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Rice Leaf Disease Classification Based on ResNet50 and MobileNetV3 Feature Extraction Using Random Forest

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ABSTRACT

Diseases in rice plants are one of the main factors contributing to decreased agricultural productivity. Early and accurate disease identification is crucial to support effective decision-making in plant disease management. This study aims to compare the performance of deep learning models based on Convolutional Neural Networks (CNN), namely ResNet50 and MobileNetV3, as well as their integration with the Random Forest (RF) algorithm for rice leaf disease classification. The dataset used consists of rice leaf images categorized into three disease classes, namely Bacterial Leaf Blight, Brown Spot, and Leaf Smut**.** Model performance was evaluated using accuracy, precision, recall, and F1-score metrics with a macro-average approach. The results show that the standalone ResNet50 and MobileNetV3 models achieved accuracies of 62.5% and 65.7%, respectively, with macro F1-scores below 0.65, indicating moderate classification performance. However, combining CNN models with Random Forest significantly improved classification performance. The ResNet50 + RF model achieved an accuracy of 99.6%, while the MobileNetV3 + RF model attained the highest accuracy of 99.8%, along with equally high macro-averaged precision, recall, and F1-score values. The superior performance of the Random Forest-based hybrids can be attributed to RF's ability to effectively handle high-dimensional CNN-extracted features, reduce overfitting through ensemble learning, and capture complex non-linear decision boundaries among disease classes. These findings demonstrate that integrating CNN feature extraction with Random Forest classification substantially enhances the robustness and accuracy of rice disease identification. Consequently, the proposed hybrid CNN–Random Forest approach shows strong potential for developing reliable image-based rice plant disease detection systems.

1. Introduction

The. Rice (Oryza sativa L.) is a major food commodity that plays a strategic role in maintaining national food security [1]. Rice crop productivity is strongly influenced by various factors, one of which is plant disease infection [2]. Diseases such as Bacterial Leaf Blight, Brown Spot, and Leaf Smut can cause significant yield losses if they are not detected and managed appropriately [3][4][5]. Therefore, early and accurate identification of rice diseases is a crucial aspect in supporting sustainable agricultural practices.

Conventional rice disease identification is generally performed through visual observation by farmers or agricultural experts [6]. However, this approach has several limitations, including dependence on the observer's experience, the subjective nature of assessments, and relatively high time and cost requirements. In addition, visual symptoms among different diseases often exhibit similarities, which can lead to misdiagnosis

[7]. These conditions highlight the need for the development of automated systems based on artificial intelligence technologies to assist in the diagnosis of rice plant diseases.

Advancements in computer vision and deep learning, particularly Convolutional Neural Networks (CNNs), have demonstrated outstanding performance in various image classification tasks, including applications in agriculture. CNNs are capable of automatically and hierarchically extracting visual features from images, making them more effective than traditional manual feature extraction methods [8]. Several popular CNN architectures, such as ResNet and MobileNet, have been widely adopted due to their ability to produce robust and discriminative feature representations. ResNet employs residual connections to address the vanishing gradient problem [9], while MobileNet is designed as a lightweight architecture based on depthwise separable convolutions, enabling computational efficiency [10].

Previous studies have explored various CNN-based approaches for rice leaf disease classification. In [11], rice leaf disease classification was performed using a Deep Neural Network optimized with the Jaya algorithm, achieving high accuracy of up to 98.9% and outperforming conventional neural network methods. Study [12] applied a simple CNN model to classify rice leaf diseases and pests, reporting an accuracy of up to 96%. In [2], rice leaf disease detection was conducted using the VGG-19 architecture with different optimizers (ADAM, RMSProp, and SGD), where the combination of VGG-19 and the ADAM optimizer yielded the best performance with an accuracy of 96.45%. Study [13] proposed a three-stage CNN architecture based on transfer learning using EfficientNet-B7 combined with progressive resizing and PReLU activation, achieving an accuracy of 93.99%. Furthermore, research in [14] employed a symptom-based rice leaf disease classification approach using a Deep CNN combined with a pre-trained ResNet-50 model, achieving superior performance with an accuracy of 97.3%.

