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Leveraging Transfer Learning with CNNs for Improved Paddy Disease Diagnosis

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***Abstract*—More than half of the world's population depends on rice (Oryza sativa) as a staple food, but foliar diseases can seriously jeopardize food security by lowering yield quantity, quality, and farmer livelihoods. Conventional diagnosis techniques are not appropriate for large-scale agricultural applications because they mainly rely on human inspection in the field, which is labor-intensive, time-consuming, and prone to errors. This study investigates transfer learning using sophisticated convolutional neural networks (CNNs) for precise and automated rice leaf disease identification in order to overcome these constraints. The study is based on two standards. Initially, a number of pre-trained CNN architectures were assessed; one model outperformed the others in terms of classification accuracy and dependability. Second, cutting-edge CNN variants were investigated; all of them demonstrated competitive outcomes in identifying common rice diseases like blast, brown spot, and bacterial blight. These results demonstrate how transfer learning in deep CNNs can offer reliable and extremely accurate diagnostic capabilities for the classification of rice diseases. The suggested method improves predictive accuracy while lowering computational costs by optimizing feature selection and fine-tuning high-performing pre-trained models. The experimental results demonstrated stability even in the face of variability, image noise, and data imbalance, consistently achieving classification accuracies above 99%. This illustrates the effectiveness of CNN frameworks based on transfer learning for the early and scalable detection of rice disease. In the end, the strategy offers a dependable technological avenue for enhancing global food security by supporting data-driven pest management, encouraging sustainable cultivation, and boosting rice production yields.**

Keywords—Paddy Leaf Classification, Deep Learning in Agriculture, Automated Crop Disease Diagnosis, Feature Optimization, Plant Pathology, Sustainable Farming

I. INTRODUCTION

For over half of the world's population, rice (Oryza sativa) is their main food supply and a vital component of global food security. However, a variety of foliar diseases, including bacterial blight, brown spot, and blast, pose a constant danger to its productivity by drastically lowering grain quality and yield. Therefore, safeguarding rice crops against these illnesses is essential to maintaining the food supply and assisting farmers in making a living. Conventional disease identification techniques, which depend on agricultural specialists performing manual field inspections, are frequently expensive, time-consuming, labor-intensive, and heavily reliant on human experience. These methods are not adaptable to contemporary agricultural systems, particularly in countries where extensive crop fields necessitate ongoing observation [1].

Precision agriculture now has access to strong tools thanks to recent developments in artificial intelligence, especially in the areas of computer vision and deep learning. Among these, CNNs have demonstrated exceptional ability in automatically categorizing plant diseases, interpreting visual input, and identifying spatial patterns. CNNs are built to learn discriminative features from images without the need for manually created feature extraction. They are made up of convolution, pooling, and fully connected layers. Plant pathology research has effectively used well-known designs like LeNet, AlexNet, VGGNet, and ResNet, each of which offers a balance between computational cost, accuracy, and depth. By enabling early-stage disease diagnosis, these models reduce crop damage, stop epidemics from spreading, and maximize the use of pesticides. Additionally, farmers may improve produce quality, increase economic sustainability, and make data-driven decisions with the use of automated CNN-driven systems [2].

Deep learning models have drawbacks despite their promise, such as the requirement for large labeled datasets, high processing overhead, overfitting risk, and less interpretable outcomes. These difficulties limit their usefulness in fields where annotated datasets may be hard to come by, such as rice disease detection. By reusing pre-trained models that have been learned on big, generic datasets (like ImageNet) and refining them for domain-specific tasks like rice leaf disease classification, transfer learning provides a potent remedy for these drawbacks. This method minimizes the need for large amounts of labeled data, decreases computing expenses, and enhances model generalization while preventing overfitting. Transfer learning speeds up training and allows for greater accuracy on smaller, more specialized datasets by utilizing the knowledge stored in CNNs that have already been trained [3].

