Implementation Of MobileNetV2 Architecture In Rice Disease Detection System Using Digital Images.

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Abstract.

Rice plant diseases pose a significant threat, reducing crop yields. Especially in agricultural areas such as the Tanjung Morawa region of Deli Serdang, accurate and rapid early detection is very difficult. Three main disease types, Bacterial Leaf Blight (BLB), Brown Spot, and Leaf Smut, are identified by the MobileNetV2 architecture in the rice disease detection system. The transfer learning method was employed to enhance training using local public data. Although metrics such as accuracy, precision, recall, and F1 score were used to measure performance, evaluation of the model showed that accuracy and detection efficiency had improved compared to traditional methods. By integrating this system into a Flask-based web application, users can upload photos of rice leaves and receive detection results directly. It is expected that this research will make a significant contribution to the development of intelligent agricultural technologies that will help farmers find rice diseases early and treat them correctly.

Keywords: *Mobilenetv2; Rice Disease Detection; Digital Imagery;Transfer Learning and Agricultural Technology.*

I. INTRODUCTION

Rice is one of the most important agricultural commodities in the Tanjung Morawa region of Deli Serdang, North Sumatra. However, rice plant diseases often pose a serious threat that can significantly reduce crop yields. This issue is further complicated by limitations in early disease detection, which to this day still heavily relies on farmers' experience and visual observation. Conventional methods are not always effective, especially when diseases have already spread widely. Therefore, a system is needed that can accurately and quickly detect rice diseases by leveraging advancements in digital technology [1]. Previous studies have shown that digital imaging technology combined with machine learning and deep learning methods can effectively classify various types of plant diseases. Studies have demonstrated the success of using CNN architecture to recognize plant diseases based on their visual characteristics [2]. However, challenges remain in terms of accuracy and processing speed, especially when dealing with large datasets [3]. To address these challenges, this study proposes the use of the MobileNetV2 architecture, specifically designed for efficient processing of rice leaf images, including on devices with limited resources [4]. According to Turahman et al. (2025), this research aims to develop an efficient and accurate rice disease detection system based on MobileNetV2 [5]. It is hoped that this system can serve as a practical solution for farmers to quickly detect diseases such as bacterial leaf blight, brown spot, and leaf smut through digital images of rice leaves. Additionally, this study aims to evaluate the performance of MobileNetV2 in detecting rice diseases compared to conventional methods involving direct observation by farmers [6].

Preliminary results indicate that the use of MobileNetV2 can improve accuracy and processing efficiency compared to traditional methods, especially when the model is trained using transfer learning techniques, even with a relatively small dataset [7]. The scope of this research is limited to the detection of three types of rice diseases, namely bacterial leaf blight, brown spot, and leaf smut, without covering other types of diseases. This research is focused on the Tanjung Morawa area, Deli Serdang, and uses data in the form of digital images of rice leaves taken directly from the field using a high-resolution smartphone camera. Other data sources, such as historical or non-image data, are not used in this research [8]. Thus, this study not only has the potential to increase crop yields but also provides new insights into the application of digital technology in the agricultural sector. Through this approach, the study is expected to contribute both theoretically and practically. Theoretically, the results of this study can serve as a reference for further research focused on the application of deep learning technology in agriculture [9]. On the other hand, the practical benefits of this research are to provide convenience for farmers, especially in Tanjung Morawa, in

detecting rice diseases more quickly and accurately, enabling them to take preventive actions on time. Additionally, this research is also expected to provide insights into the challenges of using this technology in the field, which can serve as important input for developing better systems in the future [10].

II. METHODS

Experimental (or Materials and Methods)

This research uses quantitative methods, a research approach that uses numbers and statistics to gather and analyze data. Data can be examined and analyzed statistically to test a theory or explain a phenomenon [11]. The developed model is evaluated using a dataset of rice leaf images infected with disease, and the results will be analyzed based on evaluation metrics such as accuracy, precision (measuring how accurately the model predicts a specific class), recall, and F1-score. The process begins with dataset collection, preprocessing, training the MobileNetV2 model, saving the best model, loading the model, inputting images, making predictions, obtaining prediction results, and outputting the results [12].

