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Deep Learning

Comparative Analysis of the Performance of VGG16 and ResNet50 Architectures in Multi-Class Classification of Rice Plant Diseases Based on Convolutional Neural Networks (CNN)

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ABSTRACT

Rice plant diseases significantly affect crop productivity and food security, making early and accurate disease detection essential for effective agricultural management. Recent advances in deep learning, particularly Convolutional Neural Networks (CNN), have demonstrated strong potential in image-based plant disease classification. This study presents a comparative analysis of the performance of VGG16 and ResNet50 architectures for multi-class classification of rice plant diseases using CNN-based approaches. A dataset of rice leaf images representing multiple disease classes and healthy conditions was collected and preprocessed through image resizing, normalization, and data augmentation to enhance model generalization. Both pre-trained models were fine-tuned using transfer learning to adapt them to the rice disease classification task. Model performance was evaluated using standard metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. The experimental results show that both architectures achieve high classification performance; however, ResNet50 demonstrates superior accuracy and better generalization capability compared to VGG16, particularly in handling complex disease patterns and intra-class variations. Meanwhile, VGG16 offers a simpler architecture with faster convergence and lower computational complexity. The findings of this study provide insights into the selection of appropriate CNN architectures for rice plant disease classification and support the development of intelligent decision support systems in precision agriculture.

INTRODUCTION

Rice (Oryza sativa) serves as a vital food crop in maintaining global food security, particularly in Asian regions. As a primary source of carbohydrates, rice has become deeply embedded in Indonesian culture and most Asian countries, where it constitutes an essential component of daily dietary consumption [1]. Beyond its nutritional contribution, rice holds significant social, economic, and political implications, with its availability and pricing often indicating socioeconomic stability across many Asian nations, including Indonesia.

However, rice agriculture faces substantial challenges, with disease attacks representing one of the most critical threats to crop productivity and food security. According to Indonesia's Central Bureau of Statistics, rice production in 2024 was estimated at 52.66 million tons GKG, experiencing a decrease of 1.32 million tons GKG or 2.45% compared to 2023 production levels. Disease outbreaks in rice plants can directly impact harvest yield reduction and, in severe cases, result in complete crop failure, threatening farmers' livelihoods and national food security [2].

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The implementation of computer vision technology presents an appropriate solution for identifying rice plant diseases. Convolutional Neural Networks (CNN) have emerged as a popular algorithm in deep learning applications, demonstrating exceptional superiority in various real-world implementations compared to conventional machine learning methods [3]. Unlike traditional approaches such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), or Random Forest that require manual feature extraction, CNN can automatically learn to identify visual patterns associated with various rice disease types.

This research focuses on multi-class classification of rice plant diseases, including brown spot, leaf blast, false smut, bacterial leaf blight, and healthy leaves. The study employs two prominent CNN architectures: VGG16 and ResNet50. VGG16, with its 16-layer architecture, has successfully achieved high accuracy rates in image recognition tasks across various datasets, including ImageNet [4]. Previous research by Weny Indah et. al [5] demonstrated that VGG16 achieved 98% accuracy with superior performance in recall and f1-score metrics.

Meanwhile, ResNet50 utilizes skip connections (residual connections) that help address the vanishing gradient problem, thereby enhancing training and testing processes [6]. As the ImageNet challenge winner in 2015, ResNet50 has proven its reliability in image classification tasks, with research by Memon et al. showing training accuracy of 99.49% and validation accuracy of 96.6% in plant leaf disease identification [6].

The comparison between these architectures is crucial for Indonesia's developing precision agriculture industry. Given rice's importance as a primary food source, having an accurate and effective automatic disease detection system can ultimately contribute to improved rice agricultural productivity nationwide. This study aims to evaluate and compare the performance of VGG16 and ResNet50 architectures in rice disease classification, providing valuable insights for implementing computer vision technology in agricultural disease management.

