# CHAPTER 5
# RESULTS AND DISCUSSION

This chapter presents a presentation of the conclusions and suggestions on the research that has been conducted. The conclusions are drawn based on the results of the analysis and testing of the model described in the previous chapter, so as to describe the overall achievement of the research objectives and directly answer the formulation of the problem. Suggestions are given as considerations for future research in order to develop a more optimal coffee leaf disease detection system.

## 5.1 Conclusion

The following conclusions are obtained from the test results which at the same time answer the problem formulation based on the analysis of model performance, evaluation results, and achievement of research objectives.

1. The design and implementation of the YOLOv8s-P2-CBAM architecture has been successfully carried out. The implementation stage begins with *data-centric* pre-processing in the form of manual *annotation quality* improvement and *selective offline augmentation* to overcome minority class inequality. The YOLOv8s architecture was then modified by integrating *a high-resolution detection head (P2) to process a 160x160 pixel matrix, as well as inserting* a Convolutional Block Attention Module *(CBAM) sequentially on the neck*. This model was successfully implemented through a training process with *the most optimal* hyperparameter configuration, namely *Batch Size* 32, *Optimizer* AdamW, *Learning Rate* 0.002, maximum 300 *Epoch*, and *Patience* 50.
2. The addition *of the P2 detection head* and CBAM integration have a positive influence in solving detection problems in micro-sized objects (*small objects*). The P2 extraction layer has been shown to be able to maintain the integrity of the spatial representation of small lesions so that their visual details do not fade within the inner convolutional layer. At the same time, visual analysis proved that the CBAM module effectively guided the model to filter *out the background noise* of healthy leaves and concentrate the extraction of its features on the lesion area. This success is evident in the class with the most micro instances (*Rust* class), where the ability to pull the bounding box tightly

(mAP@50-95) increases from 0.182 to 0.217, accompanied by an increase *in precision* from 0.652 to 0.686.

3. Based on the overall performance comparison, the proposed YOLOv8s-P2-CBAM model proved to be more precise, balanced, and resilient than the standard YOLOv8s model (*baseline*). Globally, the proposed model succeeded in boosting *the precision* from 0.588 to 0.633, the average precision value mAP@50 to 0.646, and increasing the balance level (*F1-score*) to 0.640. Although this structural modification logically increases the mathematical operation load from 28.4 GFLOPs to 36.7 GFLOPs, the total network parameter load actually becomes slimmer (to 10.6 million parameters). *This trade-off* is well worth it because the model successfully reduces loose guess bias, with the inference rate remaining very fast at 8.1 milliseconds per image. This confirms that the proposed model is highly capable for precision detection needs directly.

## 5.2 Suggestions

1. For further research, exploration of model compression techniques, such as *pruning* or *knowledge distillation*, can be applied. This technique is expected to be able to reduce the computational load (GFLOPs) and the number of parameters that arise due to the addition of the P2 layer, so that the proposed model can run more lightly and power-efficiently on *low-spec mobile* devices without sacrificing *the recall* value.
2. In terms of providing datasets, the use of advanced generative augmentation methods such as *Generative Adversarial Networks* (GAN) or *Diffusion* architectures can be considered. This method can be used to synthesize images of minority disease lesions with more complex leaf background variations, to further improve the model's generalization ability to natural lighting conditions in plantations.