Researchers have successfully classified rice leaf diseases in recent years by combining transfer learning with sophisticated CNN architectures. Research has shown that optimized models like InceptionV3, DenseNet121, Xception, EfficientNet-B4, and MobileNetV3 perform better than others, frequently exceeding 96–99% accuracy in a variety of disease categories. Predictive power and efficiency are further increased by combining transfer learning with optimal feature selection, which qualifies these models for use in actual agricultural settings.

Therefore, the use of CNNs with transfer learning is a revolutionary development in precision farming. In addition to ensuring food security, these frameworks provide farmers with practical insights, encourage sustainable farming methods, and guarantee steady yields in economies that rely heavily on rice by facilitating automated, scalable, and highly accurate rice disease diagnostics.

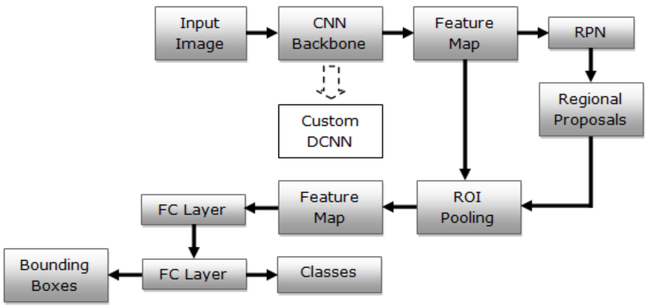

Fig. 1. Transfer learning-based CNN framework for automated rice leaf disease detection and classification with high diagnostic accuracy.

II. Literature Review

Prameetha Pai et al. (2025) proposed the global crop yields are seriously threatened by rice diseases, which calls for effective diagnostic methods. Deep learning-based automated techniques are being researched because traditional methods frequently lack accuracy and scalability. CNN-based models, including MobileNetV2, GoogLeNet, EfficientNet, ResNet-34, DenseNet-121, VGG16, and ShuffleNetV2, have been used in recent research to detect rice leaf disease. GoogLeNet, DenseNet-121, ResNet-34, and VGG16 were the ones that reduced class confusion and improved diagnostic accuracy. Multiple architecture ensemble learning techniques have demonstrated increased scalability and robustness, which makes them appropriate for real-world agricultural applications in a variety of settings [4].

Tushar V. Kafare et al. (2025) proposed the global agriculture and food security are seriously threatened by plant diseases, so prompt and precise diagnosis is essential. The subjective and time-consuming nature of traditional visual inspection techniques has led to the use of computer vision and machine learning techniques. In order to detect plant diseases, recent research has investigated transfer learning frameworks that integrate preprocessing, segmentation, feature extraction, and prediction. To improve image analysis, methods like median filtering, APIJS, and sophisticated feature descriptors like Multi-texton, PHOG, and NMA-LGIP have been used. Innovative models, such as DCA-CNN-TL, show enhanced classification accuracy and severity evaluation, highlighting the potential of transfer learning in creating accurate and effective plant disease detection systems for sustainable agriculture [5].

Muhammad Mahmood ur Rehman et al. (2024) proposed for efficient crop management, vegetable diseases must be identified accurately and promptly. Because CNNs can extract complex features from image datasets, they have recently become promising tools for automated disease detection. Major vegetable crops like potatoes, tomatoes, peppers, cucumbers, bitter gourds, carrots, cabbage, and cauliflower have all been studied using CNN models. In addition to addressing issues like computational complexity, dataset limitations, and generalization problems, studies demonstrate CNNs' excellent performance in disease classification tasks. Overall, CNN-based methods have the potential to revolutionize the diagnosis of vegetable diseases; however, more scalability and robustness improvements are still needed [6].

P. Veera Prakash et al. (2024) proposed to Improving productivity and food security requires accurate categorization of rice crop diseases, but standard models' performance is hindered by a lack of labeled data. Recent research has demonstrated how transfer learning, which reuses knowledge from similar tasks, can effectively overcome data scarcity. In comparison to traditional techniques, the accuracy and resilience of a model originally developed for the classification of nutritional deficiencies was greatly increased when it was modified for the detection of paddy disease. This method shows how transfer learning may be used to improve automated agricultural diagnostics, opening the door to precision agriculture and sustainable farming methods outside of paddy crops [7].