Introduction provides adequate background or context (problem and its significance) of the study. The subject should not be written extensively. It is expected that rationale or purpose of the study (gap analysis), the objective in general and specific, and hypothesis (if any) should be expressed clearly. Present a clear "state of the art" of the subject, which discussed literature and theoretical concepts behind it. A concise general background may be included in the article. Present at least 5 (five) recent related works to support the novelty of the research.

Related Work

Several previous studies have demonstrated the effectiveness of VGG16 and VGG19 architectures in various image classification applications. Mannepalli et al. successfully implemented VGG16 for rice plant disease diagnosis with accuracy reaching 97.77% in identifying bacterial leaf blight, leaf blast, and brown spot [7]. Handayani et al. used VGG16 and VGG19 for gender classification based on radiography, where VGG16 achieved an average accuracy of 89% and VGG19 achieved an overall accuracy of 93% [8]. Another study by Basha et al. applied VGG16 for brain tumor detection using MRI with high accuracy results reaching 99.6% and sensitivity of 99.61%, outperforming InceptionV3 and ResNet50 models [9].

Meanwhile, the ResNet50 architecture has also shown superior performance in various application domains. Cambay et al. used ResNet50 for digestive disease detection through endoscopic images with 92% accuracy for three different datasets and achieved 99.13% on the WCE dataset [10]. Li et al. applied ResNet50 for welding defect classification with an overall accuracy of 99% [11], while Chen et al. [12] used this model for Alzheimer's disease classification based on MRI data with 98.91% accuracy. Pamungkas et al. compared ResNet50 with EfficientNet-B0 for corn disease classification, where ResNet50 achieved 93% accuracy although slightly behind EfficientNet-B0 which reached 94% [13].

METHODS

This study employs Convolutional Neural Networks (CNN) methodology to classify various disease classes in rice plants through a comparative analysis between two artificial neural network architectures: VGG16 and ResNet50. CNNs are recognized for their superior capabilities in image processing and pattern recognition. These networks excel in image recognition tasks due to their ability to automatically learn and extract features from image data, thereby reducing dependency on manual feature extraction processes, which are often time-consuming and inefficient.

Data Collection

The research sample comprises images depicting diseases in rice plants, accessible through the Kaggle platform. In total, 2,095 rice leaf images were selected, encompassing several disease types: 300 brown spot (Bipolaris oryzae), 634 leaf blast (Magnaporthe oryzae), 149 false smut (Ustilaginoidea virens), 349 bacterial leaf blight (Xanthomonas oryzae), and 663 healthy leaves. The sample selection criteria include photo relevance to research objectives, adequate data availability, and image quality meeting predetermined standards. Through this approach, the study aims to provide more accurate and reliable results for rice plant disease identification. were obtained through the Kaggle platform within the timeframe of December 11, 2023, to July 7, 2024, yielding 2,095 images. Data collection over this 7-month period was purposefully designed to provide scope for gathering more diverse data, which subsequently enhances accuracy and expected outcomes for comparing the two employed models.

The literature review in this study was conducted to collect, analyze, and synthesize various previous research studies and theories. This research establishes several important objectives for the literature review. The literature review also assists in explaining the methodology employed in the research by seeking references from similar studies, journal articles, theses, and dissertations in both physical and electronic formats as part of problem-solving efforts.

Research Procedure

The research procedure constitutes a series of steps and stages utilized as a conceptual framework for addressing research problems. Within this procedure, various tools are employed for data collection and processing, along with stages that facilitate problem resolution and research report compilation. The research procedure can be illustrated as follows:

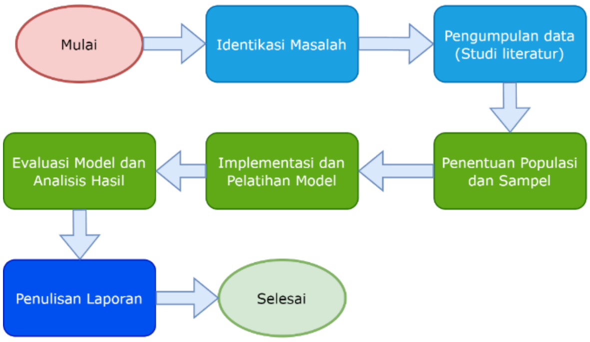


Fig. 1 Research Procedure

RESULTS AND DISCUSSION

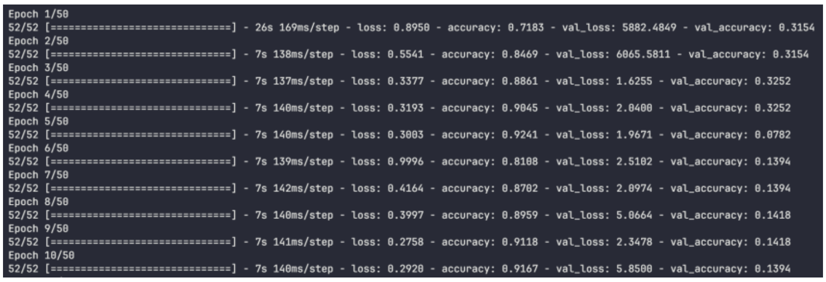
This study utilized a rice plant disease image dataset comprising 2,095 images across five categories: brown spot, leaf blight, false smut, bacterial leaf blight, and healthy leaves. All images were standardized to 244×244 pixels with normal lighting conditions to ensure optimal model performance during training. The training process involved comprehensive data preprocessing, including image resizing to 128×128 pixels, normalization (dividing pixel values by 255), and data augmentation techniques such as rotation (up to 40 degrees), horizontal and vertical shifting (20%), shearing (20%), zooming (20%), and horizontal flipping. The dataset was split into 80% training and 20% testing sets.

Both ResNet50 and VGG16 architectures were trained using pre-trained ImageNet weights with transfer learning. The models were optimized using Adam optimizer with early stopping and learning rate reduction callbacks to prevent overfitting.

Table 1. Performance Comparison Between Models

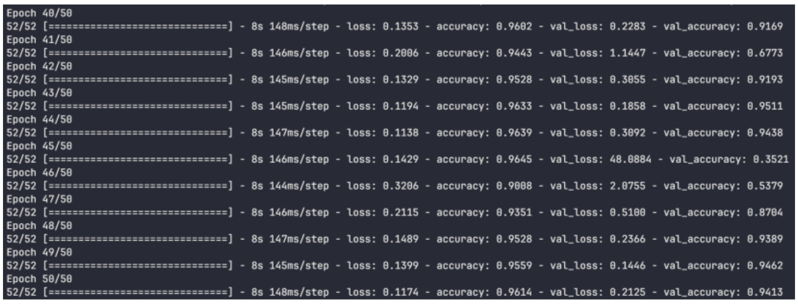
Model	**Test Loss**	**Test Accuracy**	**Average Inference Time**
ResNet50	0.2125	94.13%	33 ms/batch
VGG16	0.3108	90.95%	56 ms/batch

