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Detection of Rice Diseases using Leaf Images with Visual Geometric Group (VGG-19) Architecture and Different Optimizers

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ABSTRACT

Rice is a major food commodity in Indonesia, playing a vital role in maintaining national food security. However, rice productivity often declines due to pest and disease attacks, especially when the disease is not detected early. Currently, the process of identifying rice diseases is generally still carried out manually by farmers or experts through direct observation, which is subjective, time-consuming, and prone to errors in identification. To overcome these limitations, a technology-based solution is needed that can detect rice diseases automatically, quickly, and accurately. **This study aims** to develop a rice disease detection system based on leaf images using a deep learning approach with the Visual Geometric Group (VGG-19) architecture. **The research method** employed is experimental, comparing the performance of the VGG-19 architecture using three different types of optimizers: Adaptive Moment Estimation (ADAM), Root Mean Square Propagation (RMSProp), and Stochastic Gradient Descent (SGD), to achieve the best accuracy in rice disease classification. **The findings show** that the combination of VGG-19 with the ADAM optimizer produces the highest accuracy of 96.45%, followed by RMSProp at 95.96% and SGD at 87.08%. **These findings suggest** that the selection of optimizers plays a crucial role in enhancing the performance of deep learning models, particularly in the detection of rice diseases using leaf images.

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1. INTRODUCTION

Rice is one of Indonesia's key food commodities and plays an essential role in maintaining national food security [1]. However, its productivity is highly vulnerable to various plant diseases, including bacterial leaf blight, brown spot, and blast [2, 3]. These diseases can cause significant yield losses if not detected early [4]. Currently, disease identification is mostly performed manually through direct observation by farmers or agricultural experts—a method that is subjective, time-consuming, and susceptible to errors [4]. Until now, the process of identifying plant diseases is still mostly done manually through direct observation by farmers or agricultural experts, which is subjective, time-consuming, and prone to diagnostic errors [5]. With the development of precision agriculture, there is a need for a disease detection system that can work automatically, quickly, and accurately. One promising approach to meet this challenge is the use of image processing and artificial intelligence technologies, especially through deep learning methods [6]. By using leaf images as visual data, the system can recognize patterns of disease symptoms early and in a structured manner [7, 8]. This approach enables more timely, efficient, and data-driven decision-making in disease control and management. Previous studies have successfully applied Convolutional Neural Network (CNN) architectures to detect plant diseases using leaf images.

Study [9] compared six CNN architectures for classifying nine of the most epidemic rice diseases in Bangladesh. The ensemble framework achieved the highest accuracy at 98%, and transfer learning improved accuracy by 17% compared to SEResNeXt101 in detecting and localizing rice leaf diseases. Another study [10] used Deep Learning and transfer learning to classify nine types of rice leaf diseases using 5,932 images labeled and validated by experts. A custom CNN model was evaluated alongside other architectures, including VGG16, Xception, ResNet50, DenseNet121, InceptionResNetV2, and InceptionV3. The custom VGG16 model achieved the highest accuracy at 99.94%. Study [3] developed a transfer learning method based on VGG19 to classify six rice leaf diseases, achieving 96.08% accuracy on augmented data without normalization. Study [11] proposed a rice leaf disease detection system using various deep learning techniques. Features were extracted from 32 pretrained models and classified using several machine learning and ensemble algorithms. The combination of EfficientNetV2B3 with Extra Tree and Histogram Gradient Boosting achieved up to 94% accuracy.