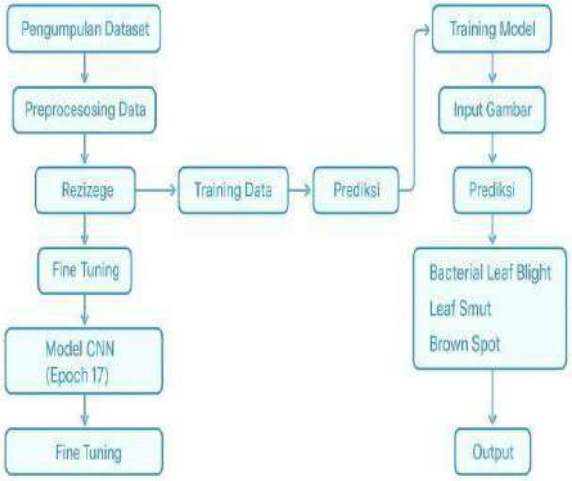

Fig 1. Process CNN, MOBILENETV2

The steps are interconnected, starting from collecting data in the form of rice leaf images from the field and public sources, followed by preprocessing such as image augmentation to increase the diversity of training data. The next step is to build a detection model by applying transfer learning to optimize the training process, even though the dataset is relatively limited. Once the model is built, training and validation are carried out using the previously divided data. The proven effective model is then integrated into a Flask-based web application that allows users to upload rice leaf images and obtain disease prediction results directly. This approach is expected to make a tangible contribution to agricultural technology development, particularly in assisting farmers in quickly and accurately detecting three diseases (brown spot, leaf smut, and bacterial leaf blight).

Dataset Collection

In this study, which contains a total of 120 images, the dataset was obtained from Kaggle via the URL: https://www.kaggle.com/datasets/rahmi21/ricedatasets, It has three different classes of rice leaf diseases, such as bacterial leaf blight, brown spot, and leaf smut. The dataset from Kaggle was chosen because it has an extensive collection and is easily accessible. Figure 2 shows sample data from each class.

Preprocessing

During the image preprocessing stage, the collected rice leaf images are resized to fit the input requirements of the MobileNetV2 architecture, which is 224x224 pixels. Next, a normalization process is performed to convert pixel values to a range of 0 to 1 so that the model can process images more optimally. If the dataset is limited, data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment are performed to increase the variety and amount of training data. Each image is then labeled according to the type of disease detected or healthy condition so that it is ready to be used in the model training process.

Brown Spot Bacterial Leaf Leaf Smut Blight

Fig 2. Data samples for each class

Dataset Distribution

In the dataset division stage, all rice leaf images obtained and processed are divided into three main parts for training and testing purposes. Approximately 80% of the entire dataset is set aside as training data to form and embed patterns and knowledge into the model. Then, 10% is set aside as validation data to monitor model performance during training and reduce overfitting. The remaining 10% is designated as test data to objectively evaluate the model's performance. The distribution is done randomly but proportionally to ensure the model can learn optimally from the various available images.

Model Development

The MobileNetV2, which is the basic architecture for the system's image processing, was chosen as the model for building the rice plant disease detection system. This model was chosen because of its high efficiency in processing images with minimal use of computer resources [13]. The model development process began with the application of transfer learning techniques, where previously trained weights were used in the model to speed up the training process and improve results. Previously processed rice leaf images obtained through the initial preprocessing stages were used as input in training this model. Next, MobileNetV2 was trained with specific parameters, and the number of epochs was set to a certain value to enable the network to learn patterns associated with bacterial leaf blight, brown spot, and leaf smut diseases related to rice leaves. Model optimization was also performed using a fine-tuning approach to improve detection results [14].