Despite these promising results, most previous studies employed CNNs in an end-to-end manner as direct classifiers. Such approaches generally require substantial computational resources and are prone to overfitting, particularly when the size of the training dataset is limited. As an alternative, a hybrid approach that utilizes CNNs as feature extractors and machine learning algorithms as final classifiers can serve as an effective solution. This approach enables the exploitation of CNNs' powerful deep feature extraction capabilities while leveraging the flexibility and efficiency of machine learning algorithms in the classification process.

Based on this background, this study proposes a hybrid approach for image-based rice disease classification using ResNet and MobileNet CNN architectures as feature extractors and a machine learning algorithm as the classifier. The objectives of this study are to analyze and compare the performance of both CNN architectures in generating representative features and to evaluate the effectiveness of combining CNNs with machine learning in improving rice disease classification accuracy. It is expected that the findings of this study will contribute to the development of accurate, efficient, and easily deployable rice disease detection systems for agricultural environments.

2. Method

The methodology of this study is designed to classify rice plant diseases based on leaf images using a hybrid approach, which employs ResNet50 and MobileNetV3 architectures as feature extractors combined with the Random Forest algorithm as the classification method. In general, the research workflow consists of several stages, including data collection, data preprocessing, feature extraction, classification using Random Forest, and model performance evaluation, as illustrated in Figure 1.

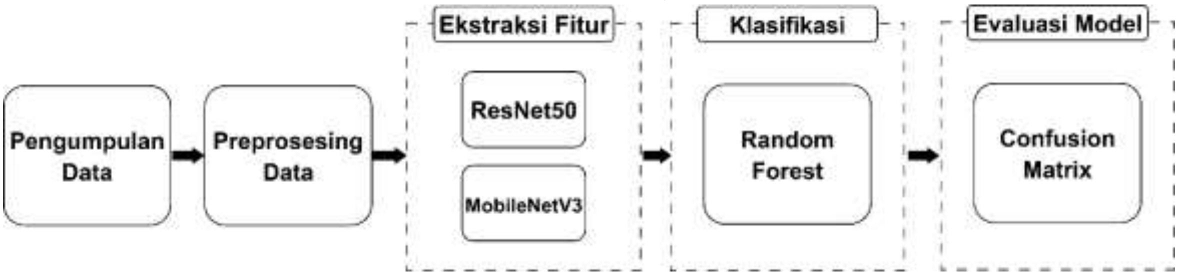

Figure 1. Research Workflow

The first stage of this study is data collection, The rice leaf image dataset used in this study was obtained from the Kaggle platform and is publicly available at https://www.kaggle.com/datasets/jay7080dev/rice-plant-diseases-dataset. The dataset consists of labeled rice leaf images representing three disease classes, namely Bacterial Blight, Brown Spot, and Leaf Smut. The use of this dataset aims to obtain representative visual samples for each disease class, enabling the model to effectively learn discriminative visual patterns. The second stage involves image preprocessing, which is a crucial step in preparing the data for subsequent processing. All images were resized to a fixed resolution of 224 × 224 pixels using direct resizing. Consequently, the original aspect ratio was not preserved. This strategy was adopted to ensure compatibility with the fixed input size requirements of the ResNet50 and MobileNetV3 architectures. Although direct resizing may introduce minor geometric distortions, convolutional neural networks are generally robust to such variations. Moreover, the use of global average pooling further reduces sensitivity to local spatial distortions.

The next stage is feature extraction using the ResNet50 and MobileNetV3 architectures. Both models employ pre-trained weights learned from the ImageNet dataset, allowing them to capture general visual characteristics such as edges, textures, and shape patterns that are relevant to rice leaf images. This transfer learning approach is adopted to improve the quality of feature representations while reducing the need for large amounts of training data. During the feature extraction process, the classification layers of each CNN architecture are removed, and feature extraction is performed at the global average pooling layer. This layer is selected because it effectively summarizes global spatial information and produces fixed-dimensional feature vectors, thereby facilitating subsequent classification. The resulting feature vectors represent the visual characteristics of rice leaf images, including differences in texture, lesion patterns, and color variations, which are key indicators of each disease type.

