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***Research Article***

# Rice Disease Classification Using Leaf Images with Mobilenetv2 Based on Mobile

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**Abstract:** Rice is a major staple food in Indonesia, including in Merauke Regency, one of the largest rice-producing regions in South Papua Province. In 2023, Merauke Regency had a harvested rice area of 49,573.50 hectares, with a production of 236,500.33 tons. However, rice cultivation still faces challenges from pests and diseases that can reduce the quality and quantity of the harvest. Manual disease identification through direct observation or consultation with Field Agricultural Extension Workers (PPL) is time-consuming and risky due to the diverse types of diseases and leaf symptoms. This research aims to develop a leaf-image-based rice plant disease classification system using a Convolutional Neural Network (CNN) with the MobileNetV2 architecture. The system, developed as an Android application, can classify diseases through the camera or gallery, displaying symptoms and treatment solutions. The dataset consists of 7,200 images with six classes: Bacterial Leaf Blight, Brown Spot, Healthy, Leaf Blast, Leaf Scald, and Tungro. Testing uses accuracy, confusion matrix, Black Box, and User Acceptance Testing (UAT). The best results were obtained at epoch 50 and a learning rate of 0.001, with a training accuracy of 99.50%, a validation accuracy of 95.00%, a testing accuracy of 95.88%, and a real-world accuracy of 76.67%. Black Box showed all features were running as expected, while UAT achieved 83.2% for farmers and 92% for admins.

**Keywords: Rice Disease Classification, CNN, MobileNetV2, Leaf Image, Android**

## 1. Introduction

Rice is a primary staple food widely consumed in Indonesia. Rice cultivation is extensively practiced throughout the country to meet national food demand. Merauke Regency is the largest producer of rice crops in South Papua Province. In 2023, the harvested area for rice reached 49,573.50 hectares (ha), with a total production of 236,500.33 tons and a productivity rate of 4.77 tons/ha [1]. Consequently, agriculture, particularly rice farming, serves as one of the main sources of income in Merauke Regency. However, the rice cultivation process is constantly vulnerable to pest infestations and disease outbreaks.

Rice diseases typically lead to a reduction in both the yield quality and quantity. Common diseases affecting paddy fields include blast disease, bacterial leaf blight, tungro, leaf scald, and brown spot. Diseases infecting rice plants are generally characterized by primary symptoms and visible features on the leaves [2]. Changes in the leaves—such as discoloration, spot formation, physical damage, or other symptoms—serve as indicators of disease infection.

Traditionally, farmers identify diseases by consulting field agricultural extension officers (Penyuluh Pertanian Lapangan or PPL), whose availability is limited. This identification process involves direct field observation and the collection of infected leaf samples, making it time-consuming. Furthermore, manual identification across diverse disease types carries a high risk of misdiagnosis. According to official data, the Agricultural Extension Center (BPP) in Merauke Regency employs only 76 extension officers—comprising 60 civil servants, 13 contract personnel, and 3 independent officers—spread across 20 districts [3].

The traditional manual classification of rice diseases, which relies on human visual inspection, can be automated using modern technology, as implemented by [4]–[7]. In Indonesia, several researchers have also deployed technological approaches to detect rice leaf diseases [8]–[12]. These prior studies utilized various deep learning architectures. Among these, the MobileNetV2 architecture emerged as one of the top-performing models for rice disease classification [13]–[14]. However, those studies were limited to model development, whereas our study extends this work by deploying the trained model into a mobile application. While earlier efforts have also explored mobile implementation, they relied on alternative deep learning architectures [15]–[17].

For this reason, the research will apply a deep learning model with the MobileNetV2 architecture. MobileNetV2 is a lightweight CNN architecture suitable for performing image classification on resource-constrained devices, such as smartphones.

Addressing these challenges, this study focuses on developing an application or system to classify leaf images using a CNN with the MobileNetV2 architecture. The developed application is capable of classifying rice diseases from gallery images or direct real-time photos, providing descriptions, symptoms, and potential treatment solutions based on the input image provided by the user.

