CHAPTER I
INTRODUCTION

1.1 Background

Rice (Oryza sativa L.) is a primary food commodity in Indonesia that holds a strategic role in maintaining national food security. Approximately 95% of the Indonesian population still relies on rice as their main staple food [1]. Based on the Food Consumption Statistics data sourced from the National Socio-Economic Survey (BPS, 2023), the national rice utilization level reaches approximately 33.7 million tons per year, with an average per capita consumption of 93.8 kilograms per year [2]. This condition renders the sustainability of rice production a crucial factor in supporting national social and economic stability. The high dependency on rice also makes the rice farming sector highly vulnerable to various disruptions, particularly those related to the decline in crop productivity.

One of the primary factors contributing to the decline in rice productivity is disease attacks on the leaves [3]. Leaves play a vital role in the photosynthesis process; therefore, damage to this part directly affects plant growth and crop yield. Several types of rice leaf diseases commonly found in Indonesia include Bacterial Leaf Blight, Leaf Blast, Brown Spot, Sheath Blight, and Rice Hispa [4].

These diseases are caused by various pathogens, such as fungi (Magnaporthe oryzae), bacteria (Xanthomonas oryzae pv. Oryzae), and pest insects (Dicladispa armigera), which attack the leaf tissue and can cause the leaves to dry out before the harvest period. The impact of rice leaf disease attacks is not only agronomic but also economic. Severe infections can significantly reduce crop yields, and it has been reported that production losses of up to 70% can occur under certain conditions [5].

In field practice, the detection of rice leaf diseases is still carried out conventionally through visual observation by farmers or agricultural extension workers. This method is highly dependent on the observer's experience, making early disease symptoms often difficult to distinguish from physiological stress caused by environmental factors. Furthermore, the similarity of symptom patterns among different rice leaf diseases further increases the potential for misidentification. As a result, incorrect diagnoses frequently occur, and diseases are generally only detected at a high severity level. This condition poses a serious problem because each type of disease requires a different treatment approach [6], [7].

Along with technological advancements, Artificial Intelligence has opened new opportunities in addressing crop disease problems. One of the approaches widely applied in agricultural image analysis is deep learning, particularly Convolutional Neural Networks (CNN) [8]. CNNs are capable of automatically extracting important visual features from digital images, such as patterns, textures, subtle lesions, and color changes on rice leaves, making them highly effective for crop disease classification tasks. Various studies have demonstrated that deep learning-based approaches can achieve high accuracy levels, even exceeding 90%, and deliver better performance compared to conventional machine learning methods [9].

However, the deployment of CNN models on mobile devices requires architectures that are not only accurate but also computationally efficient and memory-friendly [8]. This is essential to ensure that the model can run optimally on Android devices with limited resources. One of the lightweight CNN architectures designed to meet these requirements is EfficientNet, which employs a compound scaling approach to systematically balance network depth, network width, and input resolution [10].

In this study, EfficientNet-B0 was selected as the primary model because it is the base variant with the lowest complexity within the EfficientNet family. This architecture has a relatively small number of parameters, making it more suitable for implementation on mobile devices and more stable when converted to the TensorFlow Lite format. Despite being lightweight, EfficientNet-B0 is still capable of producing competitive classification performance, especially when combined with transfer learning and fine-tuning approaches [11]. Through the fine-tuning process, a portion of the network layers is retrained using the rice leaf disease dataset, enabling the model to adapt its internal feature representations to the specific visual characteristics of rice leaf images in the field.

As a comparison, this study also employs MobileNetV2, a lightweight CNN architecture specifically designed for resource-constrained computing environments. MobileNetV2 adopts the concepts of inverted residuals and linear bottlenecks, which allow the network to retain important information without significantly increasing computational complexity [12]. The selection of MobileNetV2 as the comparison model aims to analyze the performance differences between a fine-tuned lightweight CNN model and a pretrained model without further fine-tuning.

In addition to model architecture, the optimizer algorithm plays a crucial role in the CNN training process. The optimizer is responsible for iteratively updating the network weights to minimize prediction errors measured through the loss function. Therefore, this study evaluates three commonly used optimizers, namely Adam, RMSprop, and Stochastic Gradient Descent (SGD), to analyze their effects on accuracy, training stability, and model convergence [13].

The model with the best performance is subsequently converted into the TensorFlow Lite format and integrated into a Flutter-based mobile application. This implementation enables the rice leaf disease classification process to be performed offline and in real-time through Android devices, allowing farmers to obtain diagnostic results quickly and easily without relying on an internet connection [6]. This approach aligns with the digital agriculture (smart farming) concept promoted by the Ministry of Agriculture of the Republic of Indonesia [14].

Based on the above discussion, this study focuses on the comparative performance analysis of rice leaf disease classification using a CNN-based deep learning approach. This study compares a fine-tuned EfficientNet-B0 and a pretrained-based MobileNetV2 with variations of Adam, RMSprop, and SGD optimizers. The evaluation is conducted to obtain the most accurate, stable, and efficient model for implementation on mobile devices. It is expected that the results of this study can support early detection of rice leaf diseases, reduce the risk of crop failure, and strengthen the sustainable application of artificial intelligence technology in the Indonesian agricultural system.

1.2 Problem Statement

Based on the background that has been described, the problem statements of this study are formulated as follows:

1. How can the fine-tuned EfficientNet-B0 and pretrained MobileNetV2 models be applied to classify rice leaf diseases using digital images?
2. How does the performance of fine-tuned EfficientNet-B0 compare to MobileNetV2 with variations of Adam, RMSprop, and Stochastic Gradient Descent (SGD) optimizers in terms of classification accuracy, training stability, and computational efficiency?
3. How can the best-performing model resulting from the evaluation be implemented into a Flutter and TensorFlow Lite-based mobile application in terms of inference time and model size to enable offline operation on Android devices?

1.3 Research Objectives

Based on the problem statements that have been outlined, the objectives of this study are as follows:

1. To apply the fine-tuned EfficientNet-B0 and pretrained MobileNetV2 models for classifying rice leaf diseases using digital images.
2. To analyze and compare the performance of the fine-tuned EfficientNet-B0 and MobileNetV2 models with variations of Adam, RMSprop, and Stochastic Gradient Descent (SGD) optimizers based on the aspects of classification accuracy, training stability, and computational efficiency.
3. To implement the best-performing model resulting from the evaluation into a Flutter and TensorFlow Lite-based mobile application based on inference time and model size, enabling offline operation on Android devices.

1.4 Research Benefits

This study is expected to provide both theoretical and practical benefits as follows:

1.4.1 Theoretical Benefits

1. This study provides a scientific contribution to the development of artificial intelligence, particularly in the application of deep learning for rice leaf disease classification based on digital images.
2. This study adds to the scientific references related to the performance analysis of fine-tuned EfficientNet-B0 and pretrained-based MobileNetV2 models in plant image classification tasks, as well as provides an understanding of the effects of optimizer variations on classification accuracy, training stability, and computational efficiency in lightweight models.
3. This study can serve as a foundation and reference for future research focusing on the development, comparison, and evaluation of mobile-based plant image classification models.

1.4.2 Practical Benefits

1. This study assists farmers in performing early detection of rice leaf diseases quickly and accurately through the utilization of an Android-based mobile application.
2. This study produces a rice leaf disease classification system that can be used offline, making it effective in areas with limited internet access, while also supporting preliminary decision-making in rice crop disease management to ensure more appropriate and efficient interventions.
3. This study serves as a reference for the development of artificial intelligence-based digital agriculture technology (smart farming) by providing a plant disease classification solution that is efficient, user-friendly, and suitable for mobile devices.

1.5 Research Scope and Limitations

To ensure that this study has a clear direction and remains focused on the intended objectives, the scope and limitations of this study are defined as follows:

1. This study is limited to rice leaf disease classification based on digital images using single leaf images obtained from public datasets and limited data collection.
2. This study compares two lightweight CNN architectures, namely EfficientNet-B0 and MobileNetV2, both of which are designed for implementation on mobile devices, with differences in training strategies where EfficientNet-B0 is trained using a fine-tuning approach, while MobileNetV2 is used in a pretrained state without further fine-tuning. Additionally, this study evaluates the effect of three optimizers, namely Adam, RMSprop, and Stochastic Gradient Descent (SGD), on classification performance in terms of classification accuracy, training stability, and computational efficiency.
3. This study uses a dataset consisting of six classes of rice leaves, namely Healthy, Bacterial Leaf Blight, Brown Spot, Leaf Blast, Sheath Blight, and Rice Hispa, with a total of 4,770 images divided into training, validation, and test sets.
4. The system implementation is limited to an Android-based mobile application developed using Flutter and TensorFlow Lite. Performance evaluation is focused on classification metrics (Accuracy, Precision, Recall, and F1-score), as well as mobile implementation aspects including inference latency and model size.
5. This study limits the application features to the presentation of classification results, confidence scores, and basic treatment recommendations corresponding to the detected disease category.