In the subsequent stage, classification is performed using the Random Forest method, with the CNN-extracted feature vectors serving as the model input. Random Forest is an ensemble-based classification algorithm that combines multiple decision trees constructed in a randomized manner to enhance prediction accuracy and stability [15]. Each decision tree is trained using different subsets of data and features, which helps reduce model variance and improve generalization to unseen data. In this study, In this study, the Random Forest classifier was implemented using the RandomForestClassifier algorithm. The model was configured with n_estimators set to 200, representing the number of decision trees in the ensemble, and random_state set to 42 to ensure reproducibility of the experimental results. Using 200 trees enables the model to achieve stable performance by reducing variance while maintaining good generalization capability. All other parameters were kept at their default values as defined in the Scikit-learn library. The insensitivity of Random Forest to data distribution and its ability to handle high-dimensional features make it well suited for classifying feature vectors extracted by ResNet50 and MobileNetV3. Moreover, its capability to capture nonlinear relationships among features further supports the classification of rice plant diseases, which exhibit complex and diverse visual patterns.

In the final stage, model performance evaluation is conducted to assess the system’s ability to classify rice plant diseases accurately and reliably. In this study, evaluation is performed by comparing the model predictions with the true class labels of the test data. To ensure objectivity and consistency, all models are evaluated using the same dataset and evaluation scheme. The evaluation metrics employed include accuracy (1), precision (2), recall (3), and F1-score (4). Accuracy measures the proportion of correct predictions over the entire test dataset, while precision and recall assess the correctness and completeness of predictions for each disease class, respectively. The F1-score is used as a combined metric that represents the balance between precision and recall, making it more representative in cases of class imbalance [16].

$$Akurasi = \frac{TP + TN}{TP + FP + TN + FN} \tag{1}$$

$$Presisi = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - Score = \frac{2 \times Presisi + Recall}{Presisi + Recall} \tag{4}$$

3. Results and Discussion

This section presents the results of rice plant disease classification experiments based on leaf images by comparing two approaches: the use of CNN architectures as end-to-end classifiers and a hybrid CNN–Random Forest approach, in which CNNs serve as feature extractors. The discussion focuses on analyzing the performance differences between these two approaches and examining the impact of CNN architecture selection on classification accuracy and stability. The evaluation aims to assess the extent to which the hybrid approach improves classification performance compared to the direct use of CNNs as classifiers. This comparison is intended to highlight the contribution of the Random Forest algorithm in effectively utilizing CNN-extracted features, particularly in handling high-dimensional data and enhancing the model's generalization capability in rice plant disease classification.

This study utilizes rice leaf image data consisting of three disease classes, namely Bacterial Leaf Blight, Brown Spot, and Leaf Smut. Sample images from each disease class are presented in Figure 2. The data distribution is illustrated in Figure 3, dataset used in this study is naturally balanced, without the application of oversampling or undersampling techniques. The number of samples in each class is comparable, consisting of 1,604 images of Bacterial Leaf Blight, 1,620 images of Brown Spot, and 1,460 images of Leaf Smut. This balanced distribution ensures that the classification results are not biased toward a particular class and supports the reliability of the reported performance.

Prior to the modeling process, all images undergo a preprocessing stage in which they are resized to 224 × 224 pixels to match the standard input dimensions required by the ResNet50 and MobileNetV3 architectures. This step aims to standardize image dimensions and ensure data compatibility with the CNN models used. The rice leaf image dataset is then divided into two subsets: training data and testing data, with an 80%–20% split, respectively. The training data are used for feature extraction using the ResNet50 and MobileNetV3 CNN architectures. The extracted features are subsequently fed into the Random Forest algorithm to construct the rice plant disease classification models. The testing process is conducted using the test dataset to evaluate the performance of the trained models, thereby providing an objective assessment of the models' ability to classify rice diseases based on leaf images.

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Bacterial Blight *Brown Spot* *Leaf Smut*