ResNet50 demonstrated superior performance with 94.13% test accuracy compared to VGG16's 90.95%. The training process for ResNet50 showed stable convergence, with training accuracy reaching 96.14% and validation accuracy of 94.13% after 50 epochs (Figure 2, Figure 3).



```
Epoch 1/50
52/52 [==============================] - 26s 169ms/step - loss: 0.8950 - accuracy: 0.7183 - val_loss: 5882.4849 - val_accuracy: 0.3154
Epoch 2/50
52/52 [==============================] - 7s 138ms/step - loss: 0.5541 - accuracy: 0.8469 - val_loss: 6065.5811 - val_accuracy: 0.3154
Epoch 3/50
52/52 [==============================] - 7s 137ms/step - loss: 0.3377 - accuracy: 0.8861 - val_loss: 1.6255 - val_accuracy: 0.3252
Epoch 4/50
52/52 [==============================] - 7s 140ms/step - loss: 0.3193 - accuracy: 0.9045 - val_loss: 2.0400 - val_accuracy: 0.3252
Epoch 5/50
52/52 [==============================] - 7s 140ms/step - loss: 0.3003 - accuracy: 0.9241 - val_loss: 1.9671 - val_accuracy: 0.0782
Epoch 6/50
52/52 [==============================] - 7s 139ms/step - loss: 0.9996 - accuracy: 0.8108 - val_loss: 2.5102 - val_accuracy: 0.1394
Epoch 7/50
52/52 [==============================] - 7s 142ms/step - loss: 0.4164 - accuracy: 0.8702 - val_loss: 2.0974 - val_accuracy: 0.1394
Epoch 8/50
52/52 [==============================] - 7s 140ms/step - loss: 0.3997 - accuracy: 0.8959 - val_loss: 5.0664 - val_accuracy: 0.1418
Epoch 9/50
52/52 [==============================] - 7s 141ms/step - loss: 0.2758 - accuracy: 0.9118 - val_loss: 2.3478 - val_accuracy: 0.1418
Epoch 10/50
52/52 [==============================] - 7s 140ms/step - loss: 0.2920 - accuracy: 0.9167 - val_loss: 5.8500 - val_accuracy: 0.1394
```

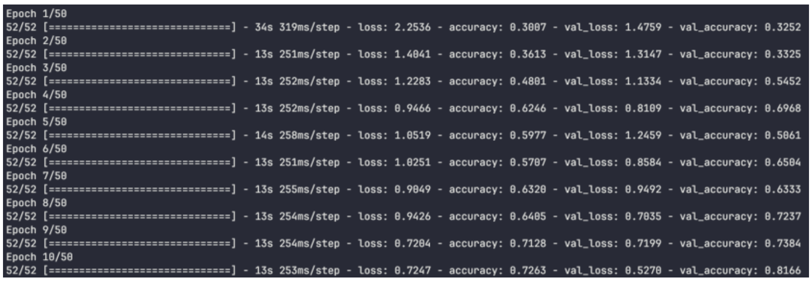
Fig. 2 Result Epochs ResNet50



```
Epoch 40/50
52/52 [==============================] - 8s 148ms/step - loss: 0.1353 - accuracy: 0.9602 - val_loss: 0.2283 - val_accuracy: 0.9169
Epoch 41/50
52/52 [==============================] - 8s 146ms/step - loss: 0.2006 - accuracy: 0.9443 - val_loss: 1.1447 - val_accuracy: 0.6773
Epoch 42/50
52/52 [==============================] - 8s 145ms/step - loss: 0.1329 - accuracy: 0.9528 - val_loss: 0.3055 - val_accuracy: 0.9193
Epoch 43/50
52/52 [==============================] - 8s 145ms/step - loss: 0.1194 - accuracy: 0.9633 - val_loss: 0.1858 - val_accuracy: 0.9511
Epoch 44/50
52/52 [==============================] - 8s 147ms/step - loss: 0.1138 - accuracy: 0.9639 - val_loss: 0.3092 - val_accuracy: 0.9438
Epoch 45/50
52/52 [==============================] - 8s 146ms/step - loss: 0.1429 - accuracy: 0.9645 - val_loss: 48.0884 - val_accuracy: 0.3521
Epoch 46/50
52/52 [==============================] - 8s 144ms/step - loss: 0.3206 - accuracy: 0.9008 - val_loss: 2.0755 - val_accuracy: 0.5379
Epoch 47/50
52/52 [==============================] - 8s 146ms/step - loss: 0.2115 - accuracy: 0.9351 - val_loss: 0.5100 - val_accuracy: 0.8704
Epoch 48/50
52/52 [==============================] - 8s 147ms/step - loss: 0.1489 - accuracy: 0.9528 - val_loss: 0.2366 - val_accuracy: 0.9389
Epoch 49/50
52/52 [==============================] - 8s 145ms/step - loss: 0.1399 - accuracy: 0.9559 - val_loss: 0.1446 - val_accuracy: 0.9462
Epoch 50/50
52/52 [==============================] - 8s 148ms/step - loss: 0.1174 - accuracy: 0.9614 - val_loss: 0.2125 - val_accuracy: 0.9413
```