Training Model

In this phase, the trained rice disease detection model is integrated into a web application developed using the Flask framework. This application is designed to allow users to easily upload images of rice leaves through a simplified, responsive web interface. Once the images are uploaded, the system automatically retrieves the images, processes them, and applies the detection model to determine the type of disease present on the rice leaves. The prediction results are immediately displayed to users in the form of output showing the type of disease, such as bacterial leaf blight, brown spot, or leaf smut. Thus, this application enables rice disease detection to be performed quickly and conveniently without the need for complex and extensive manual analysis.

III. RESULT AND DISCUSSION

This section describes the data preparation procedure, classification process, and results obtained from the application of the MobileNetV2 architecture in detecting rice plant diseases in real time. The developed model is expected to improve efficiency and accuracy in disease identification compared to conventional methods.

3.1. Training and Evaluation Results

The training and testing processes were carried out to train the dataset, produce the desired model, and evaluate the model's performance. In this study, training was carried out until the model achieved optimal performance. The results of the training process are presented in the following section.

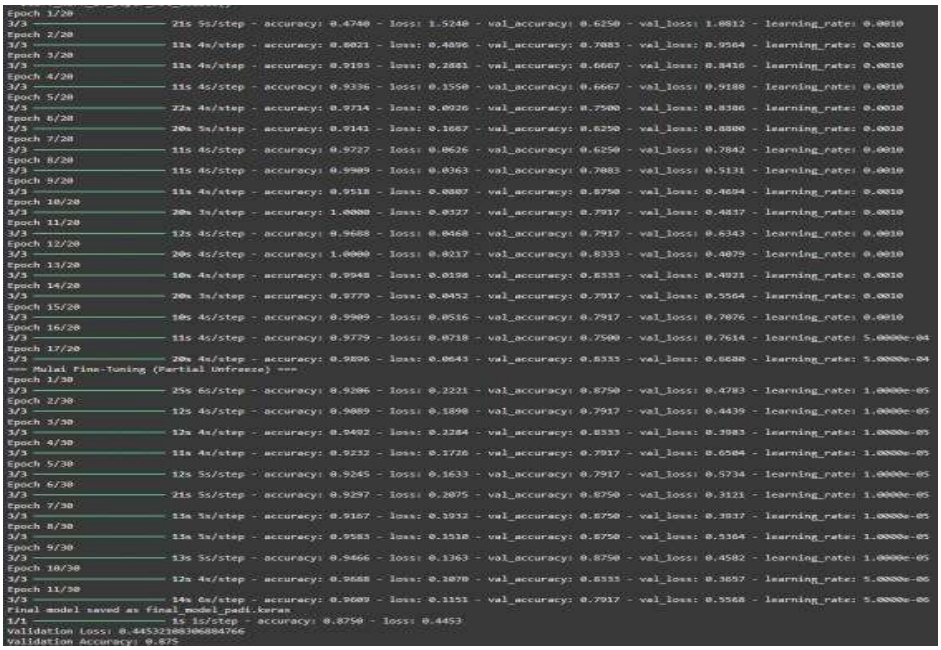

Fig 3. Training results epoch

The picture above shows the accuracy test results of the MobileNetV2 model during the first 17 epochs, where the feature extractor part remains frozen to prevent overfitting, and only the classifier part is trained. The training results show a significant increase in step accuracy, reaching a value of 0.9896 in the 17th epoch, accompanied by a decrease in the loss value, indicating that the model is becoming more stable. Validation accuracy fluctuated, with the highest value of 0.8750 at epoch 9, while validation loss tended to decrease despite some variations between epochs. At epoch 16, the learning rate was reduced from 0.0010 to 5.0000e-04 as an effort to maintain the stability of the training process. Overall, the model showed a significant improvement in performance at this stage. The next step involved fine-tuning to optimize model performance by training some of the previously frozen feature extractor layers.