Figure 2. Sample Images of Rice Leaf Disease Dataset

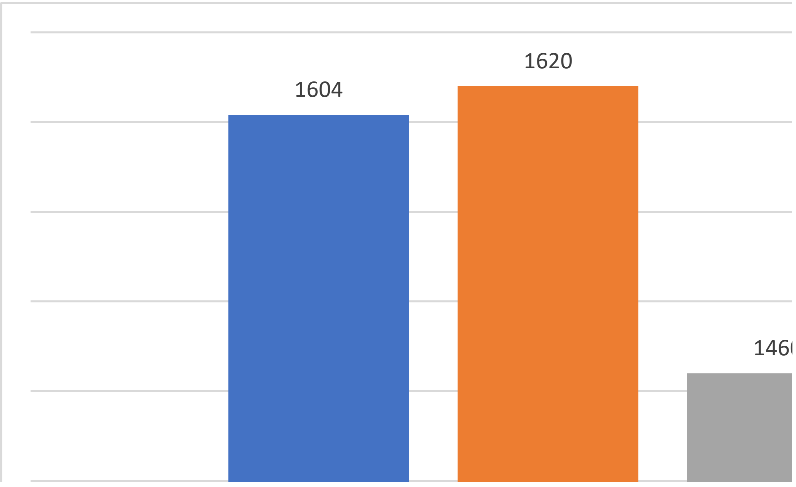

Figure 3. Distribution of Rice Leaf Disease Dataset

The confusion matrix in Figure 4, illustrates the performance of the ResNet50 architecture when used as a classifier in identifying three classes of rice plant diseases, namely Bacterial Leaf Blight, Brown Spot, and Leaf Smut. The model demonstrates relatively good performance for the Bacterial Leaf Blight and Brown Spot classes, with 241 and 271 images correctly classified, respectively, although misclassifications still occur due to similarities in visual patterns among classes. In contrast, the Leaf Smut class exhibits a higher misclassification rate, with a substantial number of images incorrectly predicted as Bacterial Leaf Blight and Brown Spot, indicating significant overlap in visual characteristics. These results suggest that using ResNet50 as an end-to-end classifier has limitations in distinguishing disease classes with complex and overlapping visual patterns. Consequently, a hybrid approach that separates the feature extraction and classification processes is required to enhance the model's generalization capability.

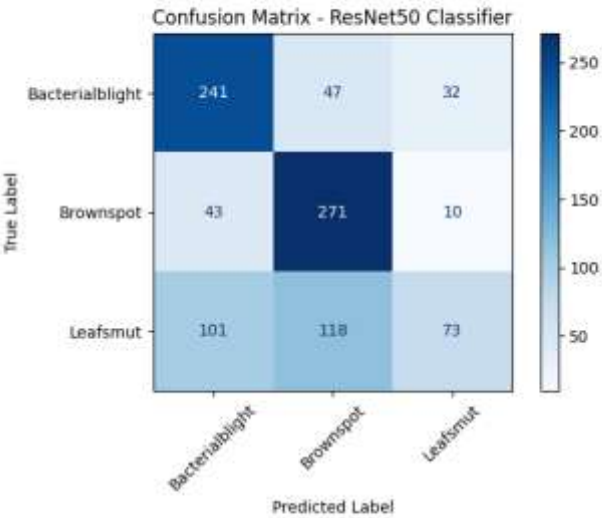

Figure 4. Confusion matrix ResNet50 Classifier

The confusion matrix in Figure 5, presents the performance of the MobileNetV3 architecture when used as a classifier in identifying three rice plant disease classes, namely Bacterial Leaf Blight, Brown Spot, and Leaf Smut. The model exhibits reasonably good performance for the Bacterial Leaf Blight and Brown Spot classes, with 233 and 259 images correctly classified, respectively, although misclassifications still occur due to similarities in visual characteristics across classes. For the Leaf Smut class, the misclassification rate remains relatively high, with several images incorrectly predicted as Bacterial Leaf Blight and Brown Spot, indicating overlapping visual patterns such as texture and leaf color variations. Compared to ResNet50 as a classifier, MobileNetV3 produces more compact feature representations and is computationally more efficient; however, this comes at the cost of reduced capability in distinguishing disease classes with complex visual characteristics. These results indicate that although MobileNetV3 is suitable for resource-constrained systems, end-to-end CNN-based classification still has inherent limitations. Therefore, a hybrid approach that separates the feature extraction and classification stages is required to improve model performance and generalization.