Gayatri Parasa et al. (2023) focused on the India's economy has historically relied heavily on agriculture, with paddy being a key crop. Nevertheless, bugs, illnesses, and erratic weather patterns have reduced its yield. According to research, paddy crop illnesses drastically lower production, necessitating the implementation of efficient preventive measures. Deep learning techniques have been investigated for automated disease identification in order to overcome this. When it comes to recognizing rice leaf diseases, CNNs have demonstrated encouraging outcomes. Metrics like Accuracy, Precision, Recall, and F-measure were used to assess a suggested 15-layer CNN model, showing how well it supports increased paddy productivity and enhances early diagnosis [8].

Munmi Gogoi et al. (2023) proposed the rice production is highly affected by diseases, making early detection critical for minimizing yield loss. CNN-based methods have proven effective, though they typically require large labeled datasets. To address this, a 3-stage CNN with transfer learning, progressive re-sizing, and PReLU was proposed, enabling efficient training on a smaller dataset. The model achieved 94% accuracy with 10-fold cross-validation, outperforming conventional methods and offering a cost-effective solution for early rice disease detection, especially in resource-limited settings [9].

Chinna Gopi Simhadri et al. (2023) proposed the as a staple crop for a large portion of the world's population, rice is extremely susceptible to biotic and abiotic stresses that result in large yield and financial losses. The time-consuming and frequently unreliable nature of traditional visual inspection techniques for disease detection has sparked interest in more sophisticated strategies. The efficiency of deep learning and machine learning methods, especially CNNs, for automated rice disease diagnosis has been demonstrated in recent studies. Results from transfer learning using multiple pre-trained CNNs have been encouraging, with InceptionV3 outperforming other models like AlexNet. These results highlight how deep learning may improve the precision and effectiveness of rice disease detection [10].

Lei Feng et al. (2021) proposed the rice diseases are a serious threat to crop growth, prompt and precise detection is crucial for efficient management. Deep transfer learning has been used in conjunction with HSI to tackle variety-specific detection issues. Several rice varieties were used to test methods like fine-tuning, CORAL, and DDC; fine-tuning had the highest accuracy (>88%). In a number of tasks, CORAL also performed better than DDC, and multi-task transfer techniques enhanced performance even more. The efficiency of transfer learning in locating important spectral features was validated by saliency map analysis. All things considered, HSI in conjunction with deep transfer learning provides a dependable and reasonably priced method for detecting rice diseases in different varieties [11].

Shreya Ghosal et al. (2020) propose the Rice, a major crop in India, is highly susceptible to diseases that are often difficult for farmers to identify manually. Deep learning, particularly CNN-based image recognition, has emerged as a promising solution for automated detection. Due to the scarcity of rice leaf disease datasets, a custom dataset was created, and transfer learning with a VGG-16-based CNN was applied. The proposed model achieved an accuracy of 92.46%, demonstrating its effectiveness in rice disease classification [12].

Junde Chen et al. (2020) proposed the food security is negatively impacted by plant diseases because they lower yield and quality, and some outbreaks result in total crop failure. In agricultural research, automatic disease identification has become more significant as a solution to this problem. Recent developments show that deep learning in particular, convolutional neural networks, or CNNs is a promising solution because of their high classification accuracy for images. With the help of pre-trained models such as VGGNet and Inception on ImageNet, transfer learning makes it possible to train effectively even with small agricultural datasets. When compared to conventional methods, studies show that transfer learning is more effective for rice disease detection, with validation accuracies exceeding 91% even in complex backgrounds [13].