## 2. Method and materials

### 2.1 Research steps

The research method is illustrated in the process flow for developing an image-based rice disease classification model. The process begins with collecting the rice disease dataset, followed by data cleaning to remove any inconsistencies. The dataset is then divided into training, validation, and testing data sets. Detailed images are shown in Figure 1.

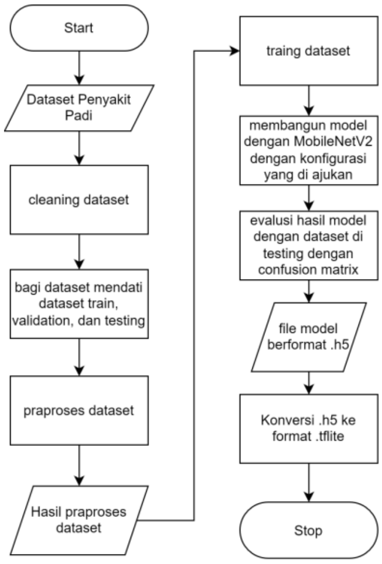


Figure 1. Flowchart Model Development

**2.2 Rrice disease dataset**

The rice disease dataset consists of six classes: Bacterial Leaf Blight, Brown Spot, Healthy, Leaf Blast, Leaf Scald, and Tungro. Each class has 1,000 images for training data, 100 images for validation data, and 100 images for testing data, resulting in a total of 1,200 images for each class. Overall, the dataset used amounts to 7,200 images, divided for training, validation, and model testing purposes to ensure optimal classification.

Table 1. dataset sharing

| class | Train | Val | Test | Σ |
|---|---|---|---|---|
| Bacterial Leaf Blight | 1000 | 100 | 100 | 1200 |
| Brown Spot | 1000 | 100 | 100 | 1200 |
| Healthy | 1000 | 100 | 100 | 1200 |
| Leaf Blast | 1000 | 100 | 100 | 1200 |
| Leaf Scald | 1000 | 100 | 100 | 1200 |
| Tungro | 1000 | 100 | 100 | 1200 |
| Total | 6000 | 600 | 600 | 7200 |

**2.2 Configuration Training parameter**

The model training process was carried out using the MobileNetV2 architecture with an input size of 224 × 224 pixels and a batch size of 32. The optimizer used was Adam, with hyperparameter variations in the number of epochs and learning rate. Testing several configurations aimed to obtain the best model performance in classifying rice plant diseases.

Table 2. Model training hyperparameter configuration

| Model Scenarion | Input Shape | Batch Size | Optimizer | Epoch | Learning Rate |
|---|---|---|---|---|---|
| 1 | 224 × 224 | 32 | Adam | 30 | 0.001 |

| Model Scenarion | Input Shape | Batch Size | Optimizer | Epoch | Learning Rate |
|---|---|---|---|---|---|
| 2 | 224 × 224 | 32 | Adam | 50 | 0.001 |
| 3 | 224 × 224 | 32 | Adam | 30 | 0.0005 |
| 4 | 224 × 224 | 32 | Adam | 50 | 0.0005 |

## 3. Result And Discussion

### 3.1. Result of Konfiguration 1

In configuration 1, training was carried out with epoch 30 and learning rate 0.001 resulting in a training accuracy of 0.9893 and a training loss of 0.0415 and a validation accuracy of 0.9467 and a loss of 0.1726. The accuracy evaluation of the testing dataset consisted of 600 images with 100 images for each class. There were errors in the bacterial leaf blight class of 2 images, brownspot 8 images, healthy 5 images, leaf blast 6 images, leaf scald 0 images, and tungro 1 image, resulting in a testing accuracy of 96% or 0.9633. The accuracy and loss graphs of the training process are shown in Figure 2, while the confusion matrix is shown in Figure 3.

