latif et al., 2022) implemented a modified VGG19-based model with high reported accuracy, yet testing was confined to the same dataset used for model development. In the work by (Li et al., 2024), multiple architectures including RegNet and other CNN variants were evaluated; however, validation was performed using internal data splits only, with no independent dataset verification. Hybrid and optimization-based approaches proposed by (Daniya & Vigneshwari, 2023) and (Noorishta Hashmi, 2025) introduced multi-stage pipelines combining clustering, feature extraction, and deep models, but these methods increase architectural complexity. Likewise, the CNN-based approach reported by (Kumar et al., 2025) and the conference study under (Venkatesh et al., 2023) present promising accuracy results without reporting external validation under varying environmental conditions.

Many studies emphasize overall accuracy while providing limited analysis of class-wise performance, early-stage symptom detection, or resilience to environmental variability such as lighting fluctuations and occlusion. Although ensemble and optimization-driven models improve classification metrics, their computational demands may constrain deployment on resource-limited mobile or edge devices commonly required in practical agricultural settings. Finally, explicit investigation of regularization strategies and systematic assessment of their impact on generalization performance are rarely applied, indicating an important gap in the current literature.

V. DISCUSSION OF FINDINGS

The reviewed studies demonstrate a consistent reliance on deep convolutional neural networks for rice leaf disease detection.

Architectures such as ResNet, DenseNet, VGG, EfficientNet, MobileNet, and YOLO-based models dominate the field, with most studies reporting classification accuracies above 90%. These results confirm the effectiveness of deep learning techniques for image-

based rice disease recognition under controlled experimental settings.

Transfer learning is widely adopted to enhance feature extraction and improve performance, particularly when datasets are limited. Ensemble and hybrid approaches are also frequently used to achieve higher predictive accuracy. However, performance evaluation is predominantly based on internal dataset splits, with limited cross-dataset validation. As a result, although reported accuracies are high, generalization across diverse environmental and field conditions remains insufficiently examined. While data augmentation is commonly applied, explicit and systematic investigation of regularization techniques to prevent overfitting and improve robustness is rarely emphasized. This indicates that future research should focus not only on architectural improvements but also on strengthening generalization performance for reliable real-world deployment.

VI. CONCLUSION

This systematic review examined recent developments in deep learning-based rice leaf disease detection published between 2018 and 2026. The analysis shows that convolutional neural networks, transfer learning approaches, ensemble frameworks, and hybrid architectures dominate current research, with most studies reporting high classification accuracy under controlled experimental conditions. These findings confirm the effectiveness of deep learning techniques for automated rice disease recognition. However, evaluation procedures are largely based on internal dataset splits, and variations in dataset characteristics and reporting standards limit direct comparison across studies. Limited emphasis on cross-dataset validation and systematic generalization assessment raises concerns regarding robustness in real agricultural environments. Although data augmentation is commonly applied, explicit investigation of regularization strategies to prevent overfitting is rarely treated as a primary objective.

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