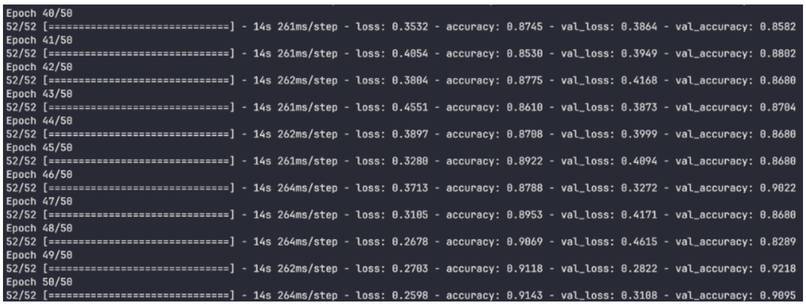
Fig. 3 Result Epochs ResNet50

VGG16 achieved 91.43% training accuracy and showed more fluctuation during validation phases (Figure 4, Figure 5).



```
Epoch 1/50
52/52 [==============================] - 34s 319ms/step - loss: 2.2536 - accuracy: 0.3007 - val_loss: 1.4759 - val_accuracy: 0.3252
Epoch 2/50
52/52 [==============================] - 13s 251ms/step - loss: 1.4041 - accuracy: 0.3613 - val_loss: 1.3147 - val_accuracy: 0.3325
Epoch 3/50
52/52 [==============================] - 13s 252ms/step - loss: 1.2283 - accuracy: 0.4801 - val_loss: 1.1334 - val_accuracy: 0.5452
Epoch 4/50
52/52 [==============================] - 13s 252ms/step - loss: 0.9466 - accuracy: 0.6246 - val_loss: 0.8109 - val_accuracy: 0.6968
Epoch 5/50
52/52 [==============================] - 14s 258ms/step - loss: 1.0519 - accuracy: 0.5977 - val_loss: 1.2459 - val_accuracy: 0.5061
Epoch 6/50
52/52 [==============================] - 13s 251ms/step - loss: 1.0251 - accuracy: 0.5707 - val_loss: 0.8584 - val_accuracy: 0.6504
Epoch 7/50
52/52 [==============================] - 13s 255ms/step - loss: 0.9049 - accuracy: 0.6320 - val_loss: 0.9492 - val_accuracy: 0.6333
Epoch 8/50
52/52 [==============================] - 13s 254ms/step - loss: 0.9426 - accuracy: 0.6405 - val_loss: 0.7035 - val_accuracy: 0.7237
Epoch 9/50
52/52 [==============================] - 13s 254ms/step - loss: 0.7204 - accuracy: 0.7128 - val_loss: 0.7199 - val_accuracy: 0.7384
Epoch 10/50
52/52 [==============================] - 13s 253ms/step - loss: 0.7247 - accuracy: 0.7263 - val_loss: 0.5270 - val_accuracy: 0.8166
```