III. Proposed Methodologies

A. Class Weights

The class imbalance occurs when some classes have fewer samples than others. This is addressed by the class weight technique. Minority classes are given higher weights, which encourages the model to give them more consideration during training and enhances performance overall. 11,200 photos from 10 classes make up the dataset used in this study, and Table 1 shows the weights assigned to each class [14].

Fig. 2. Classes of Paddy Disease.

TABLE I. Classes of Paddy Leaf and Weights

Class	Weight
Blight_Bacterial	210.45
Leaf_Streak_Bacterial	285.62
Panicle_Streak_Bacterial	298.34
Rice_Blast	64.72
Leaf_Brown_Spot	112.93
Stem_Dead_Heart	78.51
Rice_Downy_Mildew	174.29
Rice_Hispa	69.84
Healthy	61.37
Rice_Tungro_Virus	101.26

B. CNN

Because they can identify spatial relationships and hierarchical patterns that resemble human visual perception, Convolutional Neural Networks (CNNs) are a popular deep learning tool for image processing tasks. They are especially useful for detecting plant diseases from photos because they are composed of convolutional, pooling, and fully connected layers. In the classification of paddy diseases, a number of CNN architectures have shown excellent performance. For example, Xception, a 71-layer model extension of the Inception model with depthwise separable convolutions, achieves high accuracy with fewer parameters. Inverted residual blocks with depthwise and pointwise convolutions are used by MobileNetV3 Large, which is designed for resource-constrained devices such as smartphones, to lower computational costs across its 53 layers while preserving reliable accuracy. Despite having more computational requirements, DenseNet121, which has 121 layers and roughly 7.9 million parameters, uses dense connectivity to improve feature reuse and achieve state-of-the-art results in image classification and detection tasks. Similar to this, EfficientNet-B4, which has 5.3 million neurons, 24.5 million parameters, and 55 layers, uses optimized scaling to strike a balance between accuracy and efficiency, but it necessitates large training datasets. When combined with transfer learning, these CNN models provide strong and effective means of diagnosing rice plant diseases in a scalable and accurate manner [15].

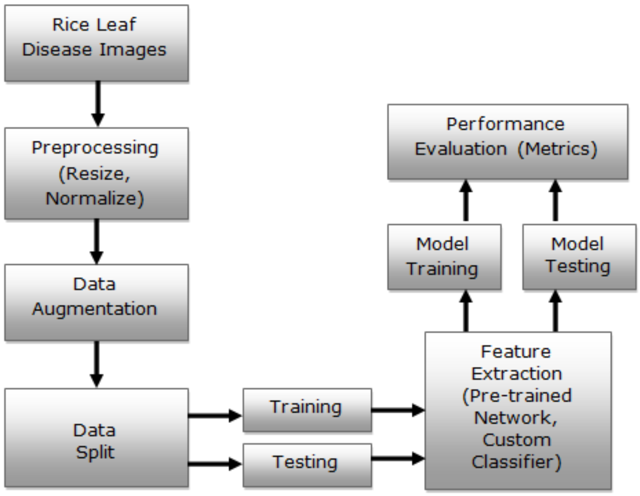

Fig. 3. Classification pipeline for rice leaf diseases.

C. Tools and a training framework

Weights & Biases (WandB) and Lightning AI were used in this paper to increase productivity and optimize the training process. Scalable deep learning training on cloud-based GPUs like the NVIDIA T4 and L4 was made possible by Lightning AI, and trial tracking, visualization, and real-time tracking of important metrics like accuracy, loss, and resource consumption were made easier by WandB. Together, these tools provided an optimized and transparent framework for large-scale experimentation, ensuring effective model performance and resource utilization.