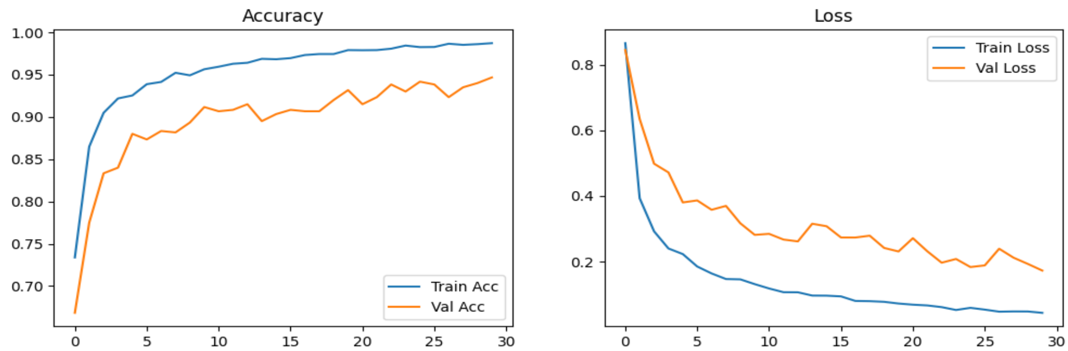


Figure 2. Accuracy and loss graph of configuration model training 1


Figure 3. Confusion matrix results for configuration 1

### 3.2. Result of Konfiguration 2

In configuration 2, training was carried out with epoch 50 and learning rate 0.001 resulting in a training accuracy of 0.9950 and a training loss of 0.0247 and a validation accuracy of 0.9500 and a loss of 0.1678. The accuracy evaluation of the testing dataset consisted of 600 images with 100 images for each class. There were errors in the bacterial leaf blight class of 2 images, brownspot 10 images, healthy 7 images, leaf blast 6 images, leaf scald 0 images, and tungro 0 images, resulting in a testing accuracy of 95.88% or 0.9588. The accuracy and loss graphs of the training process are shown in Figure 4, while the confusion matrix is shown in Figure 5.