Study [12] used a combination of VGG-16 and Faster R-CNN for feature extraction and Random Forest to classify three rice leaf diseases: bacterial leaf blight, brown spot, and leaf smut. Using data from the UCI Repository, the model achieved an accuracy of 97.3%. Study [13] applied transfer learning-based deep learning models—VGG-16 and GoogleNet—to classify disease symptoms in rice using 12,000 labeled images for three diseases. VGG-16 and GoogleNet achieved average accuracies of 92.24% and 91.28%, respectively. Study [14] proposed a VGG-based rice leaf disease detection model combined with a multi-scale convolution module to reduce the number of parameters. The model achieved 97.1% accuracy, representing a 5.87% increase over the standard VGG, while utilizing only 1.6% of VGG's memory. The results showed improvements in accuracy, speed, and memory efficiency. Study [15] compared several CNN architectures, including VGG19, XceptionNet, ResNet50, DenseNet, and SqueezeNet, for automated rice disease detection. By applying baseline and transfer learning methods to datasets from various sources, ResNet50 achieved the best performance with a top accuracy of 97.5%. Most previous studies only used one type of optimization algorithm, such as Adam or Stochastic Gradient Descent (SGD), without conducting comparative analyses of different optimization algorithms. As a result, **there are still few studies** that specifically compare the effects of different optimization algorithms on the performance of the VGG-19 architecture, particularly in the context of rice disease detection using leaf images. Selecting the right optimization algorithm is crucial for accelerating convergence, improving classification accuracy, and optimizing model training efficiency. Therefore, **this study presents a novel approach** to previous works by comparing three popular optimization algorithms—Adam, RMSProp, and SGD—on the VGG-19 architecture for detecting rice diseases using leaf images.

This study aims to analyze and evaluate the impact of the Adam, RMSProp, and SGD optimization algorithms on the performance of the VGG-19 architecture in detecting rice diseases using leaf images. The evaluation is conducted by measuring accuracy, loss, and training efficiency for each combination of model and optimization algorithm. The main contributions of this study include: (1) providing a comparative analysis of three optimization algorithms in the context of rice disease classification based on leaf images; (2) recommending the most effective optimization algorithm to improve the performance of the VGG-19 architecture in rice leaf image classification; and (3) establishing a foundation for the development of more efficient and accurate image-based plant disease detection systems to support the digital transformation of agriculture in Indonesia.

2. RESEARCH METHOD

Figure 1 shows the complete workflow of the study conducted to classify types of diseases in rice plants using leaf images and a deep learning approach based on the VGG-19 architecture. This research consists of four main stages: data collection, image processing, model development, and performance evaluation. The first stage is data collection, where rice leaf images are gathered from various sources, including public datasets and direct documentation. These images include leaves showing symptoms of diseases such as Bacterial Leaf Blight, Brown Spot, and Leaf Smut. The aim is to obtain sufficient visual samples for each disease class, enabling the model to learn the patterns effectively. The second stage is image processing, a crucial step to prepare the data before feeding it into the model. The images are first resized to 200×200 pixels to match the standard input size for the VGG-19 model. Then, they are converted from RGB to grayscale to simplify color information and reduce dimensional complexity while retaining important visual features. Data augmentation is also performed, such as rotation, horizontal flipping, shearing, and zooming, to synthetically increase the variety of training data, enhance the model's generalization ability, and reduce the risk of overfitting.

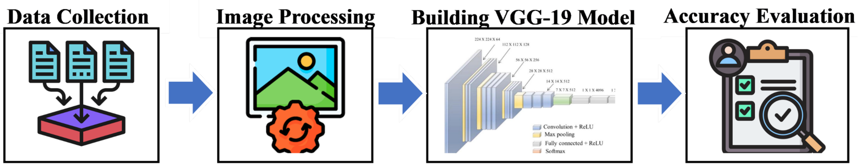

Figure 1. Research Flow

The third stage is model development using the VGG-19 architecture for image classification. VGG-19 consists of a series of convolutional and pooling layers, followed by fully connected layers and a softmax activation at the output layer, which is used to classify images into three categories of rice leaf diseases. This model is known for its depth, which allows it to extract detailed and efficient visual features from input images. VGG-19 is a Convolutional Neural Network (CNN) architecture developed by the Visual Geometry Group (VGG) [16]. It is known for its depth and structural simplicity and has been proven effective for various image recognition tasks. VGG-19 comprises 19 trainable layers, consisting of 16 convolutional layers and three fully connected layers. The convolutional layers utilize small filters (3×3) with consistent padding and stride, enabling the extraction of detailed features from images. After several convolutional layers, max pooling layers (2×2) are used to reduce feature dimensions and computational complexity. The fully connected layers at the end classify the extracted features into target classes, using softmax activation to produce prediction probabilities, as shown in Figure 2. The main strength of VGG-19 lies in its deep architecture, which enables it to learn complex feature representations from images.