D. Transfer Learning

Deep learning makes implicit processing possible by automatically learning complex and abstract representations, removing the need for manual extraction or segmentation. Traditionally, feature extraction involves choosing significant features from raw data. Because of this, rice pests and diseases can be effectively identified and categorized using CNN-based transfer learning. By updating the classification layer, fine-tuning previous layers for task-specific features, and occasionally replacing learnable layers like convolutional or fully connected layers, this method adapts pre-trained CNN models to the task and improves feature extraction of disease characteristics like lesion shape, size, and color. Although all layers in this project were trained to take advantage of sophisticated computational capabilities, some layers may be frozen to preserve generalized features in order to increase training efficiency. To guarantee strong learning and generalization, the dataset was meticulously preprocessed by resizing the images and splitting them into training and validation sets. When the re-trained CNNs were assessed using datasets related to rice leaf disease, they showed excellent accuracy and proved that transfer learning is a useful tool for crop health monitoring. Overall, the methodology increases prediction reliability, streamlines the diagnostic process, and improves rice production yield and quality.

IV. Experimental Result

A. Dataset Details

A carefully selected dataset of images of paddy leaves that depicted the most prevalent rice diseases—blast, brown spot, bacterial blight, and hispa as well as healthy samples were used in the experiments. The dataset included high-resolution photos taken in both controlled and natural field settings, guaranteeing variations in background, lighting, and leaf orientation to replicate actual situations. Open-access repositories, farmer-contributed photos, and agricultural research stations were among the sources. To improve consistency, balance class distributions, and minimize noise, pre-processing techniques like resizing, normalization, and augmentation (rotation, flipping, and contrast adjustment) were used. For training and testing, several partitioning techniques (90:10, 80:20, and 70:30) were used, and k-fold cross-validation reduced sampling bias and guaranteed reliable evaluation. Inter-class similarities, especially between blast and brown spot, created classification challenges despite balanced categories, enabling realistic evaluation of CNN architecture performance. The dataset was used as a thorough benchmark to assess the efficacy and scalability of CNNs based on transfer learning in the detection of rice disease, with the best-performing models obtaining accuracies exceeding 99%.

A number of experiments were carried out using various CNN architectures and data partitioning strategies (90:10, 80:20, and 70:30) in order to evaluate the potential of transfer learning for paddy disease classification. To reduce the effect of random splits, each experiment was conducted ten times. A variety of metrics, including accuracy, precision, recall, F1-score, specificity, MCC, and FPR, were used to assess performance. The findings showed that sophisticated models with classification accuracies above 99%, such as InceptionV3 and InceptionResNetV2, continuously produced better results. Specifically, AlexNet showed poorer results with frequent misclassifications among visually similar diseases like blast, brown spot, and hispa, while InceptionV3 achieved 99.64% accuracy with a recall of 98.32% and MCC of 0.98. When tested on the 80/20 partition, EfficientNetB0 demonstrated competitive performance as well, attaining high precision (98.48%) and MCC (0.982).

TABLE II. Performance of CNN Models on Paddy Disease Classification

Model	*Acc.*	*Prec.*	*Recall*	*F1-Score*	*Spec.*	*MCC*	*FPR*
InceptionV3	99.64	98.23	98.32	98.2	99.85	0.98	0.15
InceptionResNetV2	99.58	98.15	98.27	98.19	99.81	0.979	0.19
EfficientNetB0	99.41	98.48	98.12	98.25	99.78	0.982	0.22
AlexNet	97.35	88.39	87.55	86.03	98.49	0.86	1.51

To further evaluate generalization, k-fold cross-validation was implemented, confirming the robustness of the top-performing CNNs while also highlighting the increased computational demands of higher fold values. ROC analysis strengthened these findings, with InceptionResNetV2, Xception, and ResNet50 achieving AUC scores of 99.94%, 99.92%, and 99.91%, respectively, underscoring their excellent discriminatory ability. These findings highlight how optimized transfer learning models not only perform better than conventional methods but also continue to deliver dependable results even in the face of noise, variability, or unbalanced data. All of this shows how well CNN-based transfer learning frameworks can be used to diagnose paddy diseases early on in a scalable, accurate, and automated manner, which will enhance crop management and promote sustainable farming methods.