Parameter adjustments were made carefully, and several training control strategies were applied to avoid overfitting. In this process, callbacks such as ReduceLROnPlateau, EarlyStopping, and ModelCheckpoint were used to adaptively control the training process. Based on the results obtained, the validation accuracy reached an optimal value of 87.5%, indicating that the model was able to recognize patterns in the validation data well after undergoing transfer learning and fine-tuning. In addition, the validation loss experienced slight fluctuations but remained within a stable range, indicating that the model had reached convergence. The final validation loss value of 0.4453 showed that there was no significant overfitting because of the application of effective training control mechanisms.Thus, the fine-tuning stage conducted after transfer learning proved successful in significantly improving model performance, resulting in better validation accuracy compared to the previous stage. Based on the results of the training and evaluation process of the MobileNetV2 architecture, the accuracy curve is shown in the following figure:

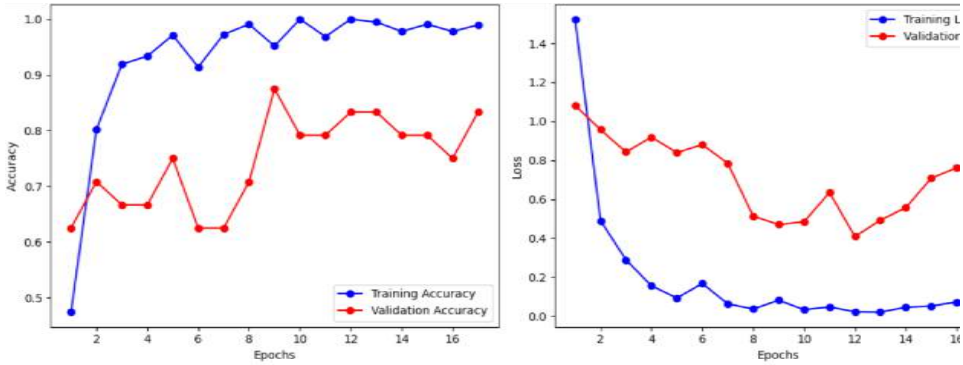

Fig 4. Graphs Training Validation Accuracy and Training Validation Loss

The picture above shows two graphs (red & blue) that illustrate changes in accuracy and loss during the MobileNetV2 model training process. The graph on the left depicts training accuracy and validation accuracy against the number of epochs, while the graph on the right shows training loss and validation loss. Based on the accuracy graph, it can be observed that training accuracy increases significantly as the number of epochs increases, reaching nearly 100% at the end of training. However, validation accuracy fluctuates after reaching a certain value, indicating variations in the model's performance on the validation data.

Meanwhile, on the loss graph, training loss shows a consistent downward trend until it reaches a very small value, indicating that the model is increasingly able to recognize patterns in the training data. However, validation loss does not experience a stable decline and tends to fluctuate after several epochs, which may be an indication of potential overfitting. This indicates that the model has learned well from the training data, but there is a possibility that the model has started to experience overfitting after several epochs, where its performance on the validation data does not improve significantly or even declines. Therefore, regulation mechanisms such as early stopping and regularization can be applied to prevent overfitting and improve model generalization. Thus, these training results show that although the model has achieved high accuracy on the training data, further evaluation of its performance on the validation data is necessary to ensure that the model not only learns specific patterns in the training data but also generalizes well to new data.

3.2. Confusion Matrix Results

The confusion matrix is used to evaluate the performance of the model in classifying data by comparing the predicted results and the actual labels. The confusion matrix results are presented in Figure 5. showing the confusion matrix used to evaluate the performance of the classification model in identifying three types of leaf diseases, namely Bacterial Leaf Blight, Brown Spot, and Leaf Smut. This confusion matrix provides an overview of the number of correct and incorrect predictions for each class based on the validation data.From the confusion matrix displayed, it can be analyzed that the model performs very well in classifying the Bacterial Leaf Blight and Brown Spot classes, with each obtaining 40 correct predictions and 0 errors. This indicates that the model can recognize the patterns of both classes very well, but for the leaf smut class, the model still experiences classification errors.

