CHAPTER V
CONCLUSION

This chapter presents the conclusions drawn from the research findings and discussion. The conclusions are presented concisely by summarizing the main findings that address the research questions and objectives. In addition, recommendations are included for consideration in future research.

5.1 Conclusion

Based on the results of a study conducted on the classification of Lumpy Skin Disease (LSD) in cattle using the ensemble Vision Transformer–DenseNet121 method, the following conclusions were obtained:

1. The ensemble Vision Transformer–DenseNet121 model is capable of effectively classifying Lumpy Skin Disease (LSD) in cattle based on digital images of the cattle's skin. Testing results on the original dataset show that the ensemble model achieved an accuracy of 91.35%, a precision of 91.41%, a recall of 91.30%, and an F1-score of 91.32%. Meanwhile, in tests using balanced data, the ensemble model performed even better, achieving an accuracy of 91.47%, precision of 91.49%, recall of 91.48%, and an F1-score of 91.45%. These results indicate that the model is highly capable of distinguishing between images of normal cattle skin and those of cattle skin infected with LSD. The trained ensemble model was then implemented into a web-based LSD classification system interface, capable of receiving input in the form of cattle skin images, performing the classification process, and displaying the predicted image class as Normal Skin or Lumpy Skin. Thus, the developed ensemble model can be used as an effective approach to assist in the identification of LSD based on digital images of cattle skin.
2. The Ensemble Vision Transformer–DenseNet121 model outperforms models based on a single architecture. In tests using the raw data, the Vision Transformer model achieved an accuracy of 89.34%, DenseNet121 achieved an accuracy of 90.24%, while the ensemble model achieved an accuracy of 91.35%. Similar results were also obtained in tests using balanced data, in which Vision Transformer achieved an accuracy of 89.53%, DenseNet121 achieved 89.40%, and the ensemble model achieved the highest accuracy of 91.47%. This performance improvement is also evident in the precision, recall, and F1-score metrics, each of which is consistently higher than those of the two single models,

indicating that the ensemble method is capable of combining the strengths of each architecture to produce a more comprehensive feature representation and better classification decisions. In addition, data balance also contributes to improved ensemble model performance, as models trained on balanced data result in higher accuracy, precision, recall, and F1-score values compared to models trained on the raw data. This indicates that a more balanced data distribution across each class helps the model obtain a more even feature representation during the training process, so that ensemble methods with balanced data have proven capable of delivering the most optimal classification performance compared to single architecture models or the use of raw data.

5.2 Suggestions

Based on the research conducted, the recommendations for future research are as follows:

1. Use a larger dataset with a wider variety of image variations in terms of lighting, shooting angles, and the condition of the cows' skin in the field, so that the model has better generalization capabilities.
2. Develop other architectures or combine models with different approaches to explore the potential for improved classification performance.
3. Develop data preprocessing and segmentation stages for the model to recognize image patterns more effectively.
4. Future research could integrate the classification system into a field ready application or website, for example by adding a feature to upload images directly from mobile devices and storing a history of prediction results.