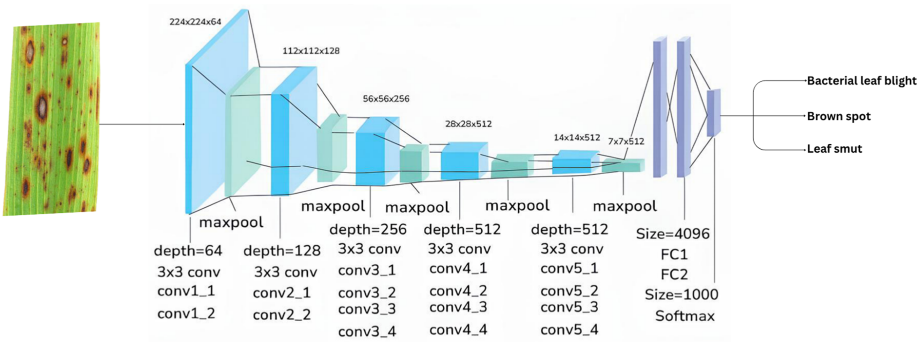

Figure 2. VGG-19 Architecture Workflow

The final stage is accuracy evaluation, which is carried out to assess the model's performance in classification. This evaluation uses a confusion matrix, which provides detailed information on the number of correct and incorrect predictions for each class. From the confusion matrix, evaluation metrics such as accuracy can be calculated—an essential indicator of the model's reliability in multi-class classification using Equation 1 [17, 18].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \tag{1}$$

3. RESULT AND ANALYSIS

This section presents the results of applying the VGG-19 architecture to detect rice diseases using images and discusses how different optimization techniques impact model performance. The evaluation is conducted to determine how well the combination of architecture and optimization methods improves classification accuracy and detection precision. The results are compared using evaluation metrics such as accuracy for each optimizer. This analysis aims to provide a clearer understanding of the effectiveness of deep learning in precision agriculture, particularly in the early detection of crop diseases. Figure 3 shows the results of the image processing and augmentation stages for rice leaf images, which aim to improve data quality and diversity. The original image (Figure 3a) shows disease symptoms in the form of dark brown spots. The image is then converted to grayscale (Figure 3b) to simplify color information and help feature extraction. The augmentation process includes shear (Figure 3c), zoom (Figure 3d), rotation (Figure 2e), and horizontal flip (Figure 3f) transformations to create variations in shape, scale, orientation, and direction. This step enriches the dataset and improves the model's ability to recognize disease patterns more accurately and robustly under changing image conditions.

