CHAPTER V
CONCLUSION

5.1 Conclusion

Based on the entire series of testing scenarios that have been carried out, it can be concluded that variations in feature variables, data split ratios, model architecture complexity, and hyperparameter configurations will have a significant effect on model performance. From the evaluation of 15 testing scenarios, the DJIA index variable proved to have a more dominant influence on the movement of the IHSG than the exchange rate of the Rupiah against the US Dollar (IDR/USD). In addition, increasing the amount of training data to 80% consistently improved the accuracy of the GRU model, as more training data provided more historical information for the model to learn. Increasing the number of layers from two to three did not always improve model performance; in some test scenarios, it even resulted in a high prediction error rate.

This study obtained the best configuration from the GRU model using the DJIA index feature, an 80:10:10 data split ratio, a two-layer GRU architecture with 32 and 64 units, a learning rate of 0.01, and a dropout rate of 0.1. The best model obtained the best evaluation score with an MSE of 3226.2419, an RMSE of 56.8, and a MAPE of 0.6186%, which was the lowest error score compared to all other test scenarios. Comparison model testing also showed that the GRU model performed better than the LSTM and XGBoost models with the same configuration. The LSTM model still achieved performance close to that of GRU, but it was still below the best accuracy of GRU. The XGBoost model obtained a much higher error value than the LSTM and GRU models because this model was less capable of capturing temporal patterns in time series data such as the IHSG value. It can be concluded that the GRU model is the most optimal algorithm for predicting the IHSG value in the dataset used in this study.

5.2 Recommendations

Based on the results of this study, future research is encouraged to incorporate a wider range of macroeconomic variables such as interest rates, inflation, exchange rates, and global stock indices. These additional variables can provide richer and more comprehensive information for predicting IHSG values. Including diverse economic indicators is expected to better capture market dynamics and external influences. This approach can help improve the accuracy and reliability of the prediction results.

In addition, using a longer historical data period is recommended to reflect long-term trends and improve model generalization. Future studies may also explore various model architectures, including advanced deep learning or hybrid models, to enhance predictive performance. Hyperparameter optimization methods such as Bayesian Optimization and Particle Swarm Optimization can be applied to obtain more optimal configurations. With these improvements, the model is expected to achieve higher accuracy and stronger robustness across different market conditions.