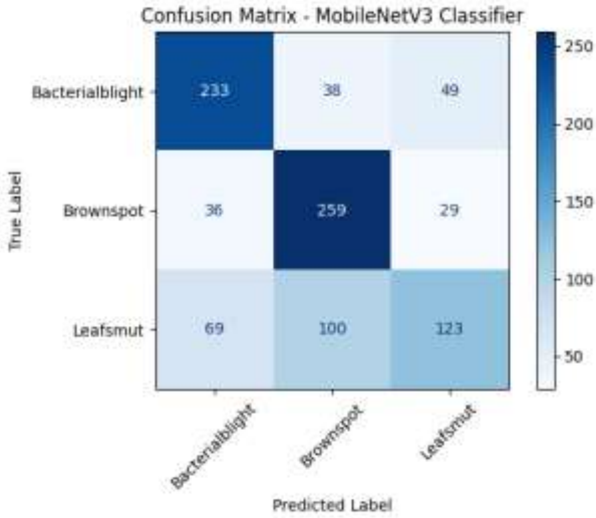

Figure 5. Confusion matrix MobileNetv3 Classifier

The confusion matrix in Figure 6 shows that the combination of ResNet50 as a feature extractor and Random Forest as a classifier achieves excellent classification performance in identifying three rice plant disease classes, namely Bacterial Leaf Blight, Brown Spot, and Leaf Smut. Nearly all samples in each class are correctly classified, with 317 Bacterial Leaf Blight images, 323 Brown Spot images, and 292 Leaf Smut images accurately predicted. Classification errors are minimal and occur only in a very small portion of the data, indicating that the feature vectors extracted by ResNet50 effectively represent the visual characteristics of the diseases in a highly discriminative manner. This performance is substantially superior to the use of CNNs as end-to-end classifiers, which previously exhibited overlapping predictions among classes. These results confirm that the hybrid approach, which separates the feature extraction and classification processes, significantly enhances the model's generalization capability and reduces misclassification, particularly for disease classes with visually similar characteristics.

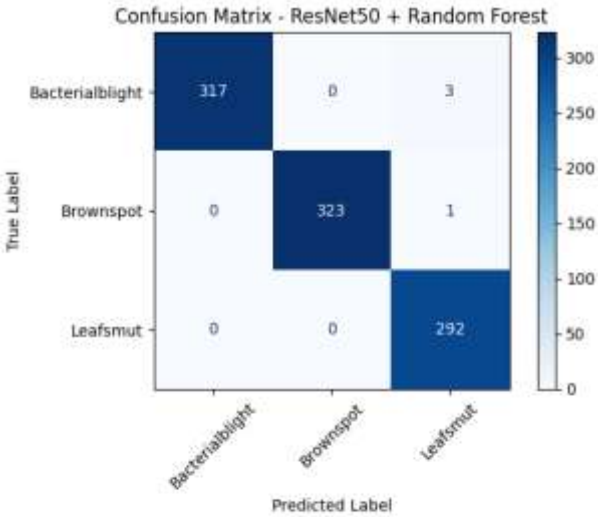

Figure 6. Confusion matrix ResNet50 + Random Forest

The confusion matrix in Figure X indicates that the combination of MobileNetV3 as a feature extractor and Random Forest as a classifier achieves excellent classification performance in identifying the three rice plant disease classes. All disease classes are classified with very high accuracy, with 318 Bacterial Leaf Blight images, 324 Brown Spot images, and 292 Leaf Smut images correctly predicted. Classification errors are almost negligible and occur only in a very small portion of the data, indicating that the features extracted by MobileNetV3 are sufficiently representative for distinguishing visual characteristics across disease classes when combined with Random Forest. Compared to the use of MobileNetV3 as an end-to-end classifier, this hybrid approach demonstrates a significant performance improvement, particularly in reducing misclassification for the Leaf Smut class. These results confirm that separating the feature extraction and classification processes enhances model stability and generalization capability, while simultaneously preserving the computational efficiency that is the primary advantage of MobileNetV3.