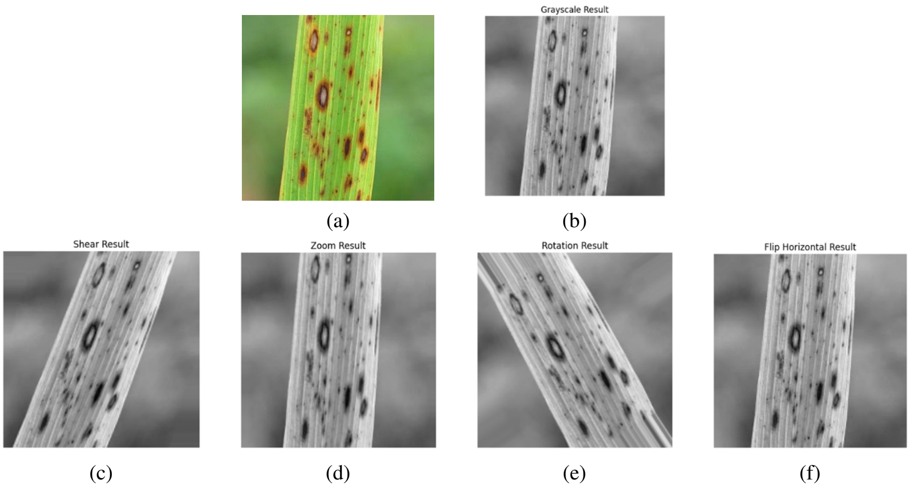

Figure 3. Image Processing Results, a). Original Data; b). Grayscale; c). Shear Results; d). Zoom Results: e). Rotation Results: f). Horizontal Flip Results

Figure 4 shows the distribution of data before and after the augmentation process. Initially, each class—Bacterial Leaf Blight, Brown Spot, and Leaf Smut—contained only 40 images. This indicates that the original dataset was very limited and imbalanced, making it unsuitable for training an accurate model. After data augmentation, the number of images increased significantly and became more balanced across the classes. Bacterial Leaf Blight had 1,025 images, Brown Spot had 1,039 images, and Leaf Smut had 982 images. The purpose of data augmentation is to expand the dataset size, reduce the risk of overfitting, and improve the model's ability to generalize when classifying rice leaf diseases. The results from the augmented data were split into training and testing sets, with 80% allocated for training and 20% for testing. The training data was used to build models from each CNN architecture with a total of 50 epochs and a batch size of 64. Next, data testing is used as an evaluation tool to measure the performance of the trained model.

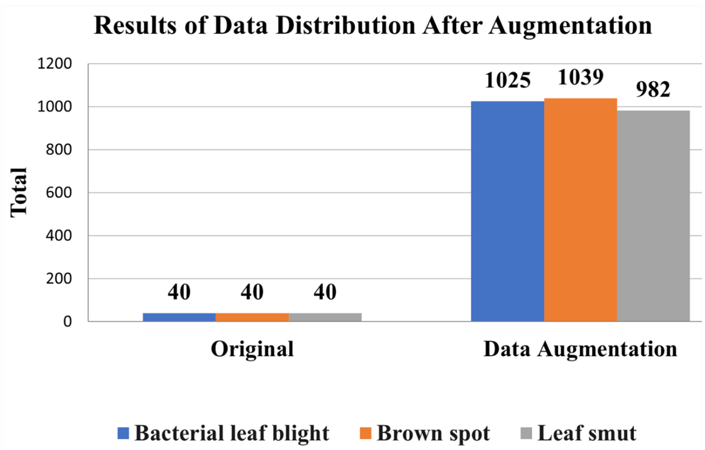

Figure 4. Result of Data Distribution After Augmentation

Figure 5 shows the confusion matrix of the classification results for rice diseases based on leaf images using the VGG19 model optimized with the ADAM algorithm. The matrix displays the model's performance in distinguishing three types of rice diseases: Bacterial Leaf Blight, Brown Spot, and Leaf Smut. According to the results, the model correctly classified all 211 images of Bacterial Leaf Blight with no errors, indicating perfect accuracy for that class. For the Brown Spot class, 202 images were classified correctly, while seven were mistakenly classified as Bacterial Leaf Blight and two as Leaf Smut. In the Leaf Smut class, the model correctly identified 184 images but made errors on seven images, classifying them as Bacterial Leaf Blight, and incorrectly classified eight images as Brown Spot. Overall, the confusion matrix results indicate that the VGG19 model with the ADAM optimizer performs very well, especially in identifying Bacterial Leaf Blight, with no misclassifications occurring. Although there were some errors in classifying Brown Spot and Leaf Smut, the numbers are relatively small and do not significantly affect the model's overall performance. Therefore, the model can be considered highly accurate and reliable in classifying types of rice leaf diseases in the given test data.

