CHAPTER V
CLOSING

5.1. Conclusion

Based on a series of experiments and analyses, several key conclusions can be drawn:

1. The XGBoost model with model parameters n_estimators=500, learning_rate=0.05, max_depth=5, subsample=0.8, colsample_bytree=0.8, random_state=42 produced the lowest error values across all evaluation metrics, namely RMSE, MAE, and MAPE. The best performance was achieved in the 6-month data set scenario with an 80:20 data split, with an RMSE of 0.52, MAE of 0.40, and MAPE of 1.42%. This indicates that the XGBoost model is highly effective in capturing the fluctuation patterns of red chili pepper prices, especially when supported by sufficient data and a larger proportion of training data. Thus, it can be concluded that ensemble learning-based approaches like XGBoost have good generalization capabilities in the case of time series prediction of food commodity prices.
2. The LSTM model with model parameters epoch=50, batch_size=16, and verbose=1, representing deep learning, demonstrated quite competitive performance, but still below that of XGBoost. In some scenarios, particularly the 3-month dataset with an 80:20 split, the LSTM was able to produce relatively low error values (RMSE 1.74 and MAPE 6.38%). However, LSTM performance tended to be unstable as the data volume increased, such as in the 6-month and 1-year datasets. This indicates that although LSTM is designed to handle sequential data, its performance is highly dependent on parameter tuning, data quality, and the complexity of the patterns present in the data. In other words, without adequate optimization, the LSTM is unable to outperform tree-based models like XGBoost in the context of this study.
3. The Neural Prophet model, with the parameters yearly_seasonality=True, weekly_seasonality=True, and daily_seasonality=True, demonstrated the lowest performance among the three models. This is evident from the very high error values, especially on the 3-month dataset, with a MAPE exceeding

1000%. Despite improvements on the 6-month and 1-year datasets, the resulting error values were still significantly higher than those of XGBoost and LSTM. This phenomenon indicates that Neural Prophet is less able to adapt to the characteristics of red chili price data, which tends to fluctuate and exhibit complex non-linear patterns. Furthermore, limitations in parameter configuration and a suboptimal training process likely impacted the model's performance.

4. Based on the overall analysis, it can be concluded that model selection significantly influences price prediction accuracy. XGBoost proved to be the best model in this study, providing the most accurate and stable prediction results. Furthermore, variations in data length and data split proportions also significantly impact model performance, with longer datasets and a larger proportion of training data tending to yield better performance.

5.2. Recommendations

5.2.1. Practical Recommendations

1. For Regional Governments (Disperindag and East Java Agriculture Office)

The results of this study can be used to develop a data-driven food price prediction system. By utilizing the LSTM model, the government can conduct distribution planning, stock control, and price intervention more effectively, especially ahead of periods with high inflation risk.

2. For the Ministry of Agriculture and State-Owned Food Enterprises

It is recommended to integrate chili price prediction results into national price monitoring platforms such as the Food Price Panel and Siskaperbapo, so that predictive information can assist strategic decision-making in maintaining price and supply stability.

3. For Farmers and Market Actors

Short-term prediction results can serve as a decision-making tool to determine optimal planting, harvesting, and distribution times. This way, farmers can reduce the risk of losses due to unexpected price fluctuations.

4. For the Private Sector and Agritech Startups

The model developed in this research can be adopted in the form of an AI-based digital application that provides commodity price forecasting features. This type of innovation can strengthen the smart agriculture ecosystem in Indonesia.

5.2.2. Academic Recommendations

1. Future research is recommended to incorporate external variables such as rainfall, temperature, production volume, and logistics data. By adding these factors, the prediction model can reflect more realistic market conditions and provide more comprehensive results.
2. Future research is recommended to explore combined methods such as LSTM–XGBoost or LSTM–Prophet to combine the advantages of high accuracy of deep learning models with the interpretability of statistical models. This hybrid approach has the potential to produce more stable and understandable prediction models.
3. Future research is recommended to expand the study to other regions in Indonesia and apply it to other commodities such as shallots, rice, or curly chilies to enrich the literature and test the model's generalizability across various national agricultural contexts.
4. Future research is recommended to test the model's stability over a long-term prediction horizon (more than one year) by considering the impact of policies, climate extremes, and global food price trends.
5. Further research is recommended to improve transparency and user trust. Further research should consider using explainable artificial intelligence approaches such as SHAP (SHapley Additive explanations) to make prediction results more easily explainable from an economic and public policy perspective.