Fig. 4 Result Epochs VGG16



```
Epoch 40/50
52/52 [==============================] - 14s 261ms/step - loss: 0.3532 - accuracy: 0.8745 - val_loss: 0.3864 - val_accuracy: 0.8582
Epoch 41/50
52/52 [==============================] - 14s 261ms/step - loss: 0.4054 - accuracy: 0.8530 - val_loss: 0.3949 - val_accuracy: 0.8802
Epoch 42/50
52/52 [==============================] - 14s 262ms/step - loss: 0.3804 - accuracy: 0.8775 - val_loss: 0.4168 - val_accuracy: 0.8680
Epoch 43/50
52/52 [==============================] - 14s 261ms/step - loss: 0.4551 - accuracy: 0.8610 - val_loss: 0.3873 - val_accuracy: 0.8704
Epoch 44/50
52/52 [==============================] - 14s 262ms/step - loss: 0.3897 - accuracy: 0.8708 - val_loss: 0.3999 - val_accuracy: 0.8680
Epoch 45/50
52/52 [==============================] - 14s 261ms/step - loss: 0.3280 - accuracy: 0.8922 - val_loss: 0.4094 - val_accuracy: 0.8680
Epoch 46/50
52/52 [==============================] - 14s 264ms/step - loss: 0.3713 - accuracy: 0.8788 - val_loss: 0.3272 - val_accuracy: 0.9022
Epoch 47/50
52/52 [==============================] - 14s 264ms/step - loss: 0.3105 - accuracy: 0.8953 - val_loss: 0.4171 - val_accuracy: 0.8680
Epoch 48/50
52/52 [==============================] - 14s 264ms/step - loss: 0.2678 - accuracy: 0.9069 - val_loss: 0.4615 - val_accuracy: 0.8289
Epoch 49/50
52/52 [==============================] - 14s 262ms/step - loss: 0.2703 - accuracy: 0.9118 - val_loss: 0.2822 - val_accuracy: 0.9218
Epoch 50/50
52/52 [==============================] - 14s 264ms/step - loss: 0.2598 - accuracy: 0.9143 - val_loss: 0.3108 - val_accuracy: 0.9095
```

Fig. 5 Result Epochs VGG16

The confusion matrix results revealed distinct classification patterns for both models. ResNet50 exhibited excellent performance across all classes, with particularly strong results for healthy leaves (131/132 correct predictions) and bacterial leaf blight (122/128 correct predictions) as shown in Figure 5.

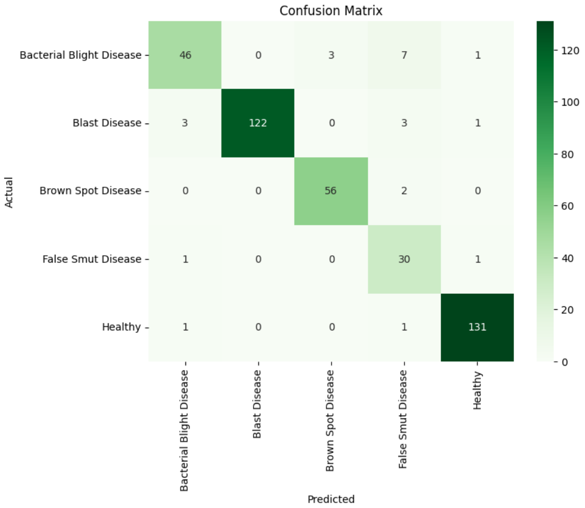


Fig. 6 Confusion Matrix ResNet50

VGG16 showed good overall performance but with more classification errors, particularly in distinguishing between brown spot and other disease categories (Figure 6).