Out of 40 leaf smut samples, 33 were classified correctly, while 3 were incorrectly classified as bacterial leaf blight, and 4 were classified as brown spot. These errors indicate that the model still experiences some confusion in distinguishing between leaf smut and the other two classes, which may be due to the similarity of visual features between classes or an imbalance in the amount of training data.Overall, the model showed excellent performance with a high accuracy rate, especially in perfectly classifying bacterial leaf blight and brown spot. However, to improve the accuracy in classifying leaf smut, improvements such as data augmentation, model architecture adjustments, or increasing the amount of training data can be made so that the model is better able to recognize the differences between classes more accurately.

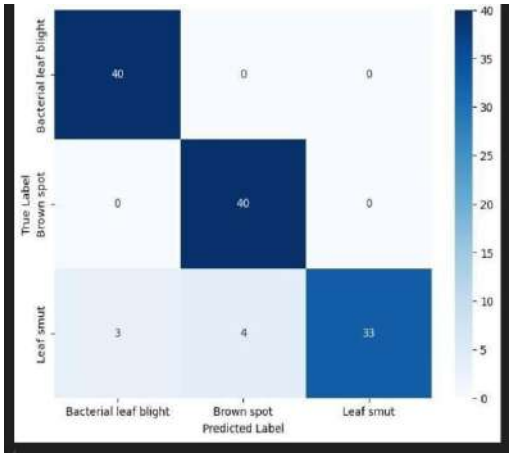

Fig 5. Confusion Matrix

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4/4 ━━━━━━━━━━━━━━━━━━━━ 10s 1s/step - accuracy: 0.9725 - loss: 0.1032
Test Loss: 0.19385112822055817
Test Accuracy: 0.9416666626930237
4/4 ━━━━━━━━━━━━━━━━━━━━ 7s 1s/step
Classification Report:
                    precision    recall  f1-score   support

Bacterial leaf blight       0.93      1.00      0.96        40
          Brown spot       0.91      1.00      0.95        40
           Leaf smut       1.00      0.82      0.90        40

            accuracy                           0.94       120
           macro avg       0.95      0.94      0.94       120
        weighted avg       0.95      0.94      0.94       120

F1 Score (macro): 0.940115321036265
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Fig 6. Classification Report

The Figure 6 above shows an accuracy of 94.17% with a test loss of 0.1938 on 120 test data consisting of three classes of leaf diseases: Bacterial Leaf Blight, Brown Spot, and Leaf Smut.

Evaluation Metrics Analysis

- **Precision**: The model achieves the highest precision for leaf smut (100%), while bacterial leaf blight and brown spot have precision rates of 93% and 91%, respectively.
- **Recall**: The model successfully identifies 100% of Bacterial Leaf Blight and Brown Spot samples, but the recall for Leaf Smut is lower (82%), indicating that some samples were misclassified.
- **F1-Score**: The model demonstrates a good balance between precision and recall with an average F1-score of 94%.
- **Macro avg & Weighted avg**: Both have a value of 0.94, indicating the model performs consistently across all classes.

3.3. Web-Based Testing Results

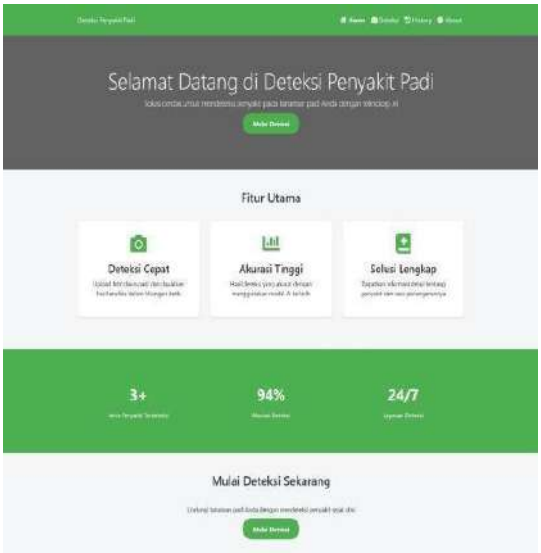

Fig 7. Image upload form

Web-based testing was conducted to evaluate the performance of the MobileNetV2 model in a rice leaf disease classification system. This system was developed to make it easier for users to identify types of diseases in rice plants through uploaded leaf images.The image above shows the initial display of the system before the user uploads an image. At this stage, the user is asked to upload an image of a rice leaf suspected of being infected using the upload feature provided. After the image is uploaded and processed by the system, the prediction results will be displayed as shown in Figure 7.

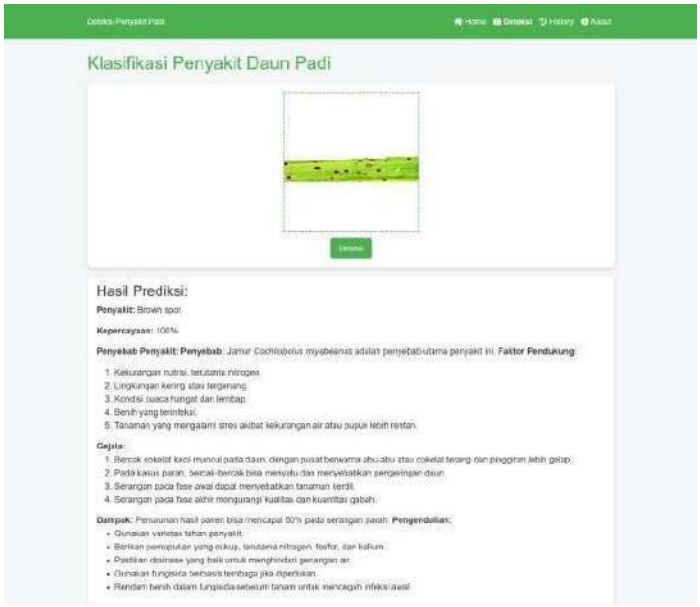

Fig 8. Form upload image form detection results

The image above shows the prediction results after the user uploaded an image of a rice leaf affected by disease. The system successfully identified Brown Spot disease with a confidence level of 100%. The main cause of this disease is the fungus Cochliobolus miyabeanus, which can develop due to several contributing factors, such as nitrogen deficiency, humid environmental conditions, and poor air circulation. In addition to disease prediction, the system also displays the symptoms that appear, such as small brown spots that enlarge and change color to gray or light brown. This disease can cause a yield reduction of up to 50%, especially if the infection occurs during the late growth stage of the plant. From the results of this testing, it can be concluded that the web-based classification system is capable of providing accurate and comprehensive information about rice leaf disease. The implementation of this system is expected to help farmers detect diseases earlier and take appropriate preventive measures to reduce the negative impact on crop yields.

IV. CONCLUSION

This conclusion shows that deep learning models, namely CNN and MobileNetV2, are capable of classifying diseases on rice leaves effectively, with CNN achieving an accuracy of 87% after 20 epochs, while MobileNetV2 achieved a higher accuracy of 94% but with initial training of 20 epochs and an additional 30 epochs of fine-tuning. Detecting rice diseases such as Bacterial Leaf Blight, Brown Spot, and Leaf Smut can be done with high accuracy, and the developed model can classify diseases efficiently compared to manual observation by farmers. Additionally, using a more diverse dataset is necessary to improve the model's generalization to different environmental conditions [15]. To improve performance, this study suggests integrating more datasets with greater variation to enhance both accuracy and generalization, as well as optimizing to prevent overfitting. Regulation techniques such as Dropout or Data Augmentation can be used to strengthen the model's robustness. Furthermore, field testing is necessary to assess the model's actual effectiveness under real-world conditions. Further exploration in testing various environmental conditions is crucial to improve the reliability and generalization of the model. Developing web or mobile applications is recommended so that farmers can easily access the technology. Finally, collaboration with agricultural institutions can help facilitate the use of technology in agriculture and expand its benefits [16].

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