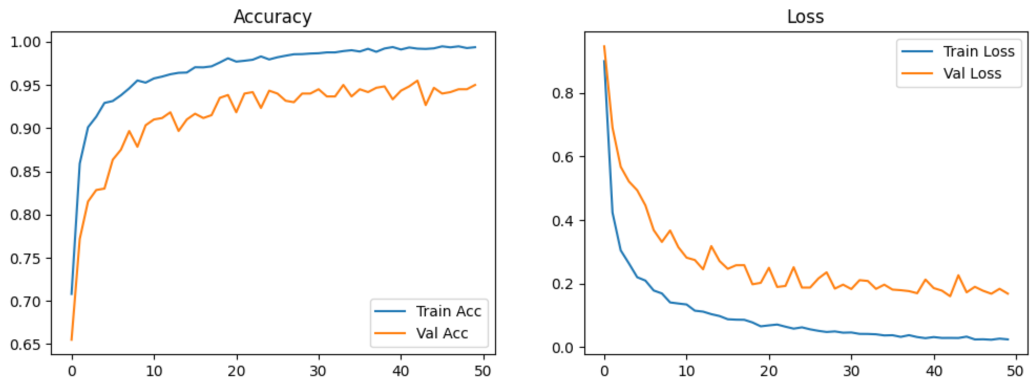


Figure 2. Accuracy and loss graph of configuration model training 2

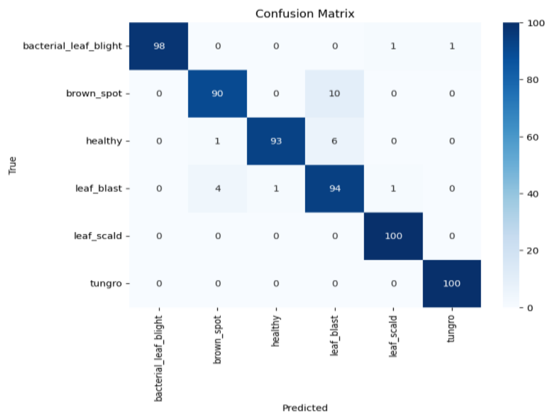


Figure 3. Confusion matrix results for configuration 2

### 3.3. Result of Konfiguration 3

In Configuration 3, training was conducted with 30 epochs and a learning rate of 0.0005, yielding a training accuracy of 0.9743, a training loss of 0.0827, a validation accuracy of 0.9267, and a validation loss of 0.2062. Evaluation on the testing dataset comprised 600 images, with 100 images per class. Misclassifications occurred in the following classes: bacterial leaf blight (8 images), brown spot (15 images), healthy (8 images), and leaf blast (5 images), whereas leaf scald and tungro recorded 0 errors. This resulted in a testing accuracy of 94.00% (or 0.9400). The accuracy and loss graphs of the training process are shown in Figure 6, while the confusion matrix is shown in Figure 7.

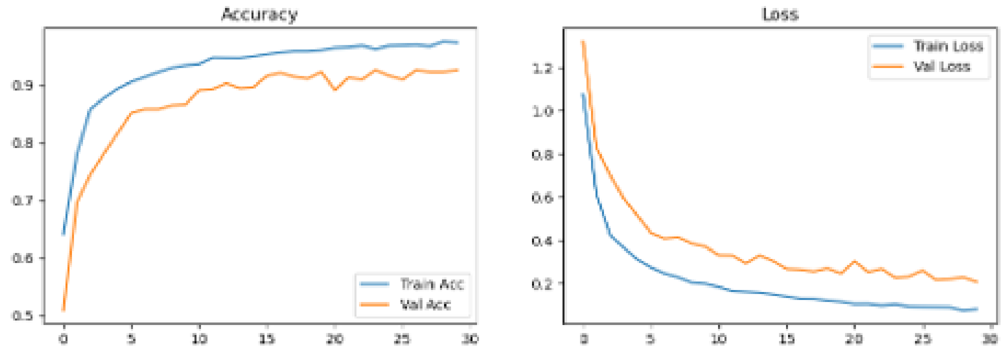


Figure 6. Accuracy and loss graph of configuration model training 3

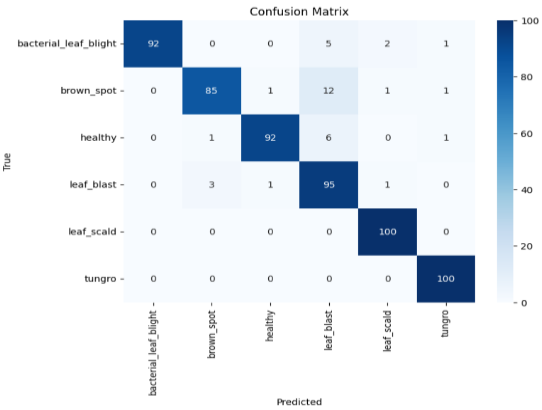


Figure 7. Confusion matrix results for configuration 3

### 3.4. Result of Konfiguration 3

In Configuration 4, training was conducted with 30 epochs and a learning rate of 0.0005, yielding a training accuracy of 0.9915, a training loss of 0.0399, a validation accuracy of 0.9383, and a validation loss of 0.1694. Evaluation on the testing dataset comprised 600 images, with 100 images per class. Misclassifications occurred in the following classes: bacterial leaf blight (4 images), brown spot (12 images), healthy (8 images), and leaf blast (6 images), whereas leaf scald and tungro recorded 0 errors. This resulted in a testing accuracy of 95.00% (or 0.9500). The accuracy and loss graphs of the training process are shown in Figure 8, while the confusion matrix is shown in Figure 9.

