CHAPTER V

CONCLUSION AND SUGGESTIONS

This chapter discusses several conclusions drawn from a series of studies that have been conducted to provide an overview of the topic and the proposed method. This chapter also presents several suggestions that may be used for future research.

5.1. Conclusion

Some conclusions that can be drawn after conducting a series of tests and research include :

1. All three GRU-TPE models achieved very good accuracy on the test data. All model scenarios produced MAPE values below 1%, namely, S1-GRU-TPE-Uni at 1.17961% (0.6673%), S2-GRU-TPE-Bi at 2.2657% (0.8401%), and S3-GRU-TPE-Tri at 1.6423% (0.6064%). This result far exceeds the good accuracy threshold (MAPE < 10%) used in commodity price prediction, indicating that all three models are suitable to be used as decision support tools.
2. TPE optimization with 100 trials per scenario consistently identified efficient hyperparameter configurations. TPE tended to select an architecture with one GRU layer for this medium-scale dataset, confirming that simpler models are often more effective than overly complex models under limited data conditions.
3. Adding the days_to_holiday feature (a quantitative variable representing the temporal distance to holidays) significantly improved the accuracy. The trivariate model GRU-TPE-Tri (S3) achieved MAE 0.011771 (Rp164.80) and MAPE 1.6423% (0.6064%), outperforming the univariate baseline model by 9.51% and 9.12 %, respectively. Conversely, adding only the binary is_holiday feature (S2) did not improve the accuracy and slightly reduced it, indicating that a quantitative temporal representation is more informative than a binary flag.

4. Best model: GRU-TPE-Tri (S3) with a configuration of 64 GRU units, 1 layer, dropout rate of 0.1, learning rate of 0.003101460711036567, and batch size 64. With a MAPE of 1.6423% (0.6064%) and an average prediction error of approximately Rp165/kg, this model has strong potential for implementation as a data-driven price prediction system in the SIMPONI-Ternak platform in Sidoarjo Regency. The GRU-TPE-Tri model also proved superior to LSTM without optimization, with an MAPE improvement of 16.35%, demonstrating the real contribution of TPE optimization to the model performance.
5. The validated GRU-TPE-Tri model was successfully implemented into an interactive web application based on streamlit as a price prediction system prototype that can be operated directly by non-technical users.
6. This study successfully (1) built a daily egg price prediction model based on GRU with TPE optimization, (2) demonstrated that the dtoh_norm feature significantly improved the accuracy compared to a model without calendar features, (3) produced a model with MAPE 0.6064%, which is highly accurate for operational planning, and (4) recommended the GRU-TPE-Tri model as the production model. (5) The best model was implemented in a Streamlit-based web application as a prototype.

5.2. Developer Suggestion

1. In subsequent research, experiments can be conducted with varying window lengths (7, 14, 21, 30) and more complex architectures (bidirectional GRU, stacked GRU with 2–3 layers, GRU with attention mechanism, or hybrid GRU-CNN).
2. Exogenous variables can be supplemented with monthly inflation data, feed prices (corn, soybean), Rupiah to dollar exchange rate, government reference prices, and weather data (temperature, rainfall) that may affect egg production and demand.
3. The performance of GRU-TPE can be compared with other methods, such as statistical methods (ARIMA, SARIMA), machine learning models (XGBoost, Random Forest, SVR), and other deep learning models (LSTM,

CNN, Transformer) to gauge relative advantages.

4. Models for 3-, 7-, and 14-day ahead predictions can be developed using recursive forecasting, direct forecasting, or sequence-to-sequence approach with a decoder..
5. The Streamlit web application developed as a prototype in this study can be further developed into a production-ready system.