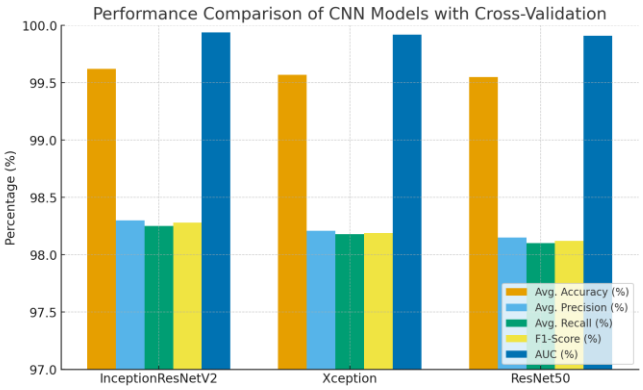

Fig. 4. Performance Comparison of CNN Models with Cross-Validation.

TABLE III. CROSS-VALIDATION AND ROC-AUC RESULTS OF TOP CNN MODELS FOR PADDY DISEASE DIAGNOSIS

Model	***Avg. Accuracy (%)***	***Avg. Precision (%)***	***Avg. Recall (%)***	***F1-Score (%)***	***AUC (%)***
InceptionResNetV2	99.62	98.3	98.25	98.28	99.94
Xception	99.57	98.21	98.18	98.19	99.92
ResNet50	99.55	98.15	98.1	98.12	99.91

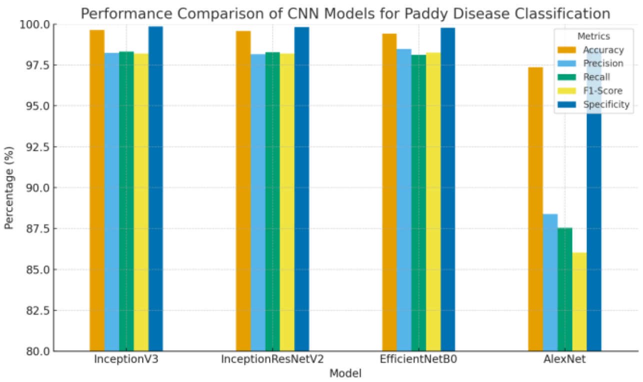

Fig. 5. Performance Comparison of CNN with Cross-Validation.

V. PERFORMANCE METRICS

Accuracy, precision, recall, F1-score, specificity, MCC, and FPR are some of the classification metrics used to assess the effectiveness and dependability of the suggested CNN-based paddy disease diagnosis framework. Precision calculates the percentage of true positives among all predicted positives, whereas Accuracy shows the percentage of correctly classified samples. The F1-score balances Precision and Recall, while Recall (Sensitivity) measures the model's capacity to identify real positive samples. While MCC offers a strong correlation measure between predicted and actual classes, ranging from -1 (total misclassification) to +1 (perfect prediction), specificity emphasizes the ability to accurately identify negative samples. Lastly, by predicting disease when it doesn't exist, FPR calculates the frequency of false alarms generated by the model. Equations (1) through (6) give these metrics' mathematical expressions:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

$$Recall\ (Sensitivity) = \frac{TP}{TP + FN} \quad (3)$$

$$F1 - Score = 2 * \frac{(Precision \times Recall)}{Precision + Recall} \quad (4)$$

$$Specificity = \frac{TN}{TN + FP} \quad (5)$$

$$MCC = \frac{(TP \times TN) - (FP \times FN)}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (6)$$

VI. DISCUSSION

Since CNNs naturally generate hierarchical feature representations from raw picture data, feature extraction is no longer an explicit step in deep learning-based crop disease detection. CNNs automatically capture intricate spatial and spectral patterns, including lesion color, form, and texture, in contrast to classical feature engineering, which necessitates manual descriptors. In addition to increasing accuracy and scalability, this implicit feature learning significantly streamlines the process of identifying pests and illnesses in rice fields.

