CHAPTER V
CONCLUSION

Based on the series of experiments conducted, beginning with data collection, preprocessing, model training, and performance evaluation, this chapter presents the conclusions drawn from the findings of the study as well as recommendations for future research. The conclusions are formulated based on the analysis and evaluation of the Swin Transformer model in classifying lung histopathological images, while the recommendations are intended to provide directions for further improvements and the development of related research in this field.

5.1. Conclusion

Based on the results of this study on lung cancer classification using the Swin Transformer model and histopathological images, the following conclusions can be drawn:

1. This study successfully implemented the Swin Transformer architecture for classifying lung histopathological images using the LC25000 dataset, which consists of three classes: Lung Adenocarcinoma (*lung_aca*), Normal Lung Tissue (*lung_n*), and Lung Squamous Cell Carcinoma (*lung_scc*).
2. The research workflow consisted of several stages, including data preprocessing through image resizing to 224 × 224 pixels, image-to-tensor conversion, pixel value normalization, dataset splitting, model training, and performance evaluation using multiple classification metrics.
3. Based on the evaluation of various hyperparameter combinations, the optimal model was obtained using an 80:10:10 dataset split with a batch size of 32, a learning rate of 0.00005, and a weight decay of 0.001.
4. The best-performing model achieved an accuracy of 98.13%, a precision of 98.13%, a recall of 98.13%, and an F1-score of 98.13%. These results demonstrate that the Swin Transformer is highly effective in learning the morphological characteristics of lung tissue and accurately distinguishing the three histopathological image classes used in this study.

5. The evaluation results based on the confusion matrix and ROC curve indicate that the proposed model achieves a low misclassification rate and excellent discriminative capability across all classes. These findings demonstrate that the Swin Transformer is an effective and reliable approach for lung cancer classification using histopathological images.

5.2. Recommendations

Based on the findings of this study, several recommendations are proposed for future research:

1. Future studies may utilize larger and more diverse datasets to improve the generalization capability of the model when applied to previously unseen data.
2. Future research may compare the performance of the Swin Transformer with other deep learning architectures, such as MobileNetV3, ConvNeXt, EfficientNet, and DenseNet121, to identify the most effective model for lung cancer classification.
3. More diverse data augmentation techniques may be applied to increase the variability of the training data, thereby improving the robustness of the model against variations in histopathological image characteristics.
4. Future studies may investigate larger variants of the Swin Transformer architecture, such as Swin Small, Swin Base, or Swin Large, to evaluate the impact of model complexity on classification performance.
5. The developed system may be integrated with datasets obtained from medical institutions or hospitals to enable further evaluation using real-world clinical data and to assess the model's applicability in practical healthcare environments.