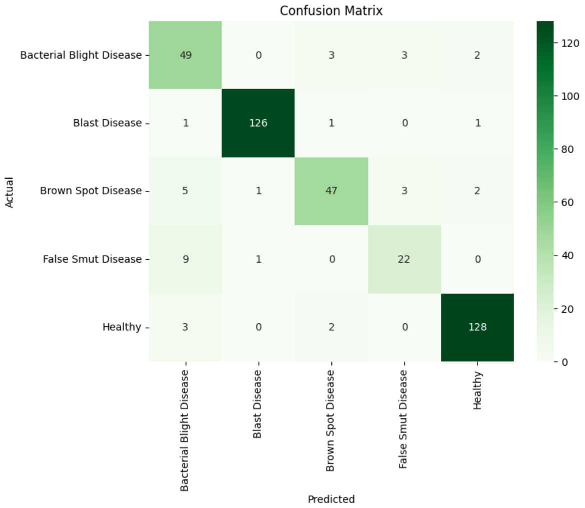
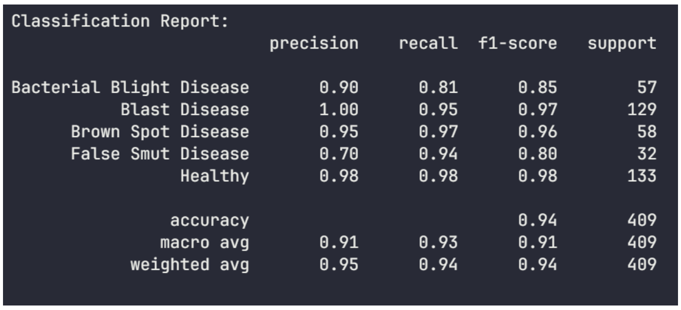


Fig. 7 Confusion Matrix VGG16

ResNet50 achieved the highest precision scores for false smut (1.00) and healthy leaves (0.98), while brown spot showed the lowest precision (0.70), indicating some misclassification challenges (Figure 7). The model demonstrated excellent recall rates, particularly for bacterial leaf blight (0.94) and healthy leaves (0.97).



```
Classification Report:
                          precision    recall  f1-score   support

Bacterial Blight Disease       0.90      0.81      0.85        57
           Blast Disease       1.00      0.95      0.97       129
      Brown Spot Disease       0.95      0.97      0.96        58
      False Smut Disease       0.70      0.94      0.80        32
                 Healthy       0.98      0.98      0.98       133

                accuracy                           0.94       409
               macro avg       0.91      0.93      0.91       409
            weighted avg       0.95      0.94      0.94       409
```

Fig. 8 Classification Report ResNet50

VGG16's classification report showed overall accuracy of 91% with strong performance for healthy leaves and bacterial leaf blight (precision of 0.98 and 0.96 respectively), but struggled with brown spot classification (precision: 0.69, recall: 0.73) as presented in Figure 8.

```
Classification Report:
                         precision    recall  f1-score   support

Bacterial Blight Disease       0.73      0.86      0.79        57
           Blast Disease       0.98      0.98      0.98       129
      Brown Spot Disease       0.89      0.81      0.85        58
      False Smut Disease       0.79      0.69      0.73        32
                 Healthy       0.96      0.96      0.96       133

                accuracy                           0.91       409
               macro avg       0.87      0.86      0.86       409
            weighted avg       0.91      0.91      0.91       409
```

Fig. 9 Classification Report VGG16

Discussion

The superior performance of ResNet50 over VGG16 can be attributed to several architectural advantages. ResNet50's deeper architecture with residual connections enables more complex feature extraction while mitigating the vanishing gradient problem through skip connections. This architectural innovation allows for more efficient learning and better generalization capabilities, as evidenced by the lower test loss (0.2125 vs 0.3108) and higher accuracy. The training curves demonstrated that ResNet50 achieved faster convergence with more stable validation performance, while VGG16 required more epochs to reach optimal performance and exhibited greater fluctuation in validation metrics (Figure 9, Figure 10).

