CHAPTER V
CONCLUSION

This chapter presents conclusions and recommendations based on the research results that have been conducted. Conclusions are drawn through a series of processes, from dataset preparation, model training with various hyperparameter configurations, performance evaluation on testing data, to model implementation into a mobile application. Additionally, this chapter also provides recommendations that can serve as references for the development of similar research in the future, with the aim of achieving more optimal results that can be applied more broadly in the agricultural sector.

5.1 Conclusion

Based on the research results and testing conducted on rice leaf disease classification using the EfficientNet-B0 architecture with a fine-tuning approach implemented in the SIPADI (Rice Leaf Disease Early Detection System) mobile application, several important points can be concluded as follows:

1. Based on the research results, the fine-tuning strategy on the EfficientNet-B0 architecture proves to be highly effective in improving rice leaf disease classification capability compared to the transfer learning approach with a frozen base model. The frozen EfficientNet-B0 model experiences total failure in the form of class collapse across all 12 testing scenarios with an accuracy of only 19.62%, where all images are predicted into a single dominant class. Conversely, when all 4,340,098 parameters are opened for retraining through the fine-tuning strategy, accuracy surges to 99.48% on validation data and 99.79% on testing data. This increase of 80.17 percentage points proves that the primary problem does not lie in the capability of the EfficientNet-B0 architecture itself, but rather in the incompatibility of pre-trained ImageNet feature representations with the crop disease image domain, which requires deep adaptation through the fine-tuning process.
2. The Fine-tuned EfficientNet-B0 model with the optimal configuration of batch size 16, epoch 50, learning rate 0.001, and Adam optimizer

demonstrates classification performance that is significantly superior compared to other models. In the testing data evaluation of 479 images, this model successfully classifies 478 images correctly and produces only 1 classification error, yielding an accuracy of 99.79% with macro average F1-score of 0.9981 and weighted average F1-score of 0.9979. Four out of six classes achieve perfect F1-score of 1.0000 (Brown Spot, Healthy Rice Leaf, Rice Hispa, and Sheath Blight), while the remaining two classes record F1-scores above 0.99. In comparison, MobileNetV2 produces 36 errors with an accuracy of 92.48%, while frozen EfficientNet-B0 produces 385 errors with an accuracy of 19.62%. These results confirm that Fine-tuned EfficientNet-B0 is the most suitable model for implementation in a rice leaf disease detection system.

3. The deployment of the Fine-tuned EfficientNet-B0 model into the SIPADI mobile application through TensorFlow Lite Standard format conversion is successfully performed while maintaining high classification capability. The model size is successfully reduced from 50.81 MB (Keras format) to 16.56 MB (TFLite Standard format) a reduction of 67.4% while the average prediction confidence level remains high at 99.2% with an inference speed of 25.0 ms in the testing environment. In functional testing on mobile devices, the application successfully detects diseases accurately and responsively (198 ms inference time on the device), and presents comprehensive educational information including disease description, symptoms, treatment methods, and prevention measures for each disease class. Accordingly, the SIPADI application has fulfilled the research objective as a deep learning-based early detection tool for rice leaf diseases that can be accessed practically through mobile devices.

5.2 Recommendations

Based on the experience and research results that have been conducted, the following recommendations can serve as references for further development:

1. For subsequent research, it is recommended to expand the quantity and variety of rice leaf disease image datasets used. The addition of data from various rice varieties, diverse lighting conditions, and varying disease severity levels can improve the model's generalization capability. Furthermore, the addition of other disease classes such as Tungro, Narrow Brown Spot, or Rice Ragged Stunt will broaden the detection coverage so that the application becomes increasingly beneficial for farmers in various regions with different disease characteristics.
2. Subsequent research can explore more advanced data augmentation techniques such as Generative Adversarial Networks (GANs) to synthetically expand training samples, as well as apply model interpretability methods such as Grad-CAM or LIME to visualize the areas on leaf images that serve as the basis for the model's classification decisions. Such visualization can increase user trust in prediction results and provide scientific insight regarding the most discriminative visual features for each disease type.
3. From the application development perspective, it is recommended to add supporting features such as online consultation with agricultural experts, GPS location-based disease spread reporting systems, and integration with local weather databases to provide early warnings regarding environmental conditions that potentially trigger the emergence of certain diseases. Usability testing involving end users (farmers and agricultural extension workers) directly also needs to be conducted to obtain feedback that can improve the ease and comfort of application usage in the field.