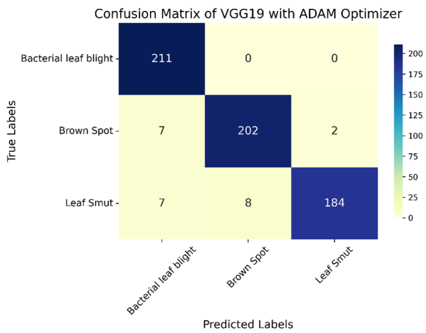

Figure 5. Results of VGG-19 Confusion Matrix with ADAM Optimization

Figure 6 displays the confusion matrix resulting from the classification using the VGG19 model, which was optimized with the RMSprop algorithm. This model was used to identify three types of rice leaf diseases: Bacterial Leaf Blight, Brown Spot, and Leaf Smut. According to the results, the model correctly classified all 211 images of Bacterial Leaf Blight without any errors. For the Brown Spot class, 201 images were correctly identified, while eight were misclassified as Bacterial Leaf Blight and two as Leaf Smut. In the Leaf Smut class, 182 images were correctly classified, with six misclassified as Bacterial Leaf Blight and 11 as Brown Spot. Overall, the VGG19 model with RMSprop demonstrated strong classification performance, especially for the Bacterial Leaf Blight class, which was recognized with perfect accuracy. Although the number of misclassifications for Brown Spot and Leaf Smut increased slightly compared to the ADAM-optimized model, the model still performed well. This indicates that RMSprop is a competitive optimizer, although it tends to result in slightly more confusion between visually similar disease classes.

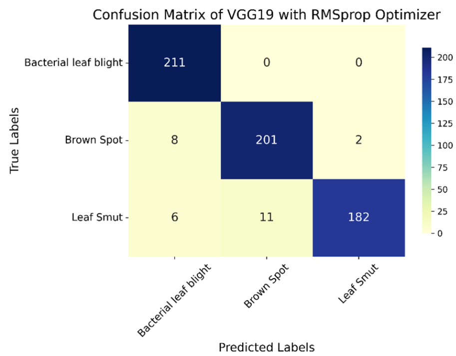

Figure 6. Results of VGG-19 Confusion Matrix with RMSProp Optimization

Figure 7 displays the confusion matrix resulting from the classification outcomes of the VGG19 model, which was optimized using the Stochastic Gradient Descent (SGD) algorithm. This model was used to distinguish between three types of rice diseases based on leaf images: Bacterial Leaf Blight, Brown Spot, and Leaf Smut. In the Bacterial Leaf Blight class, the model correctly classified all 211 images without any errors, indicating perfect performance for this category. However, in the Brown Spot class, the accuracy dropped significantly, with only 148 images correctly classified, while 61 were misclassified as Bacterial Leaf Blight and two as Leaf Smut. For the Leaf Smut class, 180 images were classified correctly, with eight misclassified as Bacterial Leaf Blight and 11 as Brown Spot. These results suggest that although the VGG19 model optimized with SGD performs excellently in identifying Bacterial Leaf Blight, its ability to distinguish Brown Spot and Leaf Smut is lower compared to models optimized with ADAM or RMSprop. The relatively high number of misclassifications in the Brown Spot class indicates that SGD struggles with the data complexity or achieving optimal convergence during model training. Therefore, overall, the model's performance with the SGD optimizer is less stable and less accurate than when using ADAM or RMSprop.