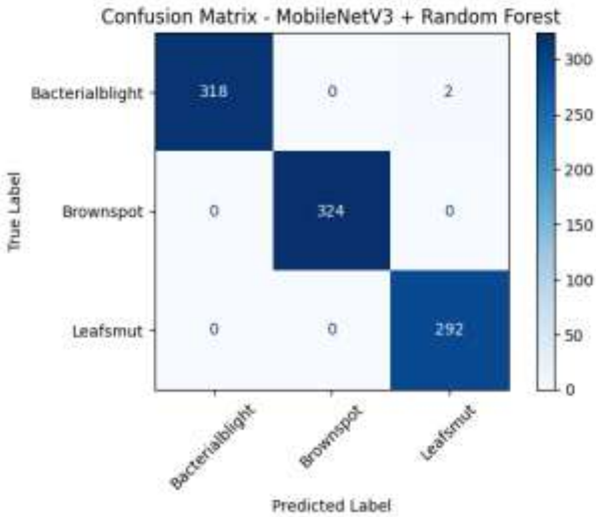

Figure 7. Confusion matrix MobileNetv3 + Random Forest

Table 1 shows the ResNet50 model achieved an accuracy of 62.5% with a macro F1-score of 0.585. These results indicate that although the model is able to recognize the Bacterial Blight and Brown Spot classes reasonably well, its performance on the Leaf Smut class remains low. This is evidenced by a large number of Leaf Smut samples being misclassified into other classes, which consequently reduces the overall recall value. This condition suggests that the model experiences difficulty in distinguishing the visual patterns of Leaf Smut, which share similarities with those of other diseases.

Meanwhile, MobileNetV3 demonstrates slightly better performance than the standalone ResNet50 model, particularly in detecting the Leaf Smut class. Nevertheless, this model still suffers from inter-class misclassifications, resulting in overall accuracy and F1-score values that have not yet reached an optimal level. These findings indicate that although the MobileNetV3 architecture is more computationally efficient, its high-level feature extraction capability remains limited when employed as an end-to-end classifier.

A highly significant performance improvement is observed with the implementation of the ResNet50 + Random Forest model. The confusion matrix results show that nearly all samples are classified correctly, with only minimal misclassification. This model achieves an accuracy close to 99%, indicating that integrating CNN-extracted features with the Random Forest algorithm substantially enhances inter-class discrimination capability. Random Forest plays a critical role in optimally separating the complex features generated by CNNs compared to the standard softmax layer.

The best performance is achieved by the MobileNetV3 + Random Forest model, which produces near-perfect classification results, with no errors in two classes and only negligible misclassification in one class. These results demonstrate that combining a lightweight yet informative CNN architecture with an ensemble-based classifier is highly effective in improving model generalization.

Table 1. Model Performance Evaluation Results

Model	Accuracy	Precision (Macro)	Recall (Macro)	F1-score (Macro)
ResNet50	0.625	0.628	0.613	0.585
MobileNetV3	0.657	0.651	0.649	0.642
ResNet50 + RF	0.996	0.996	0.996	0.996
MobileNetV3 + RF	**0.998**	**0.998**	**0.998**	**0.998**

Overall, the results of this study demonstrate that the hybrid CNN–Random Forest approach consistently outperforms standalone CNN models. This integration effectively addresses the limitations of CNNs at the final classification stage and enhances prediction stability and accuracy. These findings are further supported by previous studies [17][18][19], which report that incorporating additional classical machine learning–based classifiers is an effective solution for improving the performance of rice plant disease image classification. In particular, Random Forest has been widely adopted as a downstream classifier due to its robustness to high-dimensional feature spaces, resistance to overfitting through ensemble learning, and strong generalization capability when combined with deep feature representations [20].

4. Conclusion

Based on the conducted experiments, it can be concluded that standalone deep learning architectures exhibit reasonably good performance; however, they still face limitations in uniformly distinguishing patterns across different classes. The ResNet50 model achieved an accuracy of 62.5%, while MobileNetV3 demonstrated improved performance with an accuracy of 65.7%, indicating that a lighter and more efficient architecture is capable of extracting more representative features from rice leaf disease images. A highly significant performance improvement was obtained when features extracted from deep learning models were combined with the Random Forest algorithm. The ResNet50–Random Forest model achieved an accuracy of 99.6%, while the MobileNetV3–Random Forest model delivered the best performance with an accuracy of 99.8%, along with equally high macro-averaged precision, recall, and F1-score values. These results demonstrate that the hybrid modeling approach effectively leverages the strengths of CNN-based deep feature extraction and the classification capability of Random Forest in optimally separating classes, resulting in highly accurate and stable predictions across all disease categories. For future research, model interpretability will be further investigated to support real-world agricultural deployment. Visualization techniques such as Gradient-weighted Class Activation Mapping (Grad-CAM) and saliency maps can be incorporated to highlight disease-related regions on rice leaf images. This enhancement is expected to improve transparency, facilitate expert validation, and increase user trust in practical applications.

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