By reusing previously taught CNN models that were initially built on big datasets and customizing them for domain-specific tasks like crop disease classification, transfer learning improves this capability. In order to enable the model to identify illness categories unique to rice, the adaptation procedure usually starts with changes to the classification layer. The network can then improve its feature extraction for task-specific patterns by extending fine-tuning to earlier levels. To improve classification performance even further, extra layers are occasionally added to the learnt representations, such as more convolutional or fully connected layers. Although selective layer freezing is frequently used to lower overfitting and computational costs, this study made use of the computational resources at hand to thoroughly retrain every layer, guaranteeing optimal adaptation to the rice leaf disease dataset.

All photos were scaled and divided into training and validation sets in order to standardize inputs, guaranteeing reliable evaluation and consistent model input dimensions. The curated rice illness dataset was used to retrain the fine-tuned pre-trained CNNs, and performance was evaluated using important metrics like accuracy and loss curves. This methodical approach shed light on the modified models' advantages and disadvantages.

Weights & Biases (WandB) and Lightning AI were integrated to further optimize the training workflow. Efficient large-scale training was made possible using Lightning AI's scalable cloud-based infrastructure with GPU acceleration (NVIDIA T4 and L4). WandB made it possible to track accuracy, loss, and resource usage in real time while monitoring experimental progress using interactive dashboards. When used in tandem, these technologies expedited the process, guaranteed consistency, and facilitated data-driven choices throughout the model optimization process.

The suggested methodology shows how transfer learning can provide a strong framework for the automated and early identification of rice leaf diseases when paired with reliable infrastructure and monitoring technologies. This increases the efficiency and viability of implementing CNN-based models in actual precision agriculture, in addition to improving predicted accuracy.

A. Limitations

There are still a number of restrictions even though transfer learning has demonstrated encouraging outcomes in the classification of rice leaf diseases. The ability of models to be applied to images taken in different lighting conditions, environmental settings, or plant varieties that are not represented in the training set presents a significant challenge because performance may suffer. When datasets are unbalanced, this problem can lead to models that favor majority classes while ignoring minority ones, which can lead to misclassification and decreased reliability. Restricted training data is another drawback because models built on a small number of disease classes may misclassify rare or novel diseases as well-known ones. Furthermore, because the visual symptoms of rice diseases and nutritional deficiencies can be similar diseases often produce lesions or dark spots, while deficiencies typically cause yellowing or stunted growth it is important to distinguish between the two. Since different management approaches are needed diseases necessitate specific control measures, while deficiencies can be addressed with nutrient supplementation accurate differentiation is essential. In order to improve model robustness and guarantee dependable deployment in actual agricultural scenarios, it is imperative to address issues of data diversity, imbalance, and symptom similarity through additional research and expanded datasets, even though transfer learning provides efficiency and strong baseline performance.

VII. Conclusion

Since rice is a staple food for over half of the world's population, it is extremely susceptible to a number of diseases that can seriously reduce yield and quality. For this reason, prompt and precise diagnosis is crucial to ensuring food security. Automating the detection of rice disease has shown encouraging results thanks to recent developments in deep learning, especially transfer learning with CNNs. Models like InceptionV3 and DenseNet121 have demonstrated high accuracies, while EfficientNetB4 and MobileNetV3 Large provide resource-efficient alternatives. Integrating symptoms from various plant organs, environmental factors, and laboratory tests is still crucial because disease manifestations differ among rice varieties and plant parts, and depending only on leaf images may result in false positives. While ensemble learning and hybrid systems that integrate deep learning, computer vision, and expert knowledge can further improve robustness, reduce overfitting, and adapt to various disease scenarios, expanding datasets to include a variety of symptoms and field conditions will improve generalization. By enabling more scalable, accurate, and economical rice disease management, future directions for precision agriculture include utilizing convolutional neural networks ViTs and CNN-ViT hybrids, multimodal integration of disease and environmental data, and IoT-enabled real-time monitoring systems.

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