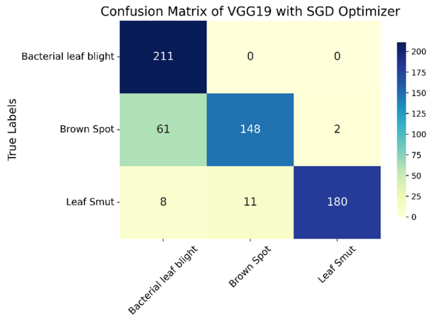

Figure 7. VGG-19 Confusion Matrix Results with SGD Optimization

Figure 8 presents a comparison of the accuracy levels of the VGG-19 model optimized using three different optimization algorithms: ADAM, RMSprop, and SGD. This chart provides quantitative information on the effectiveness of each optimizer in improving the model's classification performance on the leaf disease dataset. According to the results, the ADAM optimizer achieved the highest accuracy at 96.45%, followed by RMSprop at 95.96%, while SGD recorded the lowest accuracy at 87.08%. These accuracy values represent the proportion of correct predictions made by the model on the test data. ADAM's high accuracy can be attributed to its internal mechanism, which combines the benefits of momentum and adaptive learning rate, allowing it to converge faster while avoiding local minima or oscillations in the loss function. Although RMSprop also uses an adaptive approach, it is slightly less effective than ADAM, though it still performs well and consistently. On the other hand, SGD exhibits the lowest performance, which may be attributed to its sensitivity to learning rate settings and slower convergence, accompanied by higher fluctuations during training. Overall, the analysis in Figure 8 reveals that the choice of optimizer has a significant impact on the effectiveness of training deep learning models, particularly the VGG-19 architecture in image classification tasks. ADAM is proven to be the most reliable option for achieving high accuracy and stable classification performance compared to RMSprop and SGD, as supported by previous studies [19–21]. Therefore, in the context of image-based leaf disease classification, ADAM can be recommended as the most optimal optimizer among the three.

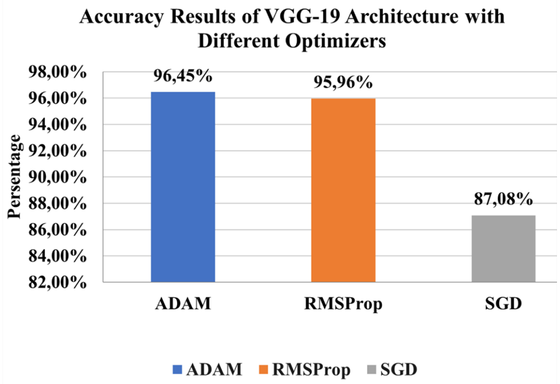

Figure 8. Comparison of the Accuracy of the VGG-19 Architecture with Different Optimizers

ADAM outperforms RMSprop and SGD in classifying rice diseases based on leaf images using the VGG-19 architecture because it combines fast convergence (through momentum) with stable parameter updates (through adaptive learning rates) [22]. This makes it highly suitable for handling complex and varied visual data, such as that found in rice disease prediction using leaf images. ADAM helps the model learn more efficiently and achieve higher and more consistent classification accuracy than RMSprop and SGD.

4. CONCLUSION

This study successfully developed an automatic rice disease detection system based on leaf images using the VGG-19 deep learning architecture. Based on the experimental results, it is evident that the selection of the optimizer type has a significant impact on the model's performance in classifying rice diseases. The ADAM optimizer produces the highest accuracy of 96.45%, followed by RMSProp at 95.96% and SGD at 87.08%. These findings suggest that utilizing the VGG-19 architecture in conjunction with the appropriate optimizer, particularly ADAM, can substantially enhance the accuracy of the rice disease detection system. With a high level of accuracy and reliable classification capabilities, this system has great potential as a precision agriculture support tool, automatically, quickly, and accurately detecting rice diseases, thereby contributing to increased national productivity and food security. For further research, it is recommended to explore other deep learning architectures to expand the performance comparison. Evaluation also needs to be carried out under various lighting conditions and backgrounds to ensure the model is more robust in real-world data. The Generative Adversarial Networks (GANs) data augmentation technique can be applied to improve model generalization. In addition, developing systems in the form of mobile applications or IoT-based devices can help farmers detect diseases directly in the field.

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6. DECLARATIONS

AI USAGE STATEMENT

During the preparation of this work, the authors used ChatGPT (OpenAI) to improve the language and clarity of the manuscript. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the publication's content.

AUTHOR CONTIBUTION

All authors contributed to the writing of this article.

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COMPETING INTEREST

The author declares that there is no conflict of interest in publishing this article.

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