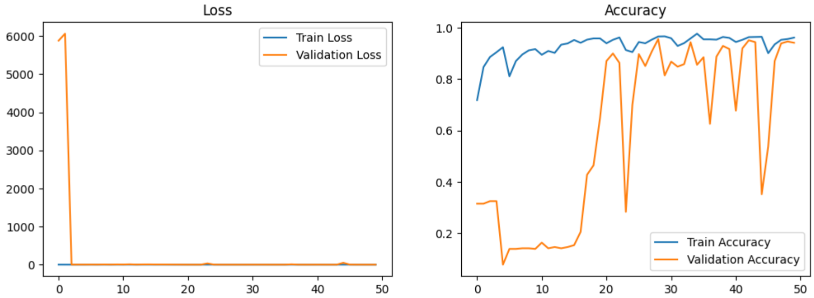


Fig. 10 ResNet50 Curves

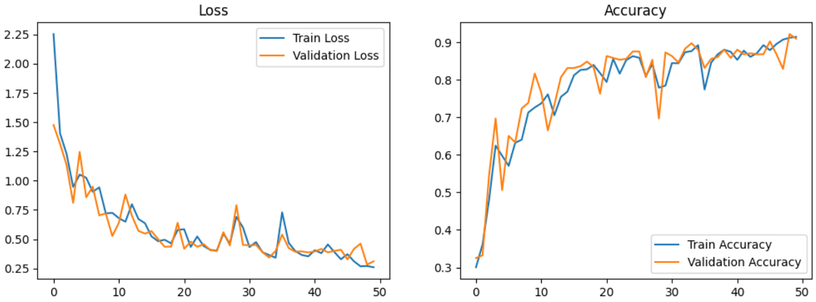


Fig. 11 VGG16 Curves

The confusion matrices revealed that brown spot classification posed the greatest challenge for both models, with frequent misclassification as other disease categories. This difficulty stems from several factors: visual similarity between brown spot and other leaf diseases, potential class imbalance in the dataset, and variations in image capture conditions such as lighting and viewing angles. The classification errors primarily occurred between visually similar disease categories, particularly between brown spot and leaf blight, suggesting the need for more discriminative features or additional data augmentation strategies to improve inter-class separability.

From a practical standpoint, ResNet50's superior accuracy (94.13%) combined with faster inference time (33 ms vs 56 ms per batch) makes it more suitable for real-time rice disease detection applications. The model's ability to correctly identify healthy plants (97% recall) and accurately detect bacterial leaf blight (94% recall) demonstrates its potential for agricultural monitoring systems. However, both models showed limitations in brown spot detection, which warrants further investigation through dataset augmentation, feature engineering, or ensemble approaches. The overall performance metrics suggest that deep learning approaches, particularly ResNet50, can effectively support precision agriculture initiatives for rice disease management.

The study confirms that transfer learning with pre-trained models significantly enhances classification performance for agricultural image analysis. ResNet50's residual learning framework proves particularly effective for handling the complexity of disease symptom variations while maintaining computational efficiency. The comprehensive evaluation using multiple metrics (accuracy, loss, confusion matrix, and classification reports) provides robust evidence for model selection in practical applications.

CONCLUSION

This comparative study between VGG16 and ResNet50 architectures for rice plant disease classification demonstrates that ResNet50 outperforms VGG16 across all evaluation metrics. ResNet50 achieved superior accuracy of 94.13% with precision, recall, and F1-score values of 0.95, 0.94, and 0.94 respectively, while VGG16 obtained 91.95% accuracy with consistent 0.91 values across precision, recall, and F1-score metrics. Both models effectively identified various rice plant diseases including brown spot, leaf blast, false smut, bacterial leaf blight, and healthy plants.

ResNet50's superior performance is further evidenced by its faster processing capabilities, requiring only 38ms/step for evaluation and 7-8 seconds average training time per epoch, compared to VGG16's 56ms/step evaluation time and 13-14 seconds training duration. The ResNet50 model achieved optimal performance with minimal loss (0.2125), demonstrating excellent convergence and generalization capabilities. These results indicate that ResNet50 provides a more efficient and practical solution for real-world agricultural applications, offering rapid inference capabilities essential for field implementation.

Future research should focus on developing models capable of identifying disease progression stages to enable more timely interventions. Additionally, enhancing model capabilities to detect multiple simultaneous infections on individual plants would significantly improve practical utility. Expanding the dataset with additional samples for underrepresented disease classes and incorporating other rice disease varieties would further strengthen model robustness and applicability across diverse agricultural contexts.

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