CHAPTER V
CONCLUSION

5.1. Conclusion

This study yielded several findings regarding the RetinaNet architecture's ability to detect emergency situations using aerial photographs. Based on the entire system implementation and testing process, the following conclusions can be drawn

1. This study successfully applied RetinaNet to classify emergency situations on the AIDER dataset, which consists of four classes: fire, flood, building collapse, and traffic accident. The test results demonstrated good accuracy based on the *Precision, Recall*, *Average Precision* (AP), and *mean Average Precision* (mAP) values obtained.
2. Using the original data and default parameters yielded better performance on *the* ResNet101 *backbone*, with a value of 0.835790, compared to using ResNet50, which achieved a value of 0.824750. However, ResNet101 does not always yield higher results across all scenarios; for example, in *upsampling* and *downsampling* data variations, the ResNet50 *backbone* produced better results. Therefore, using a model with a deeper network does not automatically improve model performance, as there are other factors that can influence it, such as training configuration and the data variations used.
3. Changes in *the learning rate, batch size,* and data distribution affect model performance; across all scenarios, the highest result was achieved by ResNet101 with *a batch size* of 8, yielding an mAP of 0.841821. Meanwhile, the lowest result was achieved by ResNet50 with *a learning rate* of $5.10^{(-5)}$, yielding 0.783098.
4. Based on the evaluation results by class, the highest AP value was achieved by the flood class at 0.924544 using ResNet50 with *downsampled* data. Meanwhile, the lowest AP value was achieved by the collapsed building class with a value of 0.591878 using ResNet101 with *upsampled* data. These results indicate that flood objects tend to be more easily recognized

by the model, whereas collapsed buildings are a class that is more difficult to detect consistently.

5. Based on the *bounding box* visualization results, it can be seen how the model is able to localize objects using *bounding boxes* and classify damage classes quite well. These results are consistent with the AP and mAP values obtained.

5.2. Recommendations for Further Development

Based on the research conducted, there are several suggestions for further development of this study:

1. Future research could use a dataset with a larger volume of data and a wider variety of objects to improve the model's generalization ability across various disaster conditions.
2. Research could be expanded by comparing RetinaNet with other object detection algorithms, such as Faster R-CNN, SSD, YOLO, or DETR, to obtain more comprehensive information regarding the performance of each method on disaster datasets.
3. The use of more diverse data augmentation techniques, such as rotation, lighting changes, and other geometric transformations, can be explored to improve the model's ability to recognize objects under different conditions.
4. Future research could employ object segmentation methods, such as Mask R-CNN, to address the limitations of bounding box annotations for objects with irregular shapes, particularly in the collapsed buildings class.
5. Further research could be conducted, for example, by using a more modern *backbone*.