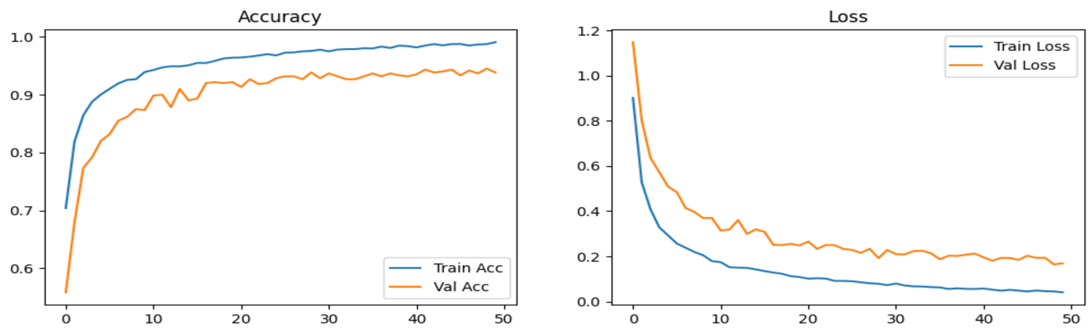


Figure 8. Accuracy and loss graph of configuration model training 3

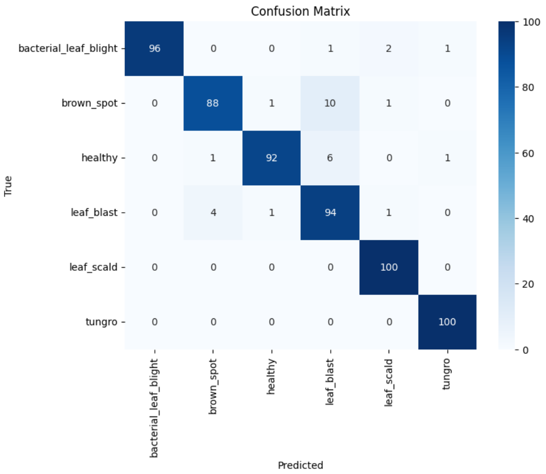


Figure 9. Confusion matrix results for configuration 4

### 3.5. Comparison of classification results

After each configuration has been trained, testing is carried out. Table 3 shows the test results for each configuration that has been implemented.

| Konfigurasi | Epoch | Learning Rate | Training Accuracy | Validation Accuracy | Testing Accuracy | Akurasi Real |
|---|---|---|---|---|---|---|
| 1 | 30 | 0.001 | 98.93% | 94.67% | 96.33% | 71.67% |
| 2 | 50 | 0.001 | 99.50% | 95.00% | 95.88% | 76.67% |
| 3 | 30 | 0.0005 | 97.43% | 92.67% | 94.00% | 70.00% |
| 4 | 50 | 0.0005 | 99.15% | 93.83% | 95.00% | 75.00% |

Based on the experimental evaluations conducted across four configurations of the MobileNetV2 CNN model, distinct performance differences were observed for each configuration used. The parameters evaluated included varying numbers of epochs and learning rates to assess their impact on overall model accuracy.

The results indicate that Configuration 2, utilizing 50 epochs and a learning rate of 0.001, achieved the best performance compared to the other configurations. This superior performance is demonstrated by a training accuracy of 99.50%, a validation accuracy of 95.00%, a testing accuracy of 95.88%, and the highest real-world testing accuracy of 76.67%.

Meanwhile, Configuration 3, which employed a lower learning rate of 0.0005, exhibited lower performance, obtaining a real-world accuracy of 70.00%. Configurations 1 and 4 demonstrated reasonable results; however, their overall performance remained below that of Configuration 2.

### 3.6. Implementation in mobile applications

After obtaining the best parameters, the model is then implemented in a mobile application. This image-based rice plant disease classification application was created to help farmers quickly and accurately identify diseases affecting rice plants based on rice leaf images. This application is designed to facilitate early disease identification, allowing farmers to identify symptoms and appropriate treatment solutions for the detected disease.

This application allows farmers to input rice plant images via the camera or gallery on their device.

Once the image is input, the application will perform a classification process to determine the type of rice plant disease. The classification results will display information such as the disease name, symptoms, and solutions or treatment actions that farmers can take based on the classification results. Furthermore, the application also provides a data import feature to update the displayed disease symptom and solution information. Figure 10 below shows the results of the main page display and the image input process for classification.

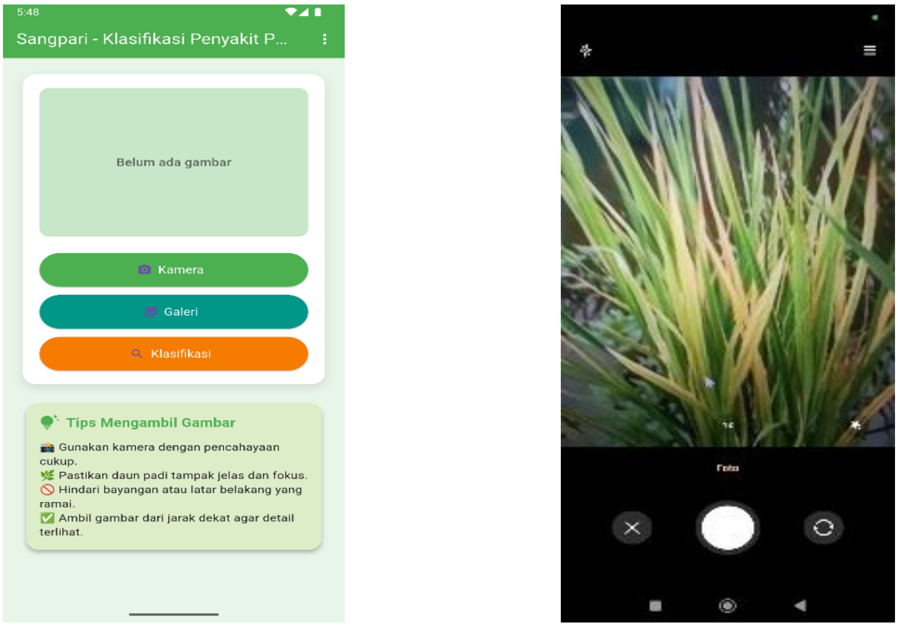


Figure 10. Implementation results on mobile

### 3.7. Mobile application test results

The successfully developed application was then tested. The research conducted black box testing and UAT testing. The black box testing results showed that across all user and admin feature test scenarios, the system was able to produce output consistent with the provided input. Therefore, it can be concluded that all main system functions performed well and met the specified functional requirements.

A User Acceptance Test (UAT) was then conducted to determine the level of user acceptance and satisfaction with the developed rice plant disease classification system. This test used a questionnaire completed by respondents after directly testing and using the system. Six respondents participated in the UAT test: one respondent acting as an admin and five respondents acting as farmers, system users. Respondents were selected based on their direct involvement in the system, both as application managers and as primary users in the rice plant disease identification process.

The UAT calculation was performed using the formula $Y = (\Sigma (N \times R) / \text{Ideal Score}) \times 100\%$. The weighting of responses used was: Strongly Agree (5), Agree (4), Fair (3), Disagree (2), and Strongly Disagree (1). The calculation yielded a percentage of 83.2%, which falls into category A (Strongly Agree). This indicates that the rice disease classification application was well-received by farmers and was deemed useful and easy to use in assisting the rice disease identification process.

## 4. Conclusion

The implementation of the Convolutional Neural Network (CNN) method with the MobileNetV2 architecture in this study successfully classified six classes of rice plant conditions, namely Bacterial Leaf Blight, Brown Spot, Healthy, Leaf Blast, Leaf Scald, and Tungro. Based on the training results across four model configurations, Configuration 2—utilizing 50 epochs and a learning rate of 0.001—emerged as the optimal setup, achieving a training accuracy of 99.50%, a validation accuracy of 95.00%, and a testing accuracy of 95.88% on 600 test samples. Furthermore, real-world testing evaluated on 60 field images yielded an average accuracy of 76.67%, representing the highest performance among all configurations. These findings demonstrate that the MobileNetV2-based CNN approach is effective for leaf image-based rice disease classification, despite a slight performance gap between the experimental test data and real-world conditions.

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