CHAPTER 5
CONCLUSIONS AND SUGGESTIONS

This chapter summarizes the main findings of the entire series of experiments to answer the formulation of the problem defined, as well as provide constructive recommendations for further research development.

5.1 Conclusion

Based on the results of the design, implementation, and comparative analysis of the U-Net architecture with the MobileNetV2 encoder and the Attention Gate mechanism for the segmentation of Coffee Leaf Rust disease, the following conclusions can be drawn:

1. **Implementation and Efficiency of Architecture**: This study successfully designed and implemented a U-Net architecture based on the MobileNetV2 encoder with Custom Convolution path modifications to maintain full spatial resolution. This explored architecture was proven to provide drastic computational efficiency compared to the VGG16 baseline, characterized by a 96% reduction in the number of parameters (from ~25 million to ~0.96 million), a ~92.8% reduction in extreme computing load (from 115.63 GFLOPs to 8.26 GFLOPs), and an increase in inference speed of ~31% (to 75.71 ms/image). This proves that the use of lightweight backbones is very effective in drastically reducing computing load.
2. **Impact of Attention Gate Mechanism:** The integration of the Attention Gate mechanism provides different impacts depending on the capacity of the encoder. On the feature-rich VGG16 encoder, the Attention Gate effectively improves focus and accuracy (F1-Score is up 5.1%). However, in the MobileNetV2 encoder which has very dense and compressed features, the addition of Attention Gate is not proven to provide a significant improvement, and even tends to introduce attentional noise that causes a slight decrease in accuracy. These findings indicate that the gating mechanism requires sufficient feature redundancy to work optimally as a selective filter.

3. **Comparative Evaluation (Ablation Study):** The results of the ablation study show a clear trade-off between accuracy and efficiency. The VGG16 + Attention U-Net model was recorded as the model with the best segmentation accuracy (F1-Score 0.8483) and became the precision reference standard. Meanwhile, U-Net's proposed MobileNetV2 + Attention model positions itself as the most efficient solution. Despite a decrease in accuracy of about 7% compared to the best model, the proposed model offers much higher implementation viability for devices with limited resources.
4. **Severity Quantification Performance:** As the final evaluation metric, segmentation prediction results are applied to calculate the severity of the disease. The lightweight architecture model recorded an average Mean Absolute Error of 16.08%. Although the statistical linear correlation ($R^2 = 0.57$) is lower than that of the baseline model ($R^2 = 0.72$) due to the attentional noise phenomenon in the background area, the absolute margin of error is only 2.03%. This margin proves that the practical accuracy of lightweight architectures is still within the operational tolerance limits that are feasible to function as a rapid assessment tool in the field, where speed and accessibility are top priorities over absolute laboratory precision.

5.2 Suggestions

In order to improve the performance and validity of the system in the future, as well as overcome the limitations found in this study, the following are suggested:

1. **Dataset Expansion:** Limited amount of trained data (89 images) was identified as the main factor causing the Custom Convolution and Attention Gate layers in MobileNetV2 to not converge optimally. Further research is strongly recommended to increase the amount of data variation, both through field acquisition and the use of generative augmentation techniques, to mature the features of these layers.
2. **Exploration of Lightweight Attention Mechanisms:** Given that standard Attention Gates have proven to be less effective on compressed features, further research may explore lighter attention mechanisms that are appropriate for mobile architectures, such as Coordinate Attention (CA) or

Convolutional Block Attention Module (CBAM), which may be able to sharpen focus without overloading computing or damaging feature signals.

3. **Development to Mobile Devices:** Since the model's efficiency has been theoretically and simulationally proven, the next logical step is to deploy the model into the TensorFlow Lite (TFLite) format and integrate it into Android-based applications. Testing directly on farmer devices will provide more accurate real-world performance validation.
4. **Multi-Disease Case Management:** This study is limited to Leaf Rust disease only. The development of models to be able to recognize and quantify other types of coffee diseases (such as Leaf Spot or Fruit Borer) in a single integrated framework will greatly increase the value of